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Study of the application of a decision support approach based on classical physics principles for managing supply chain risks and opportunities within its immersive performance management cockpit

Thibaut Cerabona

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HAL Id: tel-04368478

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THÈSE



en vue de l'obtention du

DOCTORAT DE L'UNIVERSITÉ DE TOULOUSE

délivré par
IMT – École Nationale Supérieure des Mines d'Albi-Carmaux

présentée et soutenue par
Thibaut CERABONA

le 16 mai 2023

Study of the application of a decision support approach based on classical physics principles for managing supply chain risks and opportunities within its immersive performance management cockpit

École doctorale et discipline ou spécialité :
EDSYS : Génie Industriel et Informatique

Unité de recherche :
Centre Génie Industriel, IMT Mines Albi

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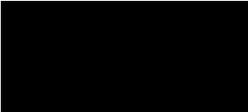
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Abstract

Due to their complex networked nature of diverse interconnected and interdependent actors, supply chains have never been more prone and fragile to instability, which has been generated by a massive increase in natural and man-made disasters over the past decades and is becoming the norm. It has become impossible to ignore and eliminate the instability that exists. Being able to cope with this instability becomes an inescapable challenge and a strong expectation of managers. To meet this need, our works study the applicability of the Physics of Decision (PoD) approach, an innovative approach to decision support based on the laws of motion of classical physics. In this approach the focus is on developing a theoretical and mathematical framework to model the impact of risks and opportunities disrupting a supply chain as physical forces, deviating it like an object from its performance objectives in its multidimensional performance framework, built from its quantitative key performance indicators. This strong connection between the achievement of the performance objectives of a supply chain and its exposure to risks and opportunities through the use of physical laws is a strong contribution of the PoD approach. It allows (1) to examine the evolution of the supply chain in its performance framework through a kinematic analysis of its multidimensional performance trajectory and (2) to propose a reactive and predictive analysis based on the identified physical forces. Thus, being able to assess and formalize these deviation forces is one of the major challenges for the application of the PoD approach. Due to the unpredictable and unquantifiable nature of disruptions, supply chain risk and opportunity management cannot simply list the forces impacting it. In this highly volatile environment, supply chains need to build resilience (their ability to resist, adapt and respond to disruptions). In the literature, two definitions of supply chain resilience can be distinguished: engineering resilience (the speed of return to equilibrium) and ecological resilience (the amount of extrinsic forces it is able to withstand). Our research seeks to investigate the contributions of the PoD approach to measure in a single approach these two fundamental views of resilience, which to our knowledge has never been proposed. The contributions of the PoD approach also lie in the mastery of the performance framework (seen as a space at the heart of the decision process) and the theoretical calculation of the overall performance of a supply chain observed as a multidimensional trajectory. However, for systems such as supply chains, it is rare for managers to limit themselves to the observation of three indicators. It is therefore imperative to find a way to make these results easy to handle and visualizable in a more than three-dimensional framework. Virtual reality is the solution being explored

to immerse decision-makers in a virtual version of the performance framework, in which they can visualize and interact with trajectories and forces, opening the door to a new generation of performance dashboards.

Keywords: Physics of decision, Supply chain management, Risk and opportunity, Resilience measurement, Virtual Reality, Performance management.

Résumé

En raison de leur nature complexe en réseau de divers acteurs interconnectés et interdépendants, les supply chains n'ont jamais été aussi sujettes et fragiles à l'instabilité, générée par une augmentation massive des catastrophes naturelles et anthropiques au cours de ces dernières décennies et devient la norme. Il est devenu impossible d'ignorer et d'éliminer l'instabilité qui y règne. Être en mesure de faire face à cette instabilité devient alors un défi incontournable et une attente forte des managers. Pour répondre à ce besoin, nos travaux étudient l'applicabilité de l'approche de la Physique de la Décision (de l'anglais *Physics of Decision*, *PoD*), une approche innovante d'aide à la décision basée sur les lois du mouvement de la physique classique. Dans cette approche l'accent est mis sur le développement d'un cadre théorique et mathématique pour modéliser l'impact des risques et des opportunités perturbant une supply chain comme des forces physiques, la déviant telle un objet de ses objectifs de performance dans son référentiel de performance multidimensionnel, construit à partir de ses indicateurs quantitatifs clés de performance. Cette connexion forte entre l'atteinte des objectifs de performance d'une supply chain et son exposition aux risques et aux opportunités à travers l'utilisation de lois physiques est une contribution forte de l'approche *PoD*. Elle permet (1) d'examiner l'évolution de la supply chain dans son référentiel de performance grâce à une analyse cinématique de sa trajectoire de performance multidimensionnelle et (2) de proposer une analyse réactive et prédictive sur la base des forces physiques identifiées. Ainsi, être capable d'évaluer et de formaliser ces forces de déviation est l'un des défis majeurs pour l'application de l'approche *PoD*. En raison de la nature imprévisible et non quantifiable des perturbations, la gestion des risques et des opportunités des supply chains ne peut se contenter de dresser une liste des forces l'impactant. Dans ce contexte de forte instabilité, les supply chains se doivent de renforcer leur résilience (leur capacité à résister, à s'adapter et à répondre aux perturbations). Dans la littérature, deux définitions de sa résilience se distinguent : la résilience technique (la rapidité de retour à l'équilibre) et la résilience écologique (la quantité de forces extrinsèques qu'elle est capable de supporter). Nos travaux de recherche cherchent à étudier les apports de l'approche *PoD* pour mesurer en une seule approche ces deux visions fondamentales de la résilience des supply chains, ce qui à notre connaissance n'a jamais été proposé. Les apports de l'approche *PoD* réside également dans la maîtrise du référentiel de performance (un espace au cœur du processus de décision) et le calcul théorique de la performance globale d'une supply chain observée comme une trajectoire multidimensionnelle. Cependant pour les supply chains, il est rare que les managers se limitent à observer trois indicateurs. Il est donc

impératif de trouver un moyen de rendre ces résultats manipulables et visualisables dans un référentiel à plus de trois dimensions. La réalité virtuelle est la solution explorée pour immerger les décideurs dans une version virtuelle du référentiel de performance, dans laquelle ils peuvent visualiser et interagir avec les trajectoires et les forces, ouvrant la porte à une nouvelle génération de tableau de bord de performance.

Mots-clés :Physique de la décision, Gestion des supply chains, Risque et opportunité, Mesure de la résilience, Réalité virtuelle, Gestion de la performance.

Résumé long en français

En raison de leur nature complexe en réseau de divers acteurs interconnectés et interdépendants, les chaînes d’approvisionnement (appelées aussi supply chains) n’ont jamais été aussi sujettes et fragiles face à l’instabilité, générée par une augmentation massive des catastrophes naturelles et anthropiques au cours de ces dernières décennies (Nakano et al., 2020; Wagner et al., 2010). Il donc est devenu impossible d’ignorer et d’éliminer l’instabilité qui y règne et devient la norme (Benaben et al., 2021; Taleb, 2007; Taleb, 2014). Être en mesure de faire face à cette instabilité devient alors un défi incontournable et une attente forte des managers. Etudier la manière dont les chaînes d’approvisionnement peuvent gérer les perturbations émanant de cette instabilité est alors devenu un sujet important tant pour les universitaires que les industriels (Sabahi et al., 2020).

Face à la complexité des chaînes d’approvisionnement modernes, choisir la bonne pratique de gestion des risques parmi la diversité d’approches proposées par la littérature n’est pas une tâche aisée (Ebrahimi et al., 2012). Les pratiques et outils traditionnels ne semblent plus efficaces face à un tel niveau de complexité et d’instabilité, ce qui crée un besoin pour des modèles dynamiques capables de considérer le dédale d’interactions caractérisant les chaînes d’approvisionnement et les sources des perturbations l’impactant (Colicchia et al., 2012). Les approches traditionnelles de gestion des risques ne sont pas assez évolutives pour répondre aux besoins en la matière pour des systèmes aussi complexes que les chaînes d’approvisionnement (Wieland et al., 2021).

Il est alors important pour les gestionnaires de développer de nouvelles mentalités sur la façon de gérer les chaînes d’approvisionnement (Adobor et al., 2018), et tout particulièrement les risques et l’instabilité, afin de prendre la pleine mesure du dynamisme des chaînes d’approvisionnement (des systèmes soumis à des changements et à des évolutions permanentes). A l’heure où l’instabilité devient la norme, les gestionnaires sont amenés à prendre des décisions dans des circonstances de plus en plus complexes (des conditions évoluant rapidement, un système dynamique, des objectifs incertains, des délais serrés, un manque de partage d’information entre des parties prenantes diversifiées, des ressources limitées, etc.), ce qui rend les techniques traditionnelles et standardes d’analyse et de prise de décision trop simplistes pour faire face à la complexité des problèmes modernes (Zhengping et al., 2013). Il est donc nécessaire de mettre en place et de développer des réflexions innovantes, des modèles de simulation et des méthodes nouvelles (Linkov et al., 2014).

PoD : une approche basée sur les lois de la physique pour la gestion des risques et opportunités

Pour répondre à ce besoin, nos travaux testent et évaluent l'application d'une nouvelle méthodologie d'aide à la décision, l'approche de la **Physique de la Décision** (de l'anglais *Physics of Decision*, PoD), décrite dans le Chapitre 1, dans le cas de la gestion (l'anticipation et le contrôle) des potentialités (risques et opportunités) impactant les chaînes d'approvisionnement. Cette approche, de par notamment les travaux réalisés par le laboratoire commun SCAN, souhaite se positionner au sommet des outils d'aide à la décision dans un contexte d'instabilité. Pour ce faire, cette approche cherche à introduire les concepts de la physique classique dans le domaine de la prise de décision et la gestion des potentialités, en proposant un système d'aide à la décision fondé sur des analogies avec les lois de la physique du mouvement, afin d'anticiper et naviguer entre les potentialités.

Son inspiration de la physique dans la définition de ses concepts amène l'approche PoD à modéliser l'impact des potentialités sous la forme de forces physiques, qui poussent ou tirent le système (une chaîne d'approvisionnement par exemple), tel un objet dans son espace de performance multidimensionnel, dans des mouvements qui le rapprochent ou l'éloignent de sa zone cible de performance (zone que cherche à atteindre les managers). Elle est construite à partir des objectifs fixés pour les valeurs quantitatives des KPIs (Key Performance Indicators), qui servent également de dimensions au référentiel orthonormé qu'est l'**espace de performance** (illustré en Figure 1.7). Cette connexion forte entre l'atteinte des objectifs de performance d'une chaîne d'approvisionnement et son exposition aux potentialités à travers l'utilisation de lois physiques est une contribution forte de l'approche PoD. Elle permet (1) d'examiner l'évolution de la chaîne d'approvisionnement dans son référentiel de performance grâce à une analyse cinématique de sa trajectoire de performance multidimensionnelle et (2) de proposer une analyse réactive et prédictive sur la base des forces physiques identifiées. Ainsi, être capable d'évaluer et de formaliser ces forces de déviation est l'un des défis majeurs pour l'application de l'approche PoD.

Sur la base des concepts précédents, l'espace de performance est vu comme un référentiel dédié à la prise de décision. Cependant, la prise de décision ne se limite pas à activer différentes forces, il faut également être capable d'offrir aux décideurs la possibilité de générer des forces de par leurs décisions, via l'activation d'attributs (des paramètres du système), servant de leviers décisionnels. Ainsi l'approche PoD nécessite un second espace orthonormé, l'**espace de description** (illustré en Figure 1.6), qui porte sur les attributs du système et les caractéristiques de son environnement. L'objectif de cet espace est de comprendre les changements potentiels que le système et son environnement peuvent subir.

Ces deux espaces permettent donc de séparer la performance du système de ses attributs et caractéristiques (paramètres de son environnement), afin d'être en mesure de décomposer autant que possible les variations des paramètres du système impliqués dans une décision et les choix pris par les décideurs pour atteindre les objectifs de performance fixés. Malgré cette décomposition, ces deux espaces sont interconnectés par des équations reliant les paramètres du système et les caractéristiques de son environnement à sa performance. Être en mesure de définir ou d'estimer ces relations représente un challenge dans l'application de l'approche PoD (dans nos travaux, ces relations ont été estimées à l'aide de modèles de simulation).

Extension des concepts de l'approche PoD pour la mesure de la résilience

L'analyse des risques est l'approche dominante de la prévention des défaillances dans l'ingénierie (Park et al., 2013). Comme présenté dans le Chapitre 1 (qui fournit une analyse riche de la littérature sur la gestion des risques), le processus de gestion des risques comprend différentes phases (illustrées dans la section 1.2) et commence généralement par une phase d'identification des différents dangers pouvant impacter le système, un exercice qui pose problème pour la gestion des systèmes complexes évoluant dans un environnement instable et aux menaces émergentes qui peuvent être inconnues (Park et al., 2013). En effet, en raison de la nature imprévisible et non quantifiable des perturbations, la gestion des risques des chaînes d'approvisionnement ne peut se contenter de dresser une liste des forces l'impactant. Généralement les événements les impactant sont les plus difficile à prédire.

Dans de tels systèmes les risques émergent en raison des relations non linéaires entre les composants et les processus du système, de la dépendance des décisions et de la réponse non stationnaire du système à une perturbation, dont l'apparition et l'impact sur ces systèmes sont stochastiques (Park et al., 2013). Ainsi la vulnérabilité de ces systèmes évolue dans le temps et de manière inattendue, les dangers émergents ne pouvant bien souvent n'être observés qu'une fois leur réalisation (Park et al., 2013). Face au caractère imprévisible et inconnaissable des perturbations (qui plus est dans un environnement instable), les chaînes d'approvisionnement se doivent de renforcer leur **résilience**, définie comme la capacité d'une entreprise à survivre, à s'adapter et à se développer en période incertaine (Chowdhury et al., 2017; Fiksel, 2006). Préconisée dans de nombreux domaines comme un remède pour faire face à des situations dynamiques et incertaines, la résilience est ainsi devenue extrêmement importante dans le domaine de la gestion des chaînes d'approvisionnement, comme en témoigne l'explosion de travaux sur ce sujet (illustrée en Figure 2.1).

Afin d'avoir un aperçu des concepts proposés dans ces travaux, le Chapitre 2 présente dans un premier temps une analyse fournie de la littérature sur le concept de résilience et sur les moyens de la mesurer. Cette revue de la littérature est effectuée principalement dans le contexte de la gestion des chaînes d'approvisionnement, mais elle est également élargie à des domaines connexes (la résilience étant un concept multidisciplinaire). Cette étude de la littérature met en avant qu'il n'existe aucune définition unanime du concept de résilience, même si des caractéristiques communes peuvent se dégager : l'existence d'une perturbation (plutôt imprévisible et importante), l'évolution du comportement du système dans le temps (avant, pendant et après) jusqu'à retrouver un état stable en termes de performance (identique ou non à son niveau de performance post-perturbation). Les définitions du concept de résilience semblent également s'accorder sur le fait qu'elle présente trois étapes essentielles : la préparation, la réponse et le rétablissement.

Cette analyse de la littérature met également en avant l'importance de considérer deux visions différentes de la résilience pour les chaînes d'approvisionnement : la **résilience technique** et la **résilience écologique**. Ces deux visions, issues des travaux d'Holling (1973), diffèrent dans leurs objectifs de conception et de gestion, notamment dans le nombre d'états d'équilibre considérés. La résilience technique ne considère qu'un seul état d'équilibre possible, selon cette vision, un système est alors résilient s'il est capable de revenir à cet état d'équilibre après une perturbation (dans un temps acceptable). La résilience écologique, quant à elle, se concentre davantage sur la capacité d'absorption

des changements dus à une perturbation, entraînant des déplacements du système dans différentes régions de l'espace, vers différents états d'équilibre.

Les concepts autour de la résilience des chaînes d'approvisionnement venant d'être résumés, se pose maintenant la question de **comment mesurer ces deux visions de la résilience** ? Une question qui reste encore floue (Kamalahmadi et al., 2016), en effet la littérature sur la gestion de la résilience des chaînes d'approvisionnement s'intéresse peu à la manière de la mesurer (Han et al., 2020; Kamalahmadi et al., 2016; Spiegler et al., 2012). Du point de vue de l'ingénierie, quantifier la résilience d'un système implique de mesurer sa performance dans le temps, en se focalisant tout particulièrement sur sa performance avant et après une perturbation (Bruneau et al., 2003; Zobel et al., 2021).

A ce jour, aucun accord sur un modèle de mesure de la résilience ne semble avoir été trouvé dans la littérature, l'évaluation de la performance de la résilience de la chaîne d'approvisionnement a été étudiée de manière structurelle, en utilisant les dimensions ou les différentes phases de la résilience. La plupart des mesures proposées dans la littérature sont créées à partir de fonctions d'un ou plusieurs indicateurs issus des différentes phases du système suite à une perturbation (comme illustrés par la Figure 2.3). Ces mesures comprennent principalement le temps de récupération, ainsi que la performance perdue sur une période de temps (par exemple l'aire bleue sur la Figure 2.3) ou à des instants spécifiques. En règle générale, la perte de performance se mesure comme la différence entre la performance après une perturbation et la performance attendue ou de référence (la performance optimale en l'absence de perturbation).

Plusieurs approches ont été développées pour mesurer la résilience en fonction du temps, soit selon des ratios entre la performance restaurée et la performance perdue, soit selon la modélisation de plusieurs trajectoires de performance possibles prenant en compte les effets de l'incertitude (Zobel et al., 2021). Parmi toutes ces approches, dans le cas de l'évaluation de la **résilience technique**, une approche largement utilisée dans la littérature est le **triangle de résilience**, proposé par Bruneau et al. (2003). Cette approche propose d'estimer la résilience d'un système à partir de la mesure de l'aire du triangle de résilience (illustré en Figure 2.4). Cette mesure repose sur le fait qu'à tout moment, la performance réelle ou potentielle d'un système peut être mesurée et caractérisée comme un point ou une trajectoire dans l'espace multidimensionnel de ses indicateurs de performance (Bruneau et al. 2003). Elle offre ainsi une mesure statique de la résilience s'appliquant à tout type de système.

Bien qu'il y ait des avantages à utiliser et mesurer la résilience à partir d'une seule valeur, cette technique présente certaines limites :

- Des combinaisons très différentes de perte de performance et de temps de rétablissement pourraient correspondre exactement à la même valeur de l'aire du triangle de résilience et donc à un niveau de résilience équivalent.
- Elle ne peut être mesurée que si le système revient à son état d'équilibre initial.
- Il n'y a pas non plus de proposition d'intervalle de temps sur lequel mesurer le triangle de résilience, ce qui rend difficile la comparaison de cette mesure pour un même système soumis à différentes perturbations.

Les études présentées dans l'analyse de la littérature proposée dans le Chapitre 2 (notamment les différents travaux sur le triangle de résilience) se concentrent principalement sur une évaluation de la résilience technique, occultant complètement l'évaluation de la résilience écologique. A notre connaissance, aucune mesure de la résilience écologique n'a été proposée dans la littérature. En effet, la diversité proposée par ces deux visions de la résilience des chaînes d'approvisionnement se retrouve rarement dans les travaux et les définitions proposés dans la littérature (Wieland et al., 2021). De ce fait, certains auteurs, comme Wieland (2021), proposent de réinterpréter la chaîne d'approvisionnement, en l'étudiant comme un système organique, afin de prendre la pleine mesure de sa complexité. L'idée derrière cette réinterprétation n'est pas de rejeter l'excellent travail lié à l'interprétation technique de la résilience (dominant une grande partie des travaux actuels), mais d'y ajouter les concepts de la résilience écologique, afin de bénéficier de leurs apports pour faire face au comportement non linéaire, incertain et souvent surprenant des chaînes d'approvisionnement (Wieland et al., 2021). Ainsi au lieu de mesurer la résilience par le temps nécessaire pour revenir à l'équilibre, le concept de résilience écologique propose de la mesurer par la quantité de forces intrinsèques, l'intensité de la perturbation qu'un système peut supporter avant qu'il n'échappe à tout contrôle.

Malgré cette réinterprétation de la gestion des chaînes d'approvisionnement, il est important de conserver les apports de ces deux types de résilience. Cependant à notre connaissance aucune approche ne permet de mesurer la résilience des chaînes d'approvisionnement en combinant ces deux visions de la résilience, offrant ainsi des perspectives d'étude pour l'approche PoD, notamment en cherchant à répondre à cette question de recherche (l'objet des travaux présentés dans le Chapitre 2) : **comment développer les capacités de résilience des chaînes d'approvisionnement (sa gestion et sa mesure) en utilisant une approche cinétique de type PoD ?**

Les principes de l'approche PoD sont directement issus de la physique classique et notamment des concepts issus du **principe fondamental de la dynamique**. Dans cette loi, Newton affirme que la résultante des forces exercées sur un objet (c'est-à-dire la force équivalente à la somme vectorielle de toutes les forces exercées sur cet objet) est directement proportionnelle à l'accélération d'un objet produite par la force résultante et la masse de l'objet. Ainsi, dans une perspective d'étudier la résilience des chaînes d'approvisionnement selon une approche cinétique, les points suivants expliquent comment lier les concepts de gestion de la résilience aux notions de la physique telles que le *déplacement*, la *vitesse* et l'*accélération* :

- Le *déplacement* est équivalent aux variations des valeurs d'un KPI selon l'axe de l'espace de performance auquel il est associé. Le déplacement permet donc de mesurer la performance perdue ou gagnée suite à une perturbation. Cette mesure est très proche des techniques proposées dans la littérature pour mesurer la résilience technique, à savoir la méthode de calcul d'aire, comme par exemple le triangle de résilience. Le déplacement fournit une mesure dynamique de la résilience à chaque instant, tandis que l'aire fournit une mesure de la résilience sur une plage de temps choisie.
- La *vitesse* est la dérivée de ce déplacement sur un intervalle δt . Elle mesure la croissance de la chaîne d'approvisionnement. Son signe indique si la croissance est positive ou négative du point de vue du KPI observé. L'évolution de son

signe va permettre de mieux appréhender et comprendre sa dynamique interne (illustrée en Figure 2.8), notamment comment elle s'organise pour absorber au mieux une perturbation (toutes les phases d'alternance de signe de la vitesse). Elle offre ainsi la possibilité de suivre la progression ou la tendance de la chaîne d'approvisionnement vers une destination donnée, généralement ses objectifs de performance (ce qui implique de connaître la zone cible de performance, afin de savoir si la vitesse va dans « le bon sens »). Bien que la résilience ait été très bien conceptualisée dans la littérature, très peu de techniques permettent d'apprendre des choses sur les capacités d'une chaîne d'approvisionnement à gérer différentes phases de croissance et de transformation. La vitesse offre donc une perspective intéressante dans l'étude de la résilience.

- L'*accélération* est la dérivée de la vitesse sur un intervalle δt . Sa norme, permet ainsi de quantifier l'ampleur de la potentialité qu'une chaîne d'approvisionnement peut tolérer. Être capable de la quantifier est très important pour mesurer la résilience d'un point de vue écologique. Etudier cette vision de la résilience selon le prisme de la physique et plus particulièrement de la cinétique, permet de définir la résilience comme l'intensité de la force générée par une potentialité que le système peut absorber avant qu'il ne se déplace d'un état d'équilibre stable à un autre. Dans le cadre des travaux présentés, nous proposons d'utiliser l'accélération pour estimer l'intensité de la force générée par une potentialité (en considérant la masse du système constante et en la négligeant comme facteur de proportionnalité).

Sur la base de ces concepts et de la volonté de l'approche PoD de modéliser la performance d'un système comme une trajectoire pluridimensionnelle, deux indicateurs de mesure, la **distance** et le **cône de résilience**, sont proposés pour quantifier les deux types de résilience (technique et écologique). La mesure de distance proposée (illustrée en Figure 2.9) s'inspire du triangle de résilience et de la mesure de la résilience associée (la surface de ce triangle), en sommant les distances entre les trajectoires de performance, afin d'estimer la surface entre ces deux trajectoires (dans le cas où les intervalles de temps entre chaque mesure de distance sont suffisamment petits selon le système étudié et les KPIs considérés). Afin de rendre la mesure proposée comparable pour différents systèmes, l'intervalle de temps entre chaque mesure de distance pourra être calculé comme une fraction d'un temps de rétablissement maximal admissible (comme proposé par R. Li et al., 2017; Zobel, 2010), à définir en fonction du système étudié. Inspiré du triangle de résilience, la mesure de distance en étend également les concepts, en permettant d'évaluer la résilience sur plus de dimensions que le triangle de résilience unidimensionnel, en particulier grâce au fait que l'espace de performance peut être composé avec autant de dimensions que le nombre de KPIs à mesurer (même s'il n'est pas possible de les visualiser au-delà de trois dimensions).

La seconde mesure définie propose de mesurer la résilience écologique à partir du volume d'un hyper-cône (illustré en Figure 2.11), modélisant l'espace défini par l'ensemble des contre-forces (actions correctives et décisions) activables à chaque instant. Avec cette nouvelle mesure de la résilience, les décideurs n'auront plus besoin d'attendre la réalisation d'une perturbation et le retour à l'équilibre du système pour être en mesure d'évaluer la résilience, contrairement aux méthodes précédentes (le calcul de distances et le triangle de résilience). Cependant, pour être applicable et robuste, cette mesure de la résilience implique :

-
- une grande connaissance du système et de son environnement, afin d'être en mesure d'identifier toutes les forces correctrices gérables à chaque instant ;
 - la capacité d'estimer le plus précisément possible leurs impacts (surement pour la plupart des forces à partir de données antérieures ou simulées) ;
 - être en mesure de définir et mesurer le volume globale résultant de ces forces (qui dans un espace de plus de trois dimensions nécessite des développements).

Ces besoins, pour rendre effective cette mesure, posent également la question de l'indépendance des forces et de leurs critères de sommabilité, deux challenges importants au cœur de cette approche.

Vers un espace immersif pour la pilotage des chaînes d'approvisionnement

Les précédents travaux sur la gestion de la résilience des chaînes d'approvisionnement, ainsi que l'état de l'art sur la gestion des potentialités présenté dans le Chapitre 1 démontrent la nécessité de développer un espace permettant d'explorer et de visualiser l'évolution de la performance, dont les apports doivent permettre de regrouper en un seul espace la gestion des potentialités et de la performance des chaînes d'approvisionnement, afin de corréliser les stratégies de gestion des potentialités et l'atteinte des objectifs de performance prédéfinis.

Pour répondre à ce besoin, l'approche PoD s'appuie sur l'espace de performance, un espace de visualisation (un élément primordial pour les décideurs) et de pilotage de la performance, dédié à la prise de décision. Il se positionne comme un cadre de référence pour l'étude et la modélisation des conséquences des différentes potentialités, sous la forme de forces physiques déviant la trajectoire de performance multidimensionnelle d'une chaîne d'approvisionnement (dont le calcul théorique est l'une des contributions de l'approche PoD), par rapport à l'atteinte de ses objectifs. Compte tenu de son fort potentiel, l'objectif est de soutenir la prise de décision des managers et le processus de gestion des risques, en utilisant cet espace de performance pour leur offrir un tableau de bord de performance dynamique, interactif et immersif pour la gestion de l'instabilité des chaînes d'approvisionnement.

Afin d'exploiter pleinement le potentiel de l'espace de performance et d'en faire le tableau de bord de performance de demain pour la prise de décision dans un contexte d'instabilité, plusieurs défis doivent être relevés :

- rendre les décisions potentielles explicables et actionnables pour les décideurs, c'est-à-dire trouver une solution permettant aux décideurs de manipuler et d'interpréter les concepts abstraits relatifs à l'application de l'approche PoD ;
- trouver une solution pour s'abstraire des limites de visualisation de l'espace de performance (une solution pour dépasser nos limites de visualisation à plus de trois dimensions), afin d'être en mesure de gérer le nombre potentiellement énorme de dimensions liées à la mesure de la performance des chaînes d'approvisionnement (il est facilement imaginable que les décideurs ne se limiteront pas à l'observation de seulement trois KPIs).

Compte tenu de ces deux besoins en termes d'interprétation de concepts abstraits et de visualisation, le Chapitre 3 se concentre sur la proposition d'une solution permettant de répondre à la cette question de recherche : **comment représenter, visualiser et piloter la performance d'une chaîne d'approvisionnement vue comme une trajectoire multidimensionnelle (définie par de nombreux KPIs et impactée par de nombreuses forces), afin d'en faire un outil d'aide à la décision exploitable de manière pertinente et ergonomique ?**

A partir de l'analyse de la littérature proposée dans le Chapitre 3, l'analyse immersive, à travers l'utilisation de la réalité virtuelle, semble être une solution pertinente pour répondre à ce défi. En effet, la réalité virtuelle offre de nombreux avantages :

- La réalité virtuelle permet de transformer des concepts abstraits en des objets visualisables et manipulables pour l'utilisateur (le décideur), à travers l'utilisation d'environnements virtuels suffisamment proches de la réalité.
- La réalité virtuelle permet ainsi d'immerger le décideur dans l'ensemble des données, améliorant grandement leur visualisation. L'analyse immersive offre aux utilisateurs une compréhension plus intuitive et complète de la situation. Les utilisateurs sont en mesure d'évoluer au sein des données, d'interagir avec elles (en les modélisant par exemple sous la forme d'objets flottant manipulables) et d'améliorer ainsi la compréhension des relations existantes entre elles (à travers l'utilisation de métaphores spatiales pour en réduire le degré d'abstraction).
- La réalité virtuelle introduit des notions plus intuitives de positionnement dans l'espace, ouvrant le champ à de nouvelles options de visualisation, tel que l'ajout du temps (par exemple sur l'axe horizontal), permettant ainsi de représenter l'occurrence de différentes situations par rapport à la distance avec cet axe (plus elle est proche de l'axe, plus elle est proche dans le temps).
- La réalité virtuelle offre également la possibilité de prendre des décisions à plusieurs, grâce à l'aspect multijoueur qu'elle apporte, et ce même si les décideurs ne se trouvent pas physiquement dans la même pièce. Elle améliore ainsi grandement la collaboration dans la prise de décision et le partage d'information.
- La réalité virtuelle permet également de participer au processus d'apprentissage du décideur dans la gestion d'un ensemble de décisions, en rejouant des scénarios passés (différentes stratégies face aux potentialités) et en tirant des enseignements (en testant ces différentes stratégies jusqu'à être en mesure d'en sélectionner la meilleure).

Bien qu'offrant de nombreux avantages, nous sommes pleinement conscients qu'ils existent actuellement des limites et des freins à l'application de la réalité virtuelle dans l'industrie, liés notamment aux coûts et aux matériels nécessaires. Cependant, nous voyons en la réalité virtuelle des analogies avec le développement des ordinateurs et de l'informatique. Dans les années 1950, la taille, le prix et les capacités des ordinateurs réduisaient toute application industrielle. Cependant, une fois sa taille réduite (pour être en mesure de tenir sur un bureau), ses capacités de calcul et de stockage augmentées et que des logiciels comme Word et Excel (pour ne citer qu'eux) ont été développés, l'ordinateur s'est largement démocratisé dans l'industrie. Nous pensons qu'il en sera de

même pour la réalité virtuelle, grâce aux travaux sur le métavers, qui conduiront à une démocratisation de son utilisation et au développement d'équipements. Ainsi l'objectif de ces travaux est de commencer à réfléchir à l'outil d'aide à la décision de demain, la réalité virtuelle étant devenue l'une des technologies fondamentales de l'industrie 4.0 (Alejandro Huerta-Torruco et al., 2022).

Ces travaux servent donc à poser les bases de notre vision du tableau de bord de performance du futur pour la prise de décision dans un contexte d'instabilité, à travers le développement de deux prototypes de réalité virtuelle (dont les fonctionnalités sont décrites dans la section 3.3). Ces deux prototypes ont été développés en utilisant le cadre Unity®, en partenariat avec la société *Immersive Factory*. Notre contribution majeure pour ces prototypes correspond à la sélection des éléments essentiels à visualiser et manipuler pour la prise de décision en situation incertaine.

Ainsi dans les environnements virtuels développés, l'utilisateur (le décideur) est plongé dans un espace dans lequel les concepts abstraits liés aux situations instables (risques ou opportunités) sont représentés sous la forme de sphères colorées, gravitant autour d'une ligne de temps, représentant également la performance optimale du système considéré. Dans ces environnements, toute l'abstraction présente repose sur le fait de ne gérer un système que par des combinaisons de déviations de sa trajectoire de performance de sa ligne optimale (une ligne droite infinie) suite à l'activation de potentialités. Le fort niveau d'interaction offert entre l'utilisateur et les objets modélisés devrait lui permettre de prendre la pleine mesure de la manipulation de la trajectoire de performance et des potentialités, qu'il pourra observer selon différents angles et points de vue. Le décideur pourra ainsi prendre pleinement conscience de l'impact d'une potentialité sur la trajectoire de performance et les objectifs associés. Dans ces environnements virtuels dédiés à la prise de décision, les décideurs peuvent expérimenter à loisir pour trouver la meilleure réponse possible à une potentialité parmi une sélection de scénarios prédéfinis (dont les micro-événements et les impacts sur la performance du système ont été obtenus grâce à des modèles de simulation développés sur le logiciel Anylogic©), afin d'atteindre les objectifs de performance fixés.

Il est important de souligner, que la contribution de nos travaux se limite à la seconde version du prototype, la première version étant réalisée lors des premiers travaux sur l'approche PoD et servant essentiellement dans ce manuscrit pour mettre en avant les directions de développement prises pour développer le tableau de bord de performance de demain (notamment la généralisation du prototype, c'est-à-dire la possibilité d'utiliser le second prototype pour n'importe quel cas d'étude grâce à l'utilisation de fichiers Excel décrits en Annexe E). Pour évaluer ces prototypes et les directions de développements prises, les deux prototypes sont évalués par le référentiel VEIM (un cadre évaluant la maturité des environnements de réalité virtuelle, développé par Congès, 2022) et à partir des 37 critères que doivent respecter un tableau de bord de performance (proposés par Bugwandeem et al., 2019).

Perspectives de recherche

Pour conclure, le Chapitre 4 dresse un ensemble de perspectives de recherche envisagées à la suite de ces travaux :

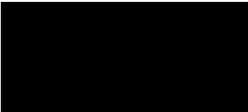
- L'usage des réseaux de neurones pour estimer les relations mathématiques existant entre l'espace de description et de l'espace de performance, à défaut du modèle

de simulation (l'approche utilisée actuellement) qui peut être fastidieux et consommateur de temps. L'utilisation de réseaux de neurones devrait permettre : (1) d'éviter de devoir formaliser et mettre en équation les forces générées par des potentialités, (2) d'augmenter le spectre d'étude (c'est-à-dire avoir plus de flexibilité dans l'étude de nouvelles potentialités) et (3) ainsi de prédire les futures trajectoires de performance pour une large gamme de potentialités.

- L'exploitation du concept de densité pour quantifier la facilité ou la difficulté d'accès à des zones pertinentes de l'espace de performance. Être en mesure de quantifier la densité impose de définir une fonction mathématique (propre à chaque système) pour quantifier le « coût » de déplacement vers ces zones. Cette fonction devra à minima lier et prendre comme contraintes le temps, les coûts et les degrés de liberté de chaque attribut à chaque instant (en se focalisant principalement sur les attributs pouvant servir de leviers décisionnels). Pour déterminer cette fonction des analogies avec la notion de travail des forces pourront être étudiées.
- L'exploitation de la trajectoire de performance pour définir des scénarios de potentialités à activer.
- La poursuite des analogies avec les lois de la Physique (dans les travaux présentés, seules des analogies avec la mécanique du point ont été proposées) et plus particulièrement avec la mécanique du solide (l'étude des propriétés de déformation et de plasticité d'un solide pourrait aider à évaluer la résilience d'un système).

Cependant, pour réaliser l'ensemble de ces perspectives, il est nécessaire de réaliser ces études pour des typologies de systèmes, impactés par des typologies de potentialités et de forces. L'obtention des données nécessaires pour réaliser ces études nécessitera de créer des modèles de simulation suffisamment exhaustifs et couvrants, mais également reconfigurables et modulaires (capables de s'adapter rapidement aux différentes configurations du système), afin d'être en mesure de formuler génériquement l'impact d'une perturbation donnée sur un système donné, sous la forme d'une fonction modélisant la force impactant sa trajectoire de performance.

Pour ce faire, les premiers travaux en cours de développement autour des prémices d'une vision atomique d'une chaîne d'approvisionnement basée sur le référentiel SCOR (décrit en Annexe B) sont introduits, afin de poursuivre les développements relatifs à l'approche PoD : trouver un moyen de formaliser des typologies de force et chercher un moyen d'estimer les variations de la masse d'une chaîne d'approvisionnement.



Acknowledgements

Avant de vous laisser découvrir les travaux exposés dans ce manuscrit, je tiens tout particulièrement à remercier toutes les personnes sans qui rien n'aurait été possible. Je veux parler des personnes qui ont initié ce beau projet et m'ont soutenu durant le long et parfois tortueux chemin qui conduit à la rédaction d'une thèse.

Mes premiers remerciements vont à mes encadrants et maîtres de thèse, Frédérick, Benoit et Matthieu. Ils sont à l'initiative de ce projet passionnant. Merci à vous trois, c'est un plaisir de travailler et découvrir le monde de la recherche à vos côtés. J'ai énormément appris grâce à vous. Merci beaucoup pour toutes les opportunités (la découverte d'Atlanta par exemple), les idées, le soutien, la confiance, la bienveillance et la liberté que vous m'avez apportés durant ce travail. Vous avez su me transmettre les joies de la recherche et m'aiguiller durant ces trois années, grâce à votre passion, vos conseils et vos esprits scientifiques aiguisés (amenant à des discussions challengeantes et motivantes, mais aussi à de nombreux commentaires toujours extrêmement pertinents lors de la rédaction de nos différentes publications). J'ai hâte de continuer notre collaboration sur de nouveaux projets. Ces quelques mots ne sauraient résumer l'ensemble du chemin parcouru au cours de ces trois années, ni ma reconnaissance et mon profond respect.

Ce travail n'aurait pas été possible sans le soutien de l'entreprise Scalian, qui l'a financé dans le cadre du laboratoire commun SCAN. C'est toujours un grand plaisir de travailler avec l'ensemble des équipes Scalian. Merci Julien, Jean-Philippe et Manon pour les discussions passionnantes que nous avons eues sur le sujet, mais aussi pour la liberté que vous m'avez laissée dans mes recherches.

Un chaleureux merci aux membres de mon jury de thèse, pour le temps consacré, leur gentillesse et tous les échanges passionnants qui ont eu lieu lors de ma soutenance et qui ont amené à de nouvelles perspectives de recherche. Un grand merci à Séverine Durieux, Maître de conférences à l'Institut Pascal, et Christopher Zobel, Professeur à Virginia Tech, pour avoir accepté de relire et rapporter mes travaux. Je tiens également à remercier Walid Klibi, Professeur à Kedge Business School, pour avoir présidé la soutenance, ainsi que Tina Comes, Professeur à Tu Delft, pour avoir accepté d'évaluer mes travaux. Merci également à Louis d'avoir accepté de faire partie de ce jury.

Merci beaucoup à tous les membres du Centre de Génie Industriel d'IMT Mines Albi pour l'ambiance et la bienveillance qui y règnent. Des petits morceaux de votre savoir ont inspiré mes travaux. Merci Nafe, mon compère de recherche, pour toutes nos

Acknowledgements

discussions sur l'approche présentée dans ce manuscrit. Merci à Paul et Audrey pour leur aide ô combien précieuse dans mes nombreuses batailles avec LaTeX. Sans oublier, Didier, pour la confiance qu'il m'a portée, en me confiant plusieurs enseignements.

Je n'oublie pas mes amis, qui ont toujours été présents pour me soutenir durant ces trois années.

Enfin, ma famille, mes parents et mon petit frère ont mes éternels remerciements. Sans eux, rien de tout ceci n'aurait été possible.

Merci à vous, lecteur, qui avez le courage de lire ce manuscrit. J'espère que sa lecture ne vous paraîtra pas fastidieuse et qu'elle ouvrira la porte à de futures discussions sur le sujet.



Introduction

In the middle of difficulty lies opportunity

Albert Einstein, *The ultimate quotable Einstein*

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Context

In today’s increasingly dynamic, uncertain and turbulent global environments (climate change, natural disasters, pandemics, etc.), instability is becoming the norm (Benaben et al., 2021; Taleb, 2007; Taleb, 2014). The Cambridge dictionary defines instability as “uncertainty caused by the possibility of a sudden change in the present situation”. In recent decades, natural and man-made disasters have increased exponentially around the world (Nakano et al., 2020; Wagner et al., 2010). Due to their complex networked nature, which brings together various interdependent and interconnected actors, supply chains are not immune to this instability and are confronted with numerous events that threaten to disrupt their operations and jeopardise their performance. The supply chain is a complex system built to manage, control and improve physical (a wide variety of products), money and information flows through all its stages, from suppliers to final customers (Hassan, 2006; Mouloudi et al., 2022; Prakash et al., 2017). A supply chain can be defined as a network of independent and interdependent entities (suppliers, manufacturers, transporters, distributors, wholesalers, retailers, customers), interconnected by different flows, which work together to ensure the functions of sourcing raw materials, transforming them into components and finished products, and distributing the finished products to customers (Lee, 1993; Mele et al., 2007), in the right quantities, at the right places, at the right time, and at minimal cost (Datta et al., 2011; Prakash et al., 2017). This network structure creates complex, non-linear and counter-intuitive links between actors (Choi et al., 2002; Manuj et al., 2008; Priya Datta

et al., 2007). This system evolves in a complex, hostile, dynamic and therefore unstable environment, generating numerous risks that can disrupt or interrupt the various links between actors and activities (Evrard Samuel, 2013; Mouloudi et al., 2022), particularly due to the cascading effects of its network structure and the dependencies this implies. Each actor in this network has different vulnerabilities, and different risk management perspectives and processes (Hearnshaw et al., 2013; Sabahi et al., 2020).

Thus, all actors in a supply chain are susceptible to disruptive events and risks (Carvalho et al., 2012; Knemeyer et al., 2009; Ponomarov et al., 2009; Soni et al., 2014). A supply chain is only as strong as its most vulnerable member (Gurtu et al., 2021). *Computer Sciences Corporation*, in its 2004 study, highlights this vulnerability of supply chains, for 60% of the companies surveyed, their supply chain is vulnerable to disruption (Sodhi et al., 2012b). The latest surveys show that the number of companies experiencing supply chain disruptions and breakdowns was five times higher in 2020 than in 2019, particularly following the Covid-19 crisis (Wicaksana et al., 2022). According to the *Business Continuity Institute* study (from 2019), 56% of global companies suffer supply chain disruptions every year (Katsaliaki et al., 2021). These disruptions can result in huge losses for companies, as has happened in recent decades to Boeing, Cisco or Pfizer, which suffered losses of \$2 billion, \$2.25 billion and \$2.8 billion respectively (Hult et al., 2010).

Driven by the globalisation of markets and increased pressure from the business environment, competition is no longer directly between companies but between supply chains themselves (Trkman et al., 2009). To deal with this pressure, the latest management methods developed advocate low inventory levels, levelled and just-in-time production, and precise scheduling of logistics operations to make supply chains more profitable and responsive (Katsaliaki et al., 2021), which does not help to facilitate their management. At the same time, the pressure to reduce costs has forced companies to outsource and relocate many production and research and development activities, and to source from low labour cost countries. Although these changes in the configuration of supply chains tend to make their operations more efficient in a stable environment, they also make them much more vulnerable and fragile (Wagner et al., 2008), especially when the environment becomes unstable. Globalisation, sustainability, customisation, outsourcing, innovation and flexibility are the main factors that have led to the acceleration of its complexity (Serdarasan, 2013) and only increase its exposure to risks, including those related to political and economic events (Harland et al., 2003).

Thus, supply chain managers have to analyse and adapt to increasingly complex situations. Faced with such a level of complexity, it has become impossible to ignore and suppress the instability and uncertainty that prevail in supply chains. According to (Helbing et al., 2006), it is difficult, if not impossible, to predict the impacts of risks or opportunities on modern supply chains. Supply chain managers then have no choice but to accept and deal with this instability (A. White et al., 2005). Managing instability therefore becomes a key expectation for them, with the aim of trying to take advantage of it or at least not suffer from it. To be able to take advantage of this instability and to manage a system as complex as supply chains, managers need to have knowledge about its network organisation and the business aspects of its operation (Persson, 2011). But also, to be able to identify and understand the causes of this instability and to determine its consequences on the supply chain activities (Cope et al., 2007). Herbert Simon (H. A. Simon, 1955), Nobel Prize in Economics, proposes in his model of bounded

rationality three essential steps for managing a system and making correct decisions in an unstable environment: *intelligence* (identifying the problem and defining the decision criteria), *design* (modelling, analysing and understanding the consequences of the different options) and *choice* (defining the mechanisms for selecting the best options). Among the main tools and approaches existing in the literature, dedicated to decision support, none of them allows to consider the three previous phases at the same time (Benaben et al., 2021), which creates a gap between the needs of managers to have tools allowing them to navigate in instability and the tools currently at their disposal.

General issue

Studying how supply chains can manage the disruptions emanating from this instability has therefore become an important topic for both academics and industry (Blackhurst et al., 2011; Craighead et al., 2007; Sabahi et al., 2020). Due to their unpredictable and unquantifiable nature, supply chains need to strengthen their ability to withstand the impact of disruptions and recover quickly (Brusset et al., 2017; Pettit et al., 2013; Pettit et al., 2010), *i.e.* build resilience. In the literature, supply chain resilience is defined as its adaptive capacity to prepare for unexpected and/or undesirable events, respond to disruptions and maintain the continuity of its operations (Barroso et al., 2011; Senna et al., 2020). Given its importance in supply chain management, resilience is of great interest, as evidenced by the explosion of research on this topic. Understanding how to measure and manage the ability of a supply chain to prepare for, respond to and recover from disruption has become fundamental (Adobor, 2019; Pettit et al., 2010; Ponomarov et al., 2009). In 2013, the *World Economic Forum* reported in its study the importance of resilience for supply chains, for 80% of the companies surveyed, its study has become a priority (Sabahi et al., 2020). Thus resilience is at the heart of the current supply chain management philosophy (Melnik et al., 2014) and complements traditional risk management processes (Fiksel, 2015). Developing resilience has even become a matter of survival for supply chains (Christopher et al., 2004b; Mena et al., 2020; Pettit et al., 2013), in the face of the significant impacts of disruptions in recent decades on business performance, financially, operationally and strategically (Craighead et al., 2007; Hendricks et al., 2005; C. S. Tang, 2006a). Faced with the need to develop resilient supply chains, the question arises:

Industrial Question

How to develop the resilience capabilities of supply chains? And more precisely, how to anticipate and control the impacts of risks and opportunities on a supply chain?

To meet the needs of decision makers in terms of tools and approaches capable of supporting their decisions in a context of instability, this manuscript proposes to study the application of a new and innovative approach for managing risks and opportunities in supply chains. This approach is called PoD, for *Physics of Decision*, and is introduced in the article “*A tentative framework for risk and opportunity detection in a collaborative environment based on data interpretation*” (Benaben et al., 2019). This approach seeks to extend the laws of classical physics to systems management science, particularly in the area of risk and opportunity management. In their most recent work, Benaben et al.

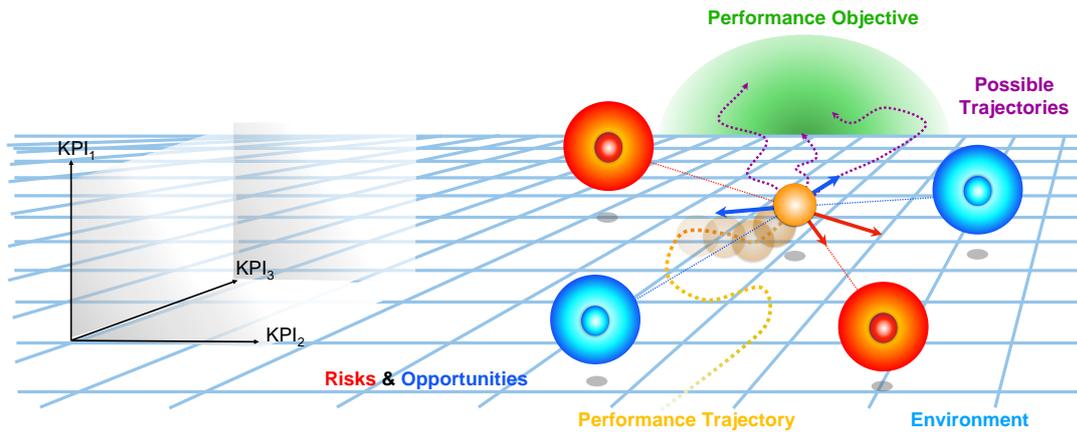


Figure 1 – General overview of PoD approach

(2021) formally define the basis of this approach, in which analogies with classical physics are used to anticipate and navigate risks and opportunities, based on the observation that instability is the new norm. With its innovative and original concepts, this approach wishes to position itself at the top of the decision support tools in a context of instability and uncertainty (Moradkhani et al., 2022a), in order to help managers try to take advantage of instability or at least not to suffer from it. This orientation in the choice of the study of this approach to manage supply chain risks and opportunities imposes the following question:

Is an approach based on analogies with classical physics a potential solution to enable better control and anticipation of risks and opportunities impacting a supply chain?

Inspired by classical physics in the definition of its concepts, the PoD approach models the impact of potentialities (risks, opportunities or decisions taken by managers) by physical forces (coloured vectors in Figure 1), which push or pull the supply chain in its performance framework, illustrated in Figure 1 (Benaben et al., 2020). This performance framework is a framework that aims to position the supply chain with respect to the dimensions of its key performance indicators (KPIs), which represent the evolution of its state over time and its objectives (Neely et al., 1995). The management of any system implies knowing in real time its state (Neely et al., 1995), which evolves according to the different efforts made or variables undergone in the achievement of predefined performance objectives (often evaluated by a set of KPIs). The evolution of the supply chain in this framework is seen as a trajectory, representing the continuous movements of the supply chain. Its movements are due to the succession of events caused by the potentialities, which change the values of the KPIs and shape the dynamics of its performance trajectory. The benefits or damages of these events are seen as deviations of this trajectory from a performance target, considered as an area of space to be reached. Basically, risks can be seen here as events, which move its performance trajectory away from its performance objectives. Conversely, opportunities and decisions taken by managers can be seen as events or actions aimed at bringing the performance trajectory closer to the performance objectives. On the basis of these initial illustrations of the concepts of the PoD approach, several questions arise, notably:

What are the challenges in using the PoD approach to anticipate and control the impacts of risks and opportunities on a supply chain?

Indeed, the PoD approach is a recent one and its application in the field of supply chain management is novel. At first sight, being able to evaluate and formalise the forces of deviations from potentialities seems to be one of the major challenges in applying the PoD approach. Its contributions to the management of supply chain risks and opportunities seem numerous, especially through the use of the proposed performance framework, in which a system is seen and controlled as a multidimensional performance trajectory. In view of the previous findings and the importance of making supply chains more resilient to cope with instability, the question arises as to how this approach can be applied to the management and measurement of supply chain resilience:

How can we take advantage of system modelling in the form of a multidimensional performance trajectory to develop the resilience capabilities of supply chains?

In order to facilitate the visualisation of performance trajectories, the performance framework in Figure 1 has been limited to three dimensions. It is easy to imagine that for a system such as a supply chain, decision-makers will not limit themselves to the observation of three performance indicators. However, being able to theoretically calculate the overall performance of the observed system as a trajectory impacted by any potentiality is one of the major contributions of the PoD approach. It is therefore imperative to find a way to make these results manipulable by decision makers and to answer the following question:

How to use this decision support approach and its vision of performance as a multidimensional trajectory in a relevant and ergonomic way?

SCAN: a collaboration between two universities and an industrial partner

All the work presented in this manuscript on the application of the PoD approach for the management of supply chain risks and opportunities is part of the research activities carried out by the SCAN joint research laboratory. Initiated in autumn 2019, SCAN, for *Systèmes de Collaborations Agiles et Numériques (Agile and Digital Collaboration Systems)*, is a joint research laboratory bringing together IMT Mines Albi's Industrial Engineering Center and the consulting company SCALIAN. The work carried out aims to support supply chain managers in their management of risks and opportunities with work done on the PoD approach, in order to improve their agility and resilience. By the nature of the work carried out, SCAN is also one of the flagship projects of the *International Associated Laboratory* linking the Physical Internet Center of the School of Industrial and Systems Engineering of Georgia Tech and the Industrial Engineering Center of IMT Mines Albi: the SIREN Lab (for *Sentient Immersive Response Networks Lab*). Each of these entities brings its know-how in the development of "immersive" solutions aimed at providing decision-makers with a dynamic, interactive and trusted

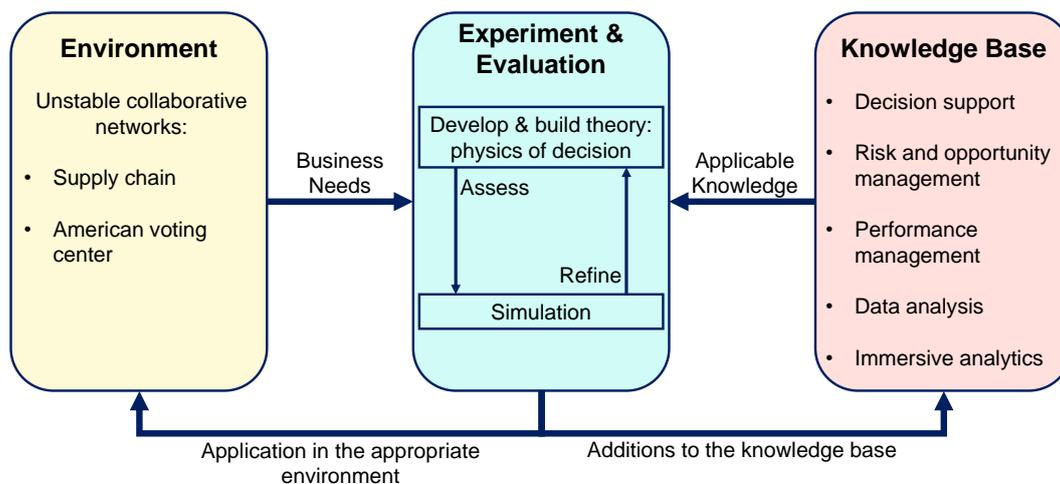


Figure 2 – Research methodology (adapted from Hevner et al., 2008; Petitdemange, 2020)

environment for decision-making. More information on the joint research laboratory SCAN is available at: <https://scan.imt-mines-albi.fr/>.

Work on the PoD approach is not limited to applications of risk and opportunity management for supply chains (Cerabona et al., 2020; Cerabona et al., 2021b), but extends to all collaborative systems and even more generically to all systems whose performance can be measured through indicators. Various concrete application cases have thus been developed and studied, notably on the themes of crisis management through the work carried out on the reconfiguration of road networks following floods affecting the Nantes ring road (Moradkhani et al., 2022b) and on the management of the Covid-19 health crisis (Moradkhani et al., 2022a). This approach was also applied to a large-scale project initiated and developed with Georgia Tech, on the management of American voting centres in the context of the last American presidential elections (Cerabona et al., 2021a; Moradkhani et al., 2021). More recently, work on the PoD approach has also been extended to the study of its contribution to project management (Le Duff et al., 2022).

Research methodology

In order to address the different issues identified, we implemented a research methodology inspired by the information systems research framework proposed by Hevner et al. (2008). Figure 2 illustrates the adaptation of this framework to our research work. According to Hevner et al. (2008), a research work is relevant if it answers and satisfies a business need, in our case to develop and evaluate an original and innovative decision support system, aiming at supporting managers in their decision making in unstable and uncertain situations. The need was identified from bibliographical research on the environment studied, namely the study of risk and opportunity management for supply chains. According to the classification of research design approaches proposed by Bairagi et al. (2019) and broken down into eleven types of research, the research introduced in this thesis falls into the categories known as “applied research” and “exploratory research”

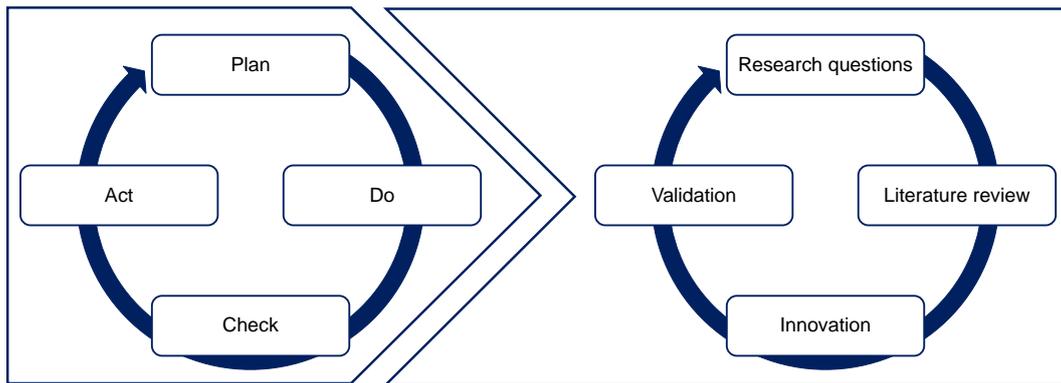


Figure 3 – Transposing a problem-solving cycle into a cycle of research activities

They define applied research as research that is used to solve a specific and current problem facing industry or society (Bairagi et al., 2019), in our case: the management of uncertainties, risks and opportunities in the decision-making mechanism of supply chains. The work carried out on the chosen approach, PoD, corresponds to a so-called “exploratory” research. Bairagi et al. (2019) define it as research whose main purpose is to invent or discover new things and approaches (usually for areas that have not received much attention or to test the possibility of research in an area). Of course, risk and opportunity management for supply chains has been the subject of much work in the literature (as Chapter 1 shows). However, the PoD approach as such has been the subject of little work to date, making the physics of decision making a relatively untouched area, especially with regard to uncertainty management in supply chains.

In order to validate the assumptions and to study the applicability of the PoD approach, this work is based on the study of several case studies. In many works in industrial engineering, case studies are particularly used to model and answer the “how” and “why” questions, especially when it is not possible to control all the events of the studied phenomenon for a complex system (Caillaud et al., 2015; Yin, 2009). To study these case studies, the approach implemented is mainly based on experiments conducted on simulation models. Simulation is one of the most, if not the most, widely used operations research and management science techniques (Law, 2013). It is a methodological approach increasingly used and advocated for theory development and validation (Davis et al., 2007; Harrison et al., 2007; Nair et al., 2009). Simulation is also widely used to test theories (Mosler et al., 2001; Neufeld et al., 2010; Serrano et al., 2005).

The sequencing of the research activities followed to carry out this research is illustrated in Figure 3. It is inspired by the methodologies introduced by Bairagi et al. (2019), Caillaud et al. (2015), and Hevner et al. (2008), while adding a cyclical dimension in the realisation of the different works carried out, as in the methodology proposed by Oger (2019), which is inspired by the continuous improvement approach to *plan-do-check-act* problem solving (Moen et al., 2009). In this approach, the *planning* stage defines the problem and the assumptions about its causes and possible solutions. The *implementation* stage corresponds to the execution. *Check* assesses the various results and draws conclusions about the knowledge to be gained from the process. Finally, *action* corresponds to the decision-making stage: adopting the change or abandoning it,

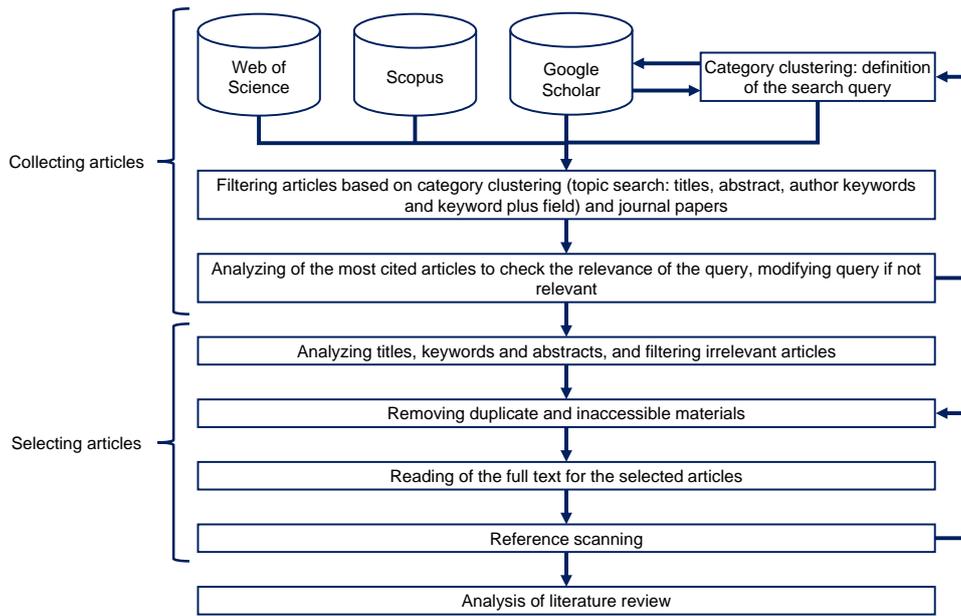


Figure 4 – Literature-review methodology (adapted from Hosseini et al., 2019a)

or starting the cycle again if the results are not satisfactory. According to Moen et al. (2009), this process offers a simple way of empowering oneself to take action that leads to useful outcomes while respecting the pragmatic tradition of learning.

Thus from these methods, four phases are defined to form an iterative process. The first phase is the *definition and refinement of the research questions*. It seeks to refine the subject as the various discoveries, validations and new assumptions are raised by the work carried out. It also allows a better positioning of the research work in relation to the expectations and needs of industry. This phase therefore makes it possible to identify all the challenges that the PoD approach must meet in order to be exploitable by industry. This phase, in its first iteration, makes it possible to take stock of the tools available (those that industrialists and managers have at their disposal in the literature before the work proposed in this manuscript) and the innovation needs that arise from the expectations identified. The second phase is the *state of the art*, which allows us to position the research work in relation to existing work in the literature, in order to take stock of the gaps (the shortcomings of the current literature in relation to the new needs of industrialists), the contributors (the existing work which will serve as a basis for our future developments identified in the previous phase, the *definition and refinement of the research questions*) and the competitors (approaches which are rivals to the PoD approach). This is a comprehensive study of the technical content related to the research keywords (Bairagi et al., 2019). The objective of this phase is to deduce research directions to address the innovation needs, identified in the *definition and refinement of the research questions* phase, for which no solutions have been found in the identified and analysed literature. There are different literature search strategies, all the state of the art proposed in this manuscript are based on the process of analysis of the existing literature illustrated in Figure 4. The process is based on an extensive and systematic search of the existing peer-reviewed literature. The process starts with the identification of the keywords to be searched, through a more or less complex boolean

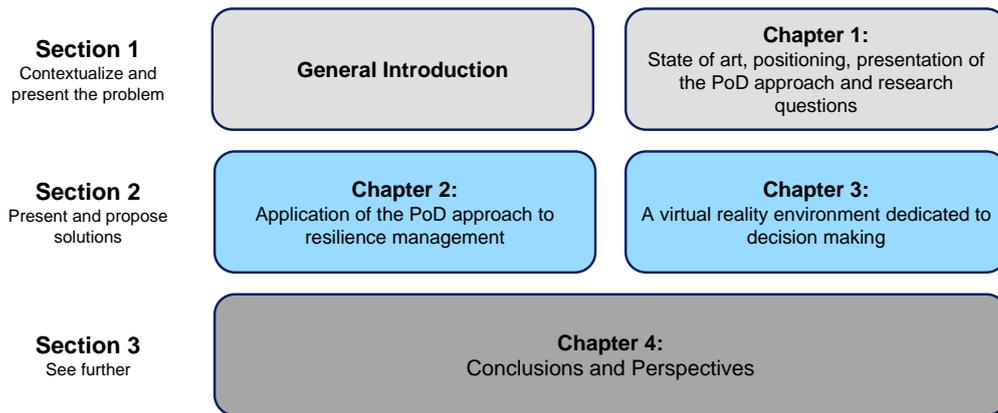


Figure 5 – Manuscript outline

query combining the identified keywords. This query is carried out on different databases (*Web of Science, Scopus and/or Google Scholar*) on the topics, *i.e* the titles of the articles, the abstract, the keywords defined by the author and the keywords relating to the field of the article. An initial analysis of the results, particularly on the most cited articles, enables the query to be validated (its creation is an iterative process until articles consistent with the desired analysis are obtained). Once the query has been validated, the articles obtained are filtered to retain only the relevant journal articles and papers, which are selected by analysing the titles and abstracts. Following this phase, duplicates and non-accessible articles are removed from the database of selected articles. The retained articles are then analysed by reading the full text of each article. At the end of the process, in order to broaden the search for articles that are relevant (but not identified by the query) to the study being conducted, the references of interest cited in the analysed articles are also studied. The third phase of the applied research process is *innovation*, which corresponds to the development and design of the different solutions proposed and studied to meet the needs and research orientations taken as a result of the two previous phases and the different research work carried out during the different cycles. It is during this phase that the work related to simulation will take place. The fourth phase is *validation*, which allows the work and contributions to be validated by industrialists during various workshops (for example, a presentation of the research work carried out during an “*EXPERT’TEASE*”, a webinar bringing together collaborators and partners of the SCALIAN consultancy company, in May 2021) and to have the work carried out and the directions taken validated by our peers through scientific valorisation by the publication of articles (all the contributions presented in this manuscript are the subject of publications that have been accepted or that are in the process of being submitted). As this process is iterative, once a first cycle consisting of these four phases has been completed, a new cycle is started, whose limits identified during the previous cycles are used to define the questions and needs of the *definition and refinement of the research questions* phase of this new cycle.

Manuscript structure

This manuscript is organised in three parts illustrated in Figure 5. The first part presents the context of the work carried out and develops the research questions. It

corresponds to this introduction and the first chapter. Chapter 1 focuses on the problem space and solution space related to the study and management of supply chain risks. It aims to conduct a state of the art on supply chain risk management. This study will identify the limits and justify the application of the PoD approach. A detailed presentation of the approach developed and applied in this thesis will be made in order to highlight the scientific problems to be addressed and overcome in order to exploit an approach such as PoD.

A second part gathers Chapters 2 and 3, develops our proposals to address all the issues identified in the introduction and Chapter 1. Each of these chapters will contain a literature review related to the concepts addressed and the tools used to achieve them.

Chapter 2 defines and illustrates the application of the PoD approach to the management and measurement of supply chain resilience. To do this, we first define the concept of resilience and the current tools for assessing it. Then, we describe the measures proposed by the PoD approach to measure and reconcile two visions of resilience: engineering and ecological. Finally, an illustration will be proposed on a fictitious case study of a supply chain and will highlight the challenges of the PoD approach.

Chapter 3 presents the immersive performance management cockpit prototypes developed to support decision making. One of the contributions of the PoD approach is the ability to calculate and model the performance of a supply chain as a trajectory deviated (positively or negatively) by any potentiality. It is therefore imperative to provide decision makers with a means of manipulating this performance trajectory effectively. This chapter presents initial work on the use of virtual reality to immerse the decision-maker in a virtual and abstract decision environment in which they can interact with the performance trajectory.

The last part, Chapter 4, presents the conclusions and perspectives resulting from this research work, including a review of the contributions made and future developments envisaged.

Positioning

Know yourself, know your enemy, your victory will never be in danger. Know the terrain, know your time, then your victory will be total.

Sun Tzu, *The Art of War*

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Introduction

This first chapter aims to position the work proposed in this manuscript and seeks to explain and justify the choice of a kinetic approach such as the Physics of Decision (PoD), as a potential solution to enable better anticipation and control of the impacts of risks and opportunities on supply chains. A state of the art on the analysis of risks and opportunities in supply chains will first be carried out in order to position and highlight the contributions of the PoD approach in this field. Section 1.1 defines the concepts of

risk and opportunity first in a general way and then in the specific context of supply chains. Section 1.2 defines the management of supply chain risks and opportunities, thus presenting their management process in four stages (*identification, assessment, treatment and monitoring*). Section 1.3 presents the rationale for using the PoD approach to address the needs of managers in terms of managing instability. In this section, the PoD approach will be presented in detail. This section will answer the main questions related to the foundations of the PoD approach: (*Q1*) how to identify and model the system under consideration, its KPIs, its initial performance and its target performance, (*Q2*) how to define risks, opportunities and potential changes in the system or its context and (*Q3*) how to relate these potential changes to the evolution of performance in order to make appropriate decisions. Finally, Section 1.4 positions the research objectives on the applicability of the PoD approach to the needs of supply chain risk management.

1.1 Risks and Opportunities

1.1.1 General concepts and definitions

Throughout history, the term risk has had many definitions. Nevertheless, it remains vague and often ill-defined. Although in everyday language the term is frequently used and easily understood (Morgan et al., 1990), its underlying concepts are difficult to define and even more difficult to assess (Heckmann et al., 2015). The origin of the word risk is not clearly determined, it could derive from the Italian *risicare* meaning to venture, to brave (Bernstein, 1996; Khan et al., 2007) or from the Greek *rhizikon* describing the need to avoid dangers at sea (Heckmann et al., 2015). These early definitions orient the definition of risk towards fear and adventure. In the fourteenth century, with the development of maritime trade between the city-states of northern Italy, merchants began to perceive the term risk as the danger of losing their ships, their investments and thus that their business might lose value, it was rare at that time for merchants to have several ships (Heckmann et al., 2015). From the seventeenth century, with the work of the mathematicians Blaise Pascal and Pierre de Fermat, a new vision of risk appeared, focusing on the probability of events that lead to a loss. The work of these two mathematicians led to the development of probability theory, a notion at the heart of the concept of risk (Bernstein, 1996). However, it was not until the 1950s that the link between probability theory and the concept of risk was realised and applied in many fields (Heckmann et al., 2015). Following major developments in technology and the increase in complexity of organisations (Grose, 1992; Khan et al., 2007; Snider, 1991).

Thanks to the work on the notion of probability, Lowrance (1980) describes risk as a measure of the probability and severity of its adverse effects. S. Kaplan et al. (1981) extend this view of risk by characterising it as a triplet (s_i, p_i, c_i) , where s_i corresponds to a risk scenario, p_i the probability of occurrence of that scenario and c_i its consequences. P. Simon et al. (1997) share this view of risk and state that risk is the probability of the occurrence of an uncertain event or set of circumstances that would have a negative effect on the performance of project activities. Mitchell (1995) proposes to evaluate the risk of an event i by the following formula: $Risk_i = P(loss_i)L(loss_i)$ where $P(loss_i)$ is the probability of loss and $L(loss_i)$ is the magnitude of the loss. This formula is then generalised into the famous formula proposed by Christopher et al. (2004b): $Risk = Probability \cdot Severity$, with *probability* a measure of the occurrence of the given

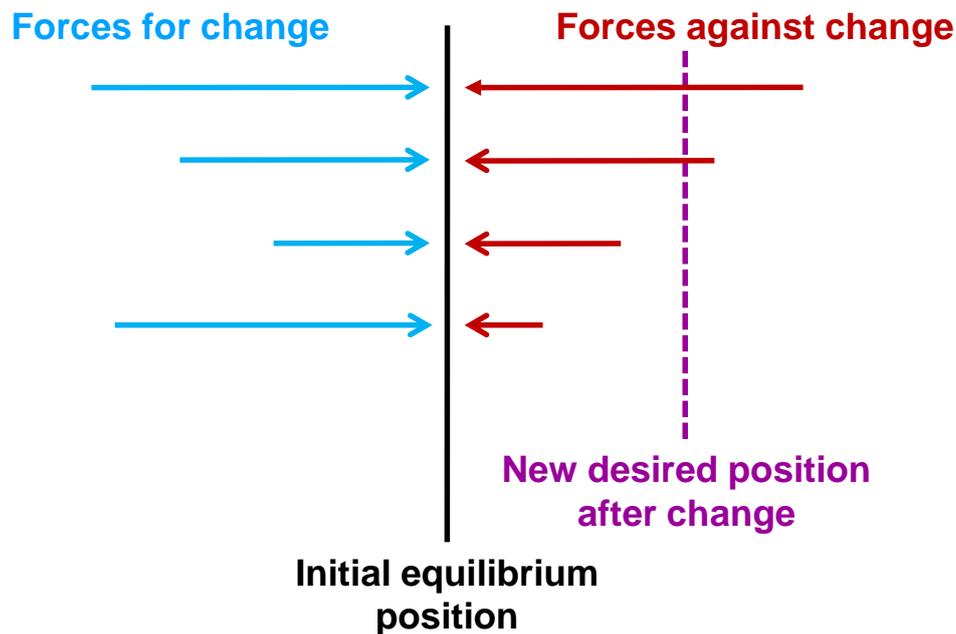


Figure 1.1 – Force field analysis (adapted from Thomas, 1985)

event (the risk) and *severity* a measure of the impact of the event on the company’s activities.

In view of the above definitions, the consequences of a risk are defined as its impact on the results of a company or project. In everyday use, the term risk is often associated with a negative connotation, which is found in the majority of definitions proposed in the literature, in the form of an event that leads to negative consequences (Ebrahimi et al., 2012). March et al. (1987) describe a risk as the negative variation in the results of a company (mainly financial). Miller (1992) extends this notion of impact to performance, for him a risk refers to the variance in results or performance. Wagner et al. (2006) define a risk as “the negative deviation from the expected value of a certain performance measure, resulting in negative consequences for the focal firm”. Gourc (2006) also refers to the notion of performance in his definition of a risk, presented as: “the possibility that an event may occur that would result in consequences (positive or negative) for the performance of the system. A risk is characterised by at least two dimensions: its probability and the measure of its potential effects”. This vision of negative or positive consequences of a risk proposed by Gourc (2006) is reflected in the definition proposed by ISO31000 (2018), which defines the term risk as: “the effect of uncertainty on objectives”. The effect is defined as: “a deviation from an expectation. It can be positive, negative or both, and address, create or result in opportunities and threats”. Thus, by these definitions, a risk can be defined as a probabilistic event whose consequences may be negative or positive for the performance of the systems affected.

This view of risk as including the possibility of “positive” risk, *i.e.* uncertainty that could have a beneficial effect on the achievement of a company’s or a project’s objectives, opens the door to combining the concepts of risk and opportunity (Hillson, 2002). Kurt Lewin, in the early 1950s, introduced force field analysis, a widely used technique for

decision making at a strategic level. Figure 1.1 schematically represents the concepts of this approach, which uses physics to quantify the elements of an organisation and its environment (forces) for (opportunities) or against (risks) change, *i.e.* movement from its current state to a new desired equilibrium state (defined in terms of the objectives to be achieved). The forces are represented by arrows or vectors, whose length represents their intensity. An equilibrium point is reached for each change when the sum of the forces of each group (the group for and the group against the change) is equal (Thomas, 1985). With these views, the question is whether the term “risk” is a generic term, encompassing both opportunity and threat (Hillson, 2002). In this case opportunity would be the positive effect of a risk and threat the negative effect. Or, if uncertainty is a two-variant term, then the terms “risk” and “opportunity” are two distinct terms, one exclusively negative and the other exclusively positive (Hillson, 2002). Opportunity would then be the opposite of risk (Olsson, 2007) and defined as an uncertain event with positive effects (conversely risk would be defined as an uncertain event with negative effects).

In the rest of this manuscript, the concepts of risk and opportunity will be treated in the same way. Opportunity will be seen as the positive term symmetrical to risk, *i.e.* an uncertain event with positive effects. This view is also consistent with that proposed in the PoD approach (developed in Section 1.3 of this chapter), in which risks and opportunities are seen and treated in the same way, and defined by the generic term: potentiality. A potentiality with positive effects is an opportunity, while a potentiality with negative effects is a risk.

Manuj et al. (2008), in their analysis of the literature, confirm this vision of risk with two main components: the potential losses generated and the probability of these losses. They also insist on the vision of a risk as the expected realisation of an uncertain event, the existence of the risk then depending on the realisation of this event. There is therefore a condition (or conditions) for the activation of a risk, which is characterised by the probability of occurrence of an event leading to its realisation. According to Desroches (2013), the existence of a risk is based on the encounter of a hazard and a vulnerable system. A hazard alone, without a vulnerable system, does not lead to the creation of a risk. Clément (2019), based on the work of Desroches et al. (2003) and Fertier (2018), defines a hazard as “any source of potential damage that results in a change in the characteristics of a system element”. A hazard has three components: its location (the geographical place where it is located), its time window (the period over which it is active) and its zone of influence (the activities of the system impacted if the hazard materialises into a risk). These notions of event and hazard are reflected in the definition of a risk proposed by Zeng et al. (2017), who define it based on three concepts: (1) a hazard generating the risk, (2) an event that involves the probability of occurrence of the risk, and (3) consequences that are the expected outcomes following the realisation of the risk. Rowe (1980) defines a risk as “the possibility of realising unwanted negative consequences from causal events”. Pfohl et al. (2010) take up this idea of causality in the definition of risk, according to them there are two ways of defining it. Firstly, according to its causes, in this case the focus is on the lack of information of decision-makers about future situations and events (Pfohl et al., 2010). Secondly, according to its effects, in this case the view of risk is focused on the consequences of a decision (Pfohl et al., 2010). T. Wu et al. (2009) identify three common elements in the majority of definitions

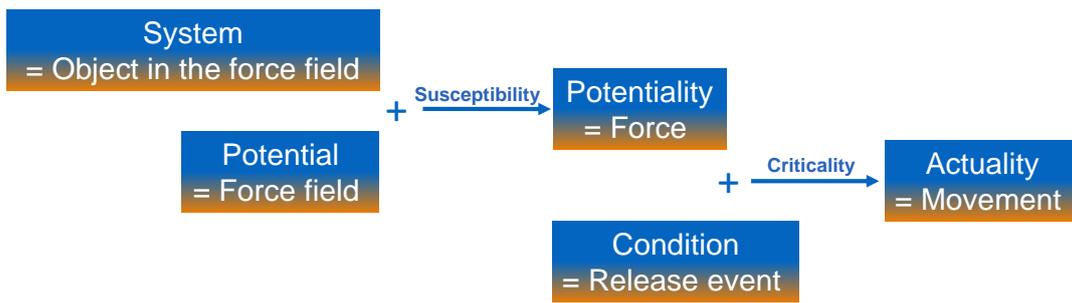


Figure 1.2 – Causality chain (adapted from Benaben et al., 2021)

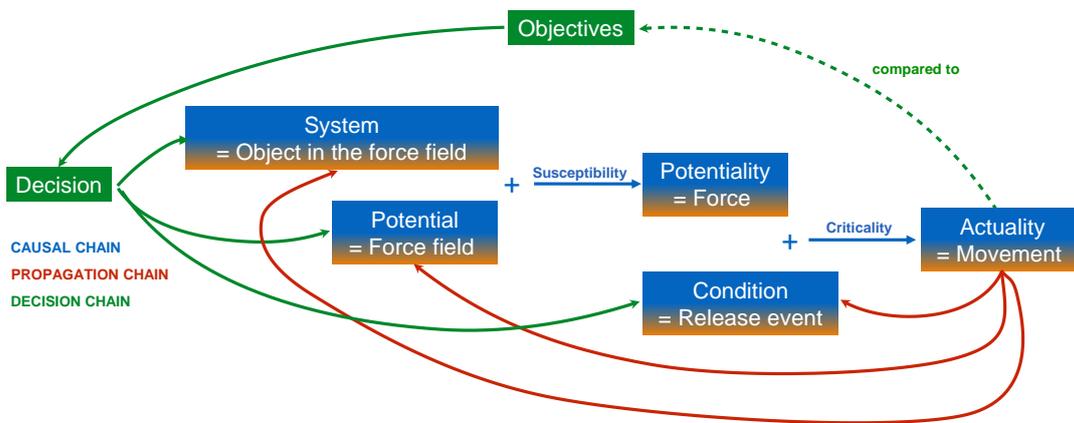


Figure 1.3 – Propagation and decision chains (adapted from Benaben et al., 2021)

in the literature to characterise a risk: (1) the probability of an event occurring, (2) the consequences of the event occurring and (3) the exposure or causal pathway leading to the event. Benaben et al. (2019) combine this view of causality with the three concepts defined by Zeng et al. (2017) and present a causal chain: *potential* (danger or benefit), *potentiality* (risk or opportunity) and *reality* (damage or benefit). This causal chain is illustrated by the blue concepts in Figure 1.2. In this view, potentialities (risks or opportunities) appear as the result of the susceptibility of the system to certain potentials and become a reality when certain conditions activate them (the concept of probability of occurrence of a potentiality being integrated into the probability of realisation of the conditions). Benaben et al. (2021) extend this notion of causal chain to concepts from physics (orange concepts in Figure 1.2), in particular to the notion of force fields, in which the system evolves like an object, with potentialities being forces that once activated make the system move in its performance framework (illustrated by Figure 1 in the introduction section).

From this causal chain two other chains follow: the propagation chain and the decision chain. The propagation chain illustrates and models the resulting dynamics of the consequences of potentialities, including how they can change, create or remove systems, potentials or conditions; and thus create new causal chains through a cascading effect (red chain in Figure 1.3). The decision chain (green chain in Figure 1.3) illustrates the actions taken by managers as a result of the realisation of potentialities. The idea of movement allows us to consider and represent the consequences of a potentiality.

Thus, it is possible to assess the impact of these consequences on the performance of the system, for example by comparing the gap between its current performance and its predefined objectives. In order to minimise the measured deviations and try to achieve the objectives, managers take decisions that may lead to changes in the system or its environment, aiming to annihilate certain conditions for activating potentials or making it susceptible to other causal chains.

These three chains offer a very complete and comprehensive vision of the notion of risk (but also of opportunity). This vision of risk is in line with all the previous definitions from the literature and will be the vision of risk retained in this manuscript.

1.1.2 In the context of Supply Chains

Supply chains, especially global and modern ones, have always been affected by predictable or unexpected events, threatening their profitability and continuity (Baryannis et al., 2019). There are several reasons why modern supply chains are susceptible to these different risks: globalisation, outsourcing, just-in-time philosophy, higher customer expectations, and the unstable, rapidly changing and volatile environment (natural disasters, pandemic, wars, etc.) in which they operate (Baryannis et al., 2019; Ponis et al., 2016; Shekarian et al., 2021). Managing risk in this environment is becoming increasingly complex (Christopher et al., 2004a; Ghadge et al., 2012) and is becoming a major concern for organisations (Kilubi, 2016; Singhal et al., 2011; Wildgoose et al., 2012). Indeed, nowadays, every actor in the supply chain is susceptible to risks (Kilubi, 2016; Knemeyer et al., 2009). Practitioners and researchers stress the importance of supply chain risk management, for them it is an essential capability, so that companies can survive and compete in this increasingly turbulent and unpredictable environment (Shekarian et al., 2021; Singhal et al., 2011).

Due to its relevance, the concept of supply chain risk management has emerged as a natural extension and an important element of supply chain management, aiming to identify the causes of its disruptive events in order to mitigate their effects, including suggesting appropriate measures and action plans to mitigate them (Baryannis et al., 2019; U. R. d. Oliveira et al., 2017; Singhal et al., 2011). This interest has increased considerably over the last decade (Ben Jbara, 2018), as shown in Figure 1.4, which represents the number of annual results for journal articles, returned by the query: “*supply chain*” AND *risk* (performed on *Google Scholar*, 02 December 2022). This reflects the efforts of the scientific community to help supply chains address this challenge and the ongoing need for new tools and approaches (Ben Jbara, 2018). Indeed, developing effective supply chain risk management is always a critical task, requiring skills and a high level of expertise in many areas (Singhal et al., 2011).

Despite its significant interest, no consensus on the definition of supply chain risks seems to have been reached (Baryannis et al., 2019; Ho et al., 2015), as shown in Table 1.1, which brings together the main definitions present in the literature. Definitions of supply chain risks tend to be vague, diverse and ambiguous, involving a wide range of fundamental characteristics (Baryannis et al., 2019; Heckmann et al., 2015), which poses a real challenge to quantify and manage them (Heckmann et al., 2015; Tran et al., 2018).

Table 1.1 – Supply chain risk definitions

Supply Chain Risk Definitions (Reference)	Scope
<p>“Any risks for the information, material and product flows from original supplier to the delivery of the final product for the end user.”</p> <p>(Jüttner et al., 2003)</p>	Information, material and product flow risks
<p>“The probability of an incident associated with inbound supply from individual supplier failures or the supply market occurring, in which its outcomes result in the inability of the purchasing firm to meet customer demand or cause threats to customer life and safety.”</p> <p>(Zsidisin, 2003)</p>	Supply risks
<p>“The negative deviation from the expected value of a certain performance measure, resulting in negative consequences for the focal firm.”</p> <p>(Wagner et al., 2006)</p>	Firm risks
<p>“Risks that can be attributed to disturbance of flow within the goods, information, and financial network, as well as the social and institutional network. They might have negative effects on the goal achievement of single companies and the whole supply chain, respectively, with regard to end customer value, costs, time, or quality.”</p> <p>(Pfohl et al., 2010)</p>	General risks
<p>“The potential loss for a supply chain in terms of its target values of efficiency and effectiveness evoked by uncertain developments of supply chain characteristics whose changes were caused by the occurrence of triggering events.”</p> <p>(Heckmann et al., 2015)</p>	General risks
<p>“The likelihood and impact of unexpected macro and/or micro level events or conditions that adversely influence any part of a supply chain leading to operational, tactical, or strategic level failures or irregularities.”</p> <p>(Ho et al., 2015)</p>	General risks
<p>“Any probabilistic event happens outside or inside the supply chain that either intentionally or unintentionally disrupts the flow of goods, information, or money, in either supply, manufacturing, or demand process, leading to a reduction in the economic, social, and environmental performance of the supply chain.”</p> <p>(Wicaksana et al., 2022)</p>	General risks

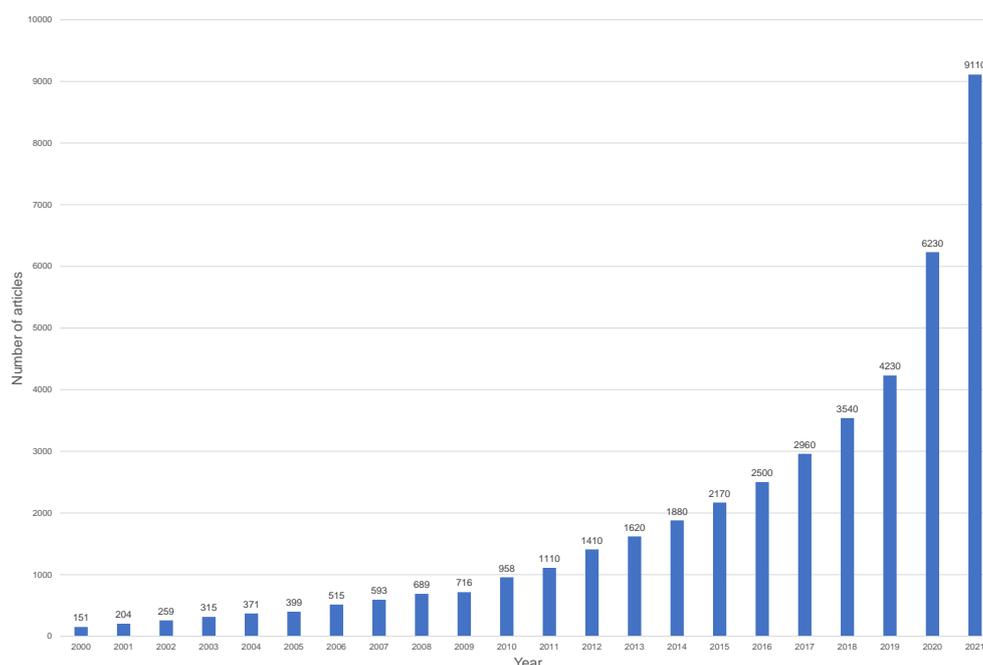


Figure 1.4 – Number of annual results for journal articles on supply chain risk (data extracted from *Google Scholar* following the query: “supply chain” AND risk).

However, despite the various proposals, there is a consensus on some characteristics of supply chain risks (Baryannis et al., 2019), in line with the concepts of risk described in the previous section. Supply chain risks are mainly defined in the literature through an event-oriented concept, defined according to its probability and consequences (Baryannis et al., 2019; Lasch, 2018; Manuj et al., 2008). We find these components in the definition of Zsidisin (2003), who defines supply risk as “the probability of an incident associated with inbound supply from individual supplier failures or the supply market occurring, in which its outcomes result in the inability of the purchasing firm to meet customer demand or cause threats to customer life and safety”. Several researchers in the field of supply chain risk management also agree that the notion of risk mainly implies negative consequences (Ebrahimi et al., 2012). Notably, Wagner et al. (2006), who define supply chain risk as “the negative deviation from the expected value of a certain performance measure, resulting in negative consequences for the focal firm”. For them, this view of risk, seen primarily as an event with negative consequences, stems directly from the human and common perception of the term (Wagner et al., 2006).

In their definition, Pfohl et al. (2010) highlight how “classical” definitions of risk fit with supply chain management, which is by nature a network of actors exchanging different flows (Ebrahimi et al., 2012). Pfohl et al. (2010) define supply chain risks as “risks that can be attributed to disturbance of flow within the goods, information, and financial network, as well as the social and institutional network. They might have negative effects on the goal achievement of single companies and the whole supply chain, respectively, with regard to end customer value, costs, time, or quality”. This way of defining supply chain risk according to flow disruption is in line with the definition of Jüttner et al. (2003) proposed a few years ago, “any risks for the information, material and product flows from original supplier to the delivery of the final product for the

end user”. In contrast to Wagner et al. (2006), their views of supply chain risk are not limited to the perimeter of a company.

Heckmann et al. (2015) extend the traditional definitions and perceptions of risk by also considering the characteristics influencing supply chain risks: the objectives of the supply chain under consideration, its exposure to risk and its attitude towards risk (Lasch, 2018). According to their literature reviews, supply chain risk assessment is closely related to the objectives it has to achieve (Heckmann et al., 2015). The degree of achievement of its objectives depends strongly on the supply chain’s exposure to unexpected and uncertain events, *i.e.* its risk exposure (Heckmann et al., 2015). Risk exposure is then segmented according to potentially disruptive triggering events, the supply chain’s ability to manage them and temporal characteristics, which align the occurrence of triggering events with the current state of the supply chain (Heckmann et al., 2015). This view of risk is very similar to that proposed by the three chains presented at the end of the previous section and illustrated in Figure 1.3. They define supply chain risk as “the potential loss for a supply chain in terms of its target values of efficiency and effectiveness evoked by uncertain developments of supply chain characteristics whose changes were caused by the occurrence of triggering events” (Heckmann et al., 2015).

Ho et al. (2015), following their literature review, define supply chain risk as “the likelihood and impact of unexpected macro and/or micro level events or conditions that adversely influence any part of a supply chain leading to operational, tactical, or strategic level failures or irregularities”. They offer a very comprehensive definition of risk: its two main components (likelihood and impact) are included; the terms macro and micro, corresponding to their classification of sources of risk (these two terms are defined in Section 1.2), group together all sources of risk in supply chains; and they locate the impact according to the three decision-making levels (operational, tactical or strategic). This definition has two limitations: (1) the absence of the notion of performance and (2) the possibility of a positive impact of risks.

Wicaksana et al. (2022), based on their literature review of selected journal articles published in the last decade (2011 to 2020), define supply chain risk as “any probabilistic event happens outside or inside the supply chain that either intentionally or unintentionally disrupts the flow of goods, information, or money, in either supply, manufacturing, or demand process, leading to a reduction in the economic, social, and environmental performance of the supply chain”. They correct one of the limitations of the Ho et al. (2015) definition, in which a clear indication of the scope of the impact of a risk is missing. They add the notion of performance and take up the flow impact view proposed by Jüttner et al. (2003) and Pfohl et al. (2010). In this definition, risk is also seen as a negative event for the economic, social and environmental performance of the supply chain.

In the literature, the terms: risk, uncertainty, disturbance, disruption, crisis and vulnerability, are very frequently used in the field of supply chain risk management and used interchangeably, although they have very distinct technical meanings (Colicchia et al., 2012; Ghadge et al., 2012; Ponis et al., 2016; Singhal et al., 2011). According to Knight (1921) risk and uncertainty are distinct, risk is something measurable, while uncertainty is not quantifiable. Vorst et al. (2002) and Paulsson (2004) propose to describe uncertainty as a specific risk situation, in which decision makers lack information about the supply chain and its environment. They are then unaware of the occurrence of a potential event, whether positive or negative for the supply chain (Colicchia et al.,

2012; Ritchie et al., 2007b). Risk is therefore the result of uncertainty, some possibilities of which imply undesirable outcomes (Ghadge et al., 2012; Hubbard, 2014). Disruptions correspond to the alteration of the stability of a supply chain following the realisation of one or more risks (Pfohl et al., 2010; Ponis et al., 2016), they are defined as “the interruption and breaking up of tranquillity, peace, rest, or settled condition” (Hornby et al., 2005). Disruptions have a wider scope and a much longer and more significant effect than disturbances (Pfohl et al., 2010), they are defined as “the action of rending or bursting asunder; violent dissolution of continuity; forcible severance” (Hornby et al., 2005). The term disruption is widely used in the literature to refer to risks caused by natural and man-made disasters (Baryannis et al., 2019). Crisis is defined as “the interruption of one or more supply chain activities, resulting in a major disruption of the normal flow of goods or services” (Natarajarathinam et al., 2009). The notion of supply chain vulnerability is closely related to the concept of risk (Colicchia et al., 2012). Vulnerability is defined as “the existence of random disturbances that lead to deviations in the supply chain from normal, expected or planned activities, all of which cause negative effects or consequences” (Svensson, 2000).

In addition to the diversity of definitions of supply chain risk (illustrated by this literature review, which only captures a sample of this multitude of definitions), several important concepts are highlighted here: (1) the link between risk and performance, more precisely the close link between the performance objectives of a supply chain and its exposure to risk, and (2) not limiting its vision and application to “negative” risks. Indeed, the definitions studied all present a negative dimension of risk (identical to the human perception and use of the term), none of them envisages that it can present a “positive” aspect (an opportunity). It is therefore interesting to study the process of risk management and to analyse whether there are similarities with the process of opportunity management, which will be the subject of the next section.

1.2 Supply Chain Risk and Opportunity Management (SCR&OM)

As with the concept of supply chain risk, many authors have proposed definitions of supply chain risk management. Table 1.2 provides an overview of the definitions in the literature. The objective of supply chain risk management is to identify, minimise, monitor and control the probability and impact of uncertain disruptive events, including implementing appropriate actions to avoid or contain them (Ho et al., 2015; Jüttner et al., 2003; Manuj et al., 2008), in order to ensure high performance, profitability and continuity (Lasch, 2018; C. S. Tang, 2006a). Supply chain risk management is an integral part of supply chain management (Kersten et al., 2007). In contrast to “traditional” risk management, the nature of the supply chain as a network of organisations makes it necessary to incorporate a cross-company orientation to the concept of risk, which requires identifying and reducing risks both at the company level and at the network level (Ebrahimi et al., 2012; Thun et al., 2011). Jüttner et al. (2003) define supply chain risk management as “the identification and management of risks for the supply chain, through a coordinated approach amongst supply chain members, to reduce supply chain

vulnerability as a whole”. Supply chain risk management emphasises the following main characteristics: a collaborative and coordinated approach among supply chain actors and inter-organisational (Ho et al., 2015; C. S. Tang, 2006a; Thun et al., 2011). For some authors, the overall objective of supply chain management is none other than to increase the resilience of supply chains (Ceryno et al., 2013; Nyoman Pujawan et al., 2009; Tran et al., 2018), which will be explored and defined in Chapter 2.

Managing systems (in particular managing supply chain risks) and making decisions in an unstable environment require an understanding of all available options and possible decisions. To do this, researchers have defined different steps for the supply chain risk management process. ISO31000 (2018) defines the risk management process as “the coordinated activities for the purpose of directing and steering an organisation with respect to risk”. Table 1.3 provides an overview of the most commonly cited steps in the literature. The definition or number of steps differs between authors, but the processes illustrated in Table 1.3 seem to converge in general towards a risk management process divided into these four steps: risk identification, risk assessment, risk treatment and risk monitoring.

Opportunity management is much less developed than risk management techniques and requires very little adaptation compared to risk management. Current risk management methods can be extended to the issue of opportunity management (Hillson, 2002). Thus, in the same way as the risk management process, the opportunity management process can also be divided into four stages: opportunity identification, opportunity assessment, opportunity processing and opportunity monitoring.

1.2.1 Risk and opportunity identification

The **risk identification step** is a fundamental step in risk management practice (Hallikas et al., 2004). It consists of gaining insight into all threats, uncertainties, vulnerabilities and unexpected events that may become a source or trigger for the realisation of a risk (Tran et al., 2018). To do this, companies study the supply chain and its environment in order to identify all the threats that can disrupt it and prevent it from achieving its objectives. The objective of this step is to develop a list or database of all identified risks (Clément, 2019), which will allow a common understanding of the future uncertainties surrounding the supply chain (Tuncel et al., 2010), in order to manage them proactively. This step “involves a comprehensive and structured determination of potential supply chain risks” (Tummala et al., 2011).

Risk identification is a crucial step in the risk management process, especially because of the many factors that act separately or together to create risks (Ho et al., 2015; Wicaksana et al., 2022). To help managers identify the risks that threaten their supply chain, the literature proposes to categorise risks according to their sources. The purpose of risk classification is to provide a global and collective view of all hazards and risk factors (the sources of risks), in order to identify as many as possible (Diabat et al., 2012). This classification is also intended to help them in the selection of methods required to assess the risks effectively, in order to select or create the best countermeasures and strategies to implement (Ben Jbara, 2018; Chopra et al., 2007). Classifying different types of supply chain risks is a difficult undertaking (Pfohl et al., 2010). Ho et al. (2015), in their literature review on supply chain risk management, identifies twenty articles on risk classification. Tables 1.4, 1.5, 1.6 provide an overview of the main classifications

Table 1.2 – Supply Chain Risk Management (SCRM) definitions

Reference	SCRM Definitions
Jüttner et al. (2003)	“The identification and management of risks for the supply chain, through a coordinated approach amongst supply chain members, to reduce supply chain vulnerability as a whole.”
C. S. Tang (2006a)	“The management of supply chain risks through coordination or collaboration among the supply chain partners so as to ensure profitability and continuity.”
Manuj et al. (2008)	“Global supply chain risk management is the identification and evaluation of risks and consequent losses in the global supply chain, and implementation of appropriate strategies through a coordinated approach among supply chain members with the objective of reducing one or more of the following – losses, probability, speed of event, speed of losses, the time for detection of the events, frequency, or exposure – for supply chain outcomes that in turn lead to close matching of actual cost savings and profitability with those desired.”
Thun et al. (2011)	“Risk management in general is described as the identification and analysis of risks as well as their control. A main particularity of Supply Chain Risk Management (SCRM) contrary to traditional risk management is that it is characterized by a cross-company orientation aiming at the identification and reduction of risks not only on the company level, but rather focusing on entire supply chains.”
Ceryno et al. (2013)	“The identification and management of risks for the supply chain through a coordinated approach amongst supply chain members to reduce supply chain vulnerability as a whole, to increase resilience.”
Ho et al. (2015)	“An inter-organisational collaborative endeavour utilising quantitative and qualitative risk management methodologies to identify, evaluate, mitigate and monitor unexpected macro and micro level events or conditions, which might adversely impact any part of a supply chain.”

Table 1.3 – Risk management process in the literature.

Reference	Stages of the risk management process
D. White (1995)	<ol style="list-style-type: none"> 1. Risk identification 2. Risk estimation 3. Risk evaluation
Jüttner et al. (2003)	<ol style="list-style-type: none"> 1. Assessing risk sources 2. Defining adverse consequences for the supply chain/ Identification of risk concepts 3. Tracking risk drivers 4. Mitigating risks
Hallikas et al. (2004)	<ol style="list-style-type: none"> 1. Risk identification 2. Risk assessment 3. Decision and implementation of risk management actions 4. Risk monitoring
Kleindorfer et al. (2005)	<ol style="list-style-type: none"> 1. Specifying sources of risks and vulnerabilities 2. Assessment 3. Mitigation
T. Wu et al. (2006)	<ol style="list-style-type: none"> 1. Risk classification 2. Risk identification 3. Risk calculation 4. Implementation and validation
Trkman et al. (2009)	<ol style="list-style-type: none"> 1. Risk classification 2. Risk analysis 3. Risk reducing/managing 4. Risk monitoring
T. Wu et al. (2009)	<ol style="list-style-type: none"> 1. Risk identification and modelling 2. Risk analysis, assessment and impact measurement 3. Risk management 4. Risk monitoring and evaluation 5. Organisational and personal learning (including knowledge transfer)
Tuncel et al. (2010)	<ol style="list-style-type: none"> 1. Risk identification 2. Risk assessment 3. Risk management actions 4. Risk monitoring
Ho et al. (2015)	<ol style="list-style-type: none"> 1. Risk identification 2. Risk assessment 3. Risk mitigation 4. Risk monitoring

proposed in the literature (drawing on the classifications identified by the literature reviews of Ho et al., 2015; Rangel et al., 2015; Sodhi et al., 2012b). In order to increase the clarity and comprehensiveness of the definition of supply chain risks, Tran et al. (2018) propose to group all definitions and classifications according to three attributes: (1) the source or triggering event of the risk (threats, hazards, vulnerability, etc.), (2) the impact of the risk on the supply chain, and (3) the object of the risk (information flows, material flows, product flows, impacted performance levels). Katsaliaki et al. (2021) propose to group the different classifications into five attributes: (1) the supply chain levels impacted, (2) the causes of the disruption, (3) the frequency of occurrence, (4) the nature and sources of the risks, and (5) what is impacted (network, companies, decision makers, etc.). Ben Jbara (2018) proposes to group the risk categories according to four major attributes: (1) probability of occurrence, (2) origin of risk, (3) controllability (the ability to control triggering events) and (4) impacts. Wicaksana et al. (2022) propose to group the different risk typologies developed in the literature over the last decade into two broad categories: risk location and risk impact. Based on these categorisations of risk typologies, we propose to group them into five categories: (1) the supply chain levels impacted, (2) the nature and sources, (3) the levels of control, (4) the frequency of occurrence, and (5) the severity of the risk (of course, due to the proposed definitions, some classifications may cut across several categories).

As illustrated in Tables 1.4, 1.5 and 1.6, some classifications include the two basic elements of risk definition, namely severity and frequency of occurrence (Chopra et al., 2007; Chopra et al., 2004; Crockford, 1986; C. S. Tang, 2006a). Some classifications even add a third dimension, which is the level and capacity of control that a company or supply chain has over risks (Chopra et al., 2004; Crockford, 1986; T. Wu et al., 2006). Most classifications focus on the nature and source of the risks, *i.e.* the location of the risks according to the risk classification proposed by Wicaksana et al. (2022). This category includes the nature of the impacted elements: the impacted flows (Cavinato, 2004; O. Tang et al., 2011; Wicaksana et al., 2022), the impacted functions and processes (Bogataj et al., 2007; Christopher et al., 2004b; Ivanov et al., 2017; Johnson, 2001; Manuj et al., 2008; Ptak et al., 2019; Sodhi et al., 2012b; Wicaksana et al., 2022) and the level of impacted activities (Cousins et al., 2004; Manuj et al., 2008; Min et al., 2002). The source of the risks can be internal or external to the supply chain (Olson et al., 2010), which seems to provide an overlay encompassing the nature of the elements impacted. Trkman et al. (2009) break down the source of risk into two categories: endogenous and exogenous. They define endogenous risks as risks whose source is internal to the supply chain, mainly resulting in changes in the relationships between its actors. Exogenous risks are defined as risks that are external to the supply chain and are divided into two categories: discrete event risks (events with a low probability but high impact) and continuous risks (events whose potential impact on costs is continuous and easy to predict). Based on the same principle and their analysis of the literature, Ho et al. (2015) divide their classification of risks into two categories: macro and micro. Macro risks are defined as adverse and relatively rare external events that can have a negative impact on companies (Ho et al., 2015). Macro risks include so-called “catastrophic” risks, *i.e.* natural disasters or man-made risks such as war, terrorism or political instability. Micro-risks refer to relatively recurrent events arising directly from the internal activities of companies or from the existing relationships between the different actors in the logistics network (Ho et al., 2015). Ho et al. (2015) propose to divide micro-risks into four sub-categories of risks related

to: demand (events impacting a company's customers), manufacturing (events that affect a company's capacity to produce goods or services, the quality of its products or services, its production times or/and its profitability), supply (events impacting a company's suppliers) and infrastructure (events impacting information technology, transportation and financial systems). Ho et al. (2015) thus extend internal supply chain risks into four categories, whereas the majority of classifications, in the same way as that proposed by Samvedi et al. (2013), only three are described: process (risks internal to the company, arising from disruptions to the flow of product through the various processes within a company), demand (risks internal to the supply chain but external to the company concerned, arising from fluctuations in demand) and supply (risks internal to the supply chain but external to the company concerned, arising from events disrupting the downstream flow of product). Thus, the category on infrastructure risks seems to group together all the risks impacting the so-called support systems for the supply chain, which are essential to ensure its proper functioning.

Although the previous studies make an important contribution to risk classification, they have three limitations according to Wicaksana et al. (2022): (1) few classifications focus on both the location and the impact of risks; (2) few cover risks according to both their characteristics, *i.e.* the sources (endogenous or exogenous) and the motivation (intentional or accidental) of the risks, which affect the dimension of the impact of a risk and determine the treatment strategies to be taken (DuHadway et al., 2019); and (3) they also do not include emerging and hidden risks, such as reputational risks like fraud (Wicaksana et al., 2022). To overcome these three limitations, Wicaksana et al. (2022) propose to classify risks according to three dimensions: (1) the characteristics of the risks (sources and motivations), (2) the location of the risks (risks related to the structure and flows of the supply chain) and (3) the impact of risks (economic, social and environmental). This classification is in line with the conceptual view of supply chain risk management, which according to some practitioners and researchers is defined as a process of managing: (1) the probability of risk (assessed through risk characteristics), (2) the spread of risk (analysed through risk location) and (3) the impact of risk (Wicaksana et al., 2022; Zsidisin et al., 2019).

Giannakis et al. (2011) propose to identify risks through the use of quantitative models, which are based on the monitoring of various KPIs (mainly related to the performance of the different supply chain partners) over specific periods of time, over which the values of the monitored KPIs are compared to predefined values (which can be described in the agreements signed between the different partners). Inventory levels, production capacity, capacity utilisation and delivery times are some of the KPIs that can be used to identify risks (Giannakis et al., 2011).

These methods and models can also be applied to the **identification of opportunities**, although to our knowledge no work has been done on a classification of opportunity types. Generic methods, such as the *SWOT matrix*, allow both risks and opportunities to be identified. However, experience shows that there is a reluctance to extend risk techniques to include positive risks (opportunities), due to the habit of users to focus primarily on identifying negative risks (threats) with these methods (Hillson, 2002). Therefore, the development of new approaches to risk identification (in the broad sense of both positive and negative) seems to be necessary (Hillson, 2002).

Table 1.4 – Supply chain risk classifications proposed in the literature from 1986 to 2004

Reference	Risk categories	Attributes				
		Impacted levels	Nature and source	Control level	Occurrence frequency	Severity
Crockford (1986)	<ul style="list-style-type: none"> • Trivial (very high frequency, very low severity, very high predictability) • Minor (high frequency, low severity, reasonable predictability) • Medium (low frequency, medium severity, reasonable predictability) • Important (very low frequency, high severity, minimal predictability) 			✓	✓	✓
Johnson (2001)	<ul style="list-style-type: none"> • Procurement • Demand 	✓	✓			
Min et al. (2002)	<ul style="list-style-type: none"> • Competitive strategy risks • Tactical risks • Operational routine risks 		✓			
Jüttner et al. (2003)	<ul style="list-style-type: none"> • Environment • Networks risks • Organisational risks 	✓	✓			
Cavinato (2004)	<ul style="list-style-type: none"> • Physical • Financial • Information • Relationship • Innovation 		✓			
Chopra et al. (2004)	<ul style="list-style-type: none"> • Disruptions and disasters (the “abnormal” risks, unpredictable and rare, but often quite damaging) • Delays (the “normal” risks that can be encountered in the management of a supply chain) • Systems • Forecast • Intellectual property • Procurement • Claims • Inventory • Capacity 		✓	✓	✓	✓
Christopher et al. (2004b)	<ul style="list-style-type: none"> • External to the network (environment) • External to the company but internal to the supply chain (demand and supply) • Internal to the company (process and control) 	✓	✓			
Cousins et al. (2004)	<ul style="list-style-type: none"> • Technological • Strategic 		✓			

Table 1.5 – Supply chain risk classifications proposed in the literature from 2006 to 2011

Reference	Risk categories	Attributes				
		Impacted levels	Nature and source	Control level	Occurrence frequency	Severity
C. S. Tang (2006a)	<ul style="list-style-type: none"> Operational Disruption (major disruptions caused by natural or man-made disasters) 		✓		✓	✓
T. Wu et al. (2006)	<ul style="list-style-type: none"> Internal: controllable, partially controllable, uncontrollable External: controllable, partially controllable, uncontrollable 		✓	✓		
Bogataj et al. (2007)	<ul style="list-style-type: none"> Supply Process (production or distribution) Demand Control Environmental 		✓			
Chopra et al. (2007)	<ul style="list-style-type: none"> Non-recurring Recurring 				✓	
Manuj et al. (2008)	<ul style="list-style-type: none"> Supply Demand Operational Others (security and currency risks) 		✓			
Trkman et al. (2009)	<ul style="list-style-type: none"> Endogenous (the source of risk is internal to the supply chain, which can lead to changes in the relationships between actors due to market and technology turbulence) Exogenous (the source of the risk is external to the supply chain, divided into two categories: discrete and continuous events) 		✓	✓	✓	✓
Olson et al. (2010)	<ul style="list-style-type: none"> Internal External 		✓			
O. Tang et al. (2011)	<ul style="list-style-type: none"> Material flows Financial flows Information flows 		✓			
Tummala et al. (2011)	<ul style="list-style-type: none"> Demand Delay Disruption Inventory Manufacturing Capacity Supply System Sovereign Transportation 	✓	✓			

Table 1.6 – Supply chain risk classifications proposed in the literature from 2012 to 2022

Reference	Risk categories	Attributes				
		Impacted levels	Nature and source	Control level	Occurrence frequency	Severity
Sodhi et al. (2012a)	<ul style="list-style-type: none"> • Supply • Processes • Demand • Risks at company level 	✓	✓			
Samvedi et al. (2013)	<ul style="list-style-type: none"> • Environment (risks external to the company that may affect a player in the chain or the entire supply chain) • Processes (risks internal to the company, arising from disruptions in the flow of products through the various processes of the company) • Demand (risks internal to the chain but external to the company concerned, resulting from fluctuations in demand) • Supply (risks internal to the chain but external to the company concerned, resulting from problems in the downstream product flow) 	✓	✓			
Ho et al. (2015)	<ul style="list-style-type: none"> • Macro-risks (adverse and relatively rare external events) • Micro-risks (recurring events arising from internal company activities and/or relationships between supply chain actors) 	✓	✓		✓	
Ivanov et al. (2017)	<ul style="list-style-type: none"> • Production • Supply • Transportation disruptions 		✓			
Ptak et al. (2019)	<ul style="list-style-type: none"> • Supply • Demand • Manufacturing • Management 		✓			
Wicaksana et al. (2022)	<ul style="list-style-type: none"> • Characteristics of risks (exogenous <i>vs.</i> endogenous, intentional <i>vs.</i> unintentional) • Location of risks (supply chain structures and flow) • Impact of risks (social, economic and environmental) 	✓	✓		✓	✓

Risk and opportunity identification is a fundamental step in the practice of risk management. To assist managers in this phase, many methods of classifying risks according to their sources have been developed, the aim of which is to provide a global and collective view of all hazards and risk factors. However, due to the instability that is becoming the norm, this number of factors is constantly increasing (some acting separately or together to create risks). The solution proposed by Giannakis et al. (2011), based on the identification of risks on the basis of monitoring deviations of quantitative KPIs from targets, seems to be the most appropriate, especially given the close link between performance and risks. Imagining a framework dedicated to visualising performance in the form of various trajectories, whose dynamics are shaped by risks and opportunities, as proposed in Figure 1, would greatly contribute to risk identification. Moreover, such a detection method based on the measurement of performance gaps between the current and the optimal situation would allow the detection of both risks and opportunities (considering damages or benefits as deviations from the trajectory aimed at achieving the set objectives), thus filling the gap identified by Hillson (2002).

1.2.2 Risk and opportunity assessment

The objective of the **risk assessment step** is to provide a detailed analysis of each of the risks identified in the previous step. This means estimating or measuring the probability of occurrence of that risk (more precisely, the probability of occurrence of the event or events that trigger the risk) and its impact on the supply chain. Associating probabilities with risks is not an easy task and requires tedious work (Tuncel et al., 2010). Feedback, benchmarking methods (seeking to compare the performance results of other companies or supply chains) or predictive analysis methods can be used to estimate the probability of occurrence of risks (Tuncel et al., 2010).

The aim of this step is to obtain a hierarchy of risks, in order to deal with them effectively. This hierarchy of risks is obtained by calculating the criticality level of a risk (usually calculated as the product between the occurrence of a risk and its impact), in order to be able to focus the next step on dealing with the most critical risks (it is usually rare to be able to deal with all identified risks). However, the objectives and results of risk assessment are not only to prioritise risks, but also to quantify the impact of the risk to establish the most appropriate actions (Tran et al., 2018).

Recently, researchers and industry have expanded risk measures, not only in terms of probability and impact, but also detectability and resilience (recovery time), or dependencies between risks (Tran et al., 2018). Calculating the impact of various factors on a risk may require the use of decision support tools. Assessing risks at the supply chain level is therefore extremely difficult and complex (Bradley, 2010; Heckmann et al., 2015; Jüttner et al., 2003; Tazelaar et al., 2013). Yet it is an essential step in helping decision-makers make the right decisions, especially in terms of prioritisation and resource allocation (Sodhi et al., 2012b).

How risk is understood, *i.e.* how it is defined, has a great influence on how it will be evaluated (Ben Jbara, 2018). He defines supply chain risks as “a scenario triggered by an event originating within the supply chain or outside which incurs negative effects on

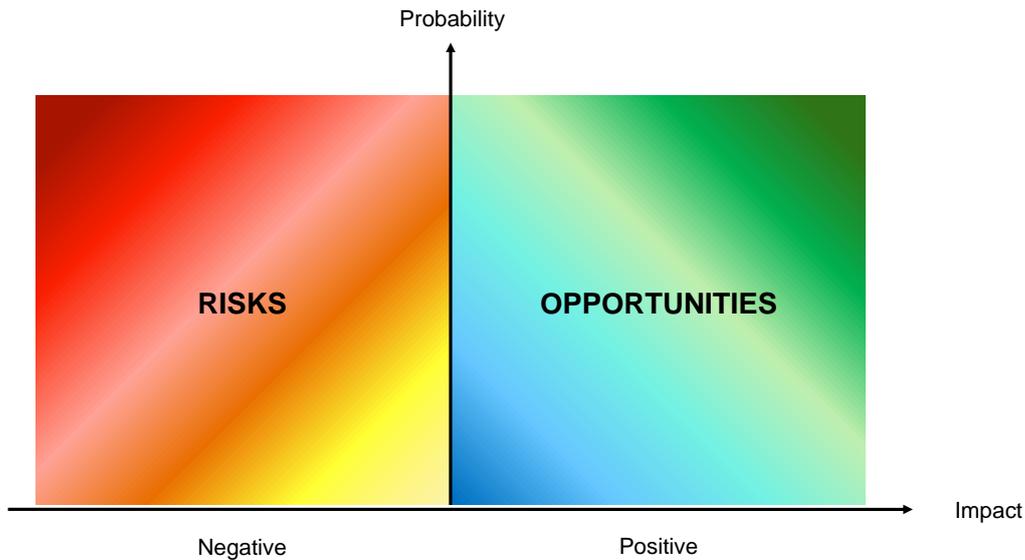


Figure 1.5 – Extended impact-probability matrix (adapted from Benaben et al., 2020)

the objective of one or more elements of the supply chain. The realization of the scenario depends on both the realization of the source event and the state of the supply chain when the risk occurs” (Ben Jbara, 2018). From this definition, it is therefore essential to master and be able to quantify three elements: the source event, the state of the system and the impact of the risks. These three elements are very close to the concepts of the causal chain (the basis of the vision of risk adopted in this manuscript), illustrated in Figure 1.2. The source event refers to the triggering element of the causal chain, *i.e.* the activation condition. The state of the system is measured from an assessment of the system parameters that influence the propagation and realisation of the causal chain (*i.e.* measuring the susceptibility of the system to certain potentials). Impacts refer to the effects and consequences of a risk on system performance, *i.e.* the actualities, the modelling and physical measurement of which corresponds to a shift in the performance framework (illustrated by Figure 1).

Finally, Tran et al. (2018) define the risk assessment step as all activities aimed at qualitatively or quantitatively judging, analysing, calculating, quantifying, measuring and modelling the individual indicators, aggregate score or overall level of risks that have been identified in supply chains in order to create a solid basis for decision making and strategy selection in the next stage.

Again, the same methods can be applied to both **risk and opportunity assessment**. Qualitative methods, such as impact-probability risk matrices, can be extended to the notion of opportunity. In these matrices, risks are positioned in a two-dimensional grid, with each axis representing one of the two main components of a risk: its impact and its probability of occurrence. In order to consider opportunities as well, the axis reflecting the impact of an uncertain event could represent both negative and positive impacts, as illustrated in Figure 1.5.

An essential step in helping decision-makers to make the right decisions, assessing risks and opportunities across the supply chain is extremely difficult and may require the use of decision support tools. Understanding the risk or opportunity, including its drivers, is critical to this step, justifying the value and control of the three chains described at the end of the Section 1.1, a risk and opportunity meta-model that forms the basis of the PoD approach. The importance of this step and the difficulty in carrying it out highlights the need for an approach that links (via mathematical relationships) a space for describing the system and the various factors of a risk or opportunity to a space for measuring their impacts.

1.2.3 Risk and opportunity treatment

The objective of the **risk treatment step** is to define the appropriate actions (countermeasures) to be put in place to control supply chain risks (Tran et al., 2018), seeking to decrease the occurrence and/or impact of risks. These actions can be preventive (risk mitigation actions aiming to act on its likelihood of occurrence and/or impact) or corrective (active actions put in place to react to the realisation of a risk, thus they aim to reduce its impact). The aim of this stage is to decide on the most appropriate response to manage each of the identified risks (D. White, 1995). The performance of this step is highly dependent on the previous two steps (Tran et al., 2018). Designing appropriate countermeasures is not an easy task and requires a lot of research (Ben Jbara, 2018). According to Chopra et al. (2004), the main challenge in designing countermeasures is that these actions must both reduce risk levels, while allowing profit to be maintained (or at least limiting losses). Decision-making in supply chain risk management requires managers to decide on strategies (including how best to manage the allocation of limited resources), which is not an easy decision given the many aspects and factors that can influence these decisions (T. Wu et al., 2009). Risk response strategies are generally grouped according to the intended effect on the risk being addressed (Hillson, 2002). Thus, four types of strategy can be defined (Aqlan et al., 2015; Hillson, 2002):

- Avoidance: this strategy seeks to make it impossible for a risk to occur by eliminating its root causes (its activation condition) by reducing its probability of occurrence to 0%, and/or to render the risk totally inactive by measures that annihilate its consequences;
- Sharing: means transferring a risk to another member of the network who is better able to manage it;
- Mitigation: means acting to reduce the impact of a risk;
- Accept: no measures (preventive or corrective) put in place to deal with a risk, apart from measures to monitor the status of the risk.

In the case of **opportunity treatment**, new strategies to take advantage of their benefits must be put in place. Only strategies to share or accept risks can be retained. For avoidance and mitigation strategies, positive symmetrical strategies have to be defined (Cerabona et al., 2020; Hillson, 2002):

- **Exploit:** a positive strategy symmetrical to the avoidance strategy, unlike the avoidance strategy, it seeks to increase the chances of an opportunity being realised, by seeking to increase its probability of occurrence (ideally to 100%);
- **Enhance:** a positive strategy that is symmetrical to mitigation and involves taking action to increase the impact of an opportunity in order to maximise its benefit.

Manual step, relying on the ability of decision-makers to analyse and interpret all the data collected in the previous two stages, appears to be less covered than the previous two stages. As with the previous steps, this step applies to both risks and opportunities, and requires little modification to accommodate opportunities. Indeed, due to their different characteristics, all strategies aimed at reducing the probability of occurrence or the impact of risks must be transformed into positive strategies aimed at ensuring the realisation of opportunities while trying to gain the maximum benefit.

1.2.4 Risk and opportunity monitoring

The last step is the **risk monitoring**. This is a risk status monitoring stage, in which the supply chain is supervised, in order to observe and detect which risk (identified risks but also new detected risks) is impacting in real time (Hillson, 2002; Tuncel et al., 2010). This step therefore aims to monitor the evolution of the overall risk exposure of the supply chain. The objective of this step is also to ensure that the treatment actions implemented correctly fulfil their role (in terms of relevance and effectiveness) and that they do not generate new risks or causal chains. This step therefore verifies the effectiveness of the risk management process applied, to ensure that it meets the (new) risk management needs of the supply chain. This step should not be underestimated, as many companies fail at this stage of the process by not following through with the strategies put in place (Hillson, 2002).

Compared to the previous steps, risk monitoring has attracted less attention in the literature. Among the 224 articles (published between 2003 and 2013 on the field of supply chain risk management) reviewed by Ho et al. (2015), only one article studied risk monitoring in their approach. This can be explained by the fact that monitoring has been considered as an exclusively human activity (Benaben et al., 2021). However, due to the increasing complexity of supply chains and their increasing vulnerability to uncertainty, practitioners and researchers recognise the importance of further developments for this step (Ben Jbara, 2018). Visibility is an essential element of supply chain agility (Christopher et al., 2004b). There is therefore a need to develop dynamic, real-time visualisation and measurement tools to support this stage (Blackhurst et al., 2005; Souza et al., 2015).

In the case of **opportunities**, this step does not require any change, the same approaches can be applied in order to observe the impact of the opportunities and to monitor the good functioning of the actions put in place (their relevance and effectiveness) in order to get the maximum benefit from the opportunities identified and realised.

The risk monitoring step compared to the previous steps has been little studied in the literature, despite its importance. This could be explained by the fact that this step is considered an exclusively “human” step (Benaben et al., 2021).

Taking into account all the elements presented in this section, the four steps of risk management can be extended to opportunity management, only the risk treatment step presents some differences, notably in the list of possible strategies. In the remainder of this manuscript, risks and opportunities will be treated in the same way and grouped under the generic term of potentiality. The identification and assessment stages seem to converge into a generic stage dedicated to the detection and modelling of potentialities, a stage dedicated to the preparation of the necessary materials to enable decision makers to take decisions. The processing and monitoring steps, which are highly dependent on the results of the two previous stages and more manual, could be grouped into a step focusing more on choices and decision-making.

1.3 The Physics of Decision approach: a new way to manage supply chain risks and opportunities

1.3.1 The fundamentals

Faced with the complexity of modern supply chains, choosing the right risk management practice from the variety of approaches proposed in the literature is not an easy task (Ebrahimi et al., 2012). According to Ebrahimi et al. (2012), there are no generic tools integrating risk analysis to support managers in their decision-making processes. The existing tools in the literature are specific to given problems or tested on specific supply chain case studies, they usually require advanced knowledge in a high-level programming or modelling tool (Ebrahimi et al., 2012). However, supply chain managers are particularly interested in decision support systems that can identify and monitor disruptions in real time, understand the predisposition of the logistics network (its resilience) to disruptions and support them in choosing the best actions to take during pre- and post-disruption periods (Ivanov et al., 2021). Decision support systems are central to risk and opportunity management (Fang et al., 2012). Given the complexity of supply chains, the massive amount of data they generate and the relationships between the various actors in the network, these systems have become essential (Bekefi et al., 2008). The current instability only reinforces this need. Decision support systems can be seen as approaches to identify and evaluate multiple control variables (attributes, criteria or parameters) that would have an impact on the performance of the supply chain (Yazdani et al., 2017).

Need 1

Need for a space to connect the system to its environment. This space must be able to: (1) describe the observed system, its environment and the relationships between the two; (2) identify and evaluate the attributes that have an impact on the system’s performance; and (3) identify and evaluate the attributes over which managers have decision-making power.

Implementing a decision support system in the area of performance management that analyses the evolution of KPIs to support managers in their decision-making processes, seeking to link strategic objectives to operations, has been a long-standing challenge (Bititci et al., 2012). Managing performance is a norm in all industrial sectors, in order to be competitive, especially in complex and volatile environments (Bititci et al., 2012). However, despite its importance, the study of the effects of supply chain risk management on its performance remains unexplored (Wieland et al., 2012). Very few contributions in the literature have studied the relationships between supply chain risks and its performance (Colicchia et al., 2012). These relationships have neither been supported by empirical evidence nor supported by theory (Colicchia et al., 2012). As mentioned in the famous maxim “that which isn’t measured isn’t managed” (Dalziell et al., 2004), studying the relationships between risk and performance at the level of the firm and the supply chain as a whole then becomes a necessity, especially given their interconnectedness (Ritchie et al., 2007a). According to (Chapman et al., 2011), current risk management methods offer a very limited perspective on performance management. Chapman et al. (2011) attribute these limitations mainly to the weakness of these methods in managing risks (threats) and opportunities, which deprives managers of access to information that allows them to both “maintain” a level of performance (the goal of risk management, which aims to neutralise threats and keep the system on track) and to assess any possibilities that could improve the system’s performance (opportunities).

Need 2

Need for a space to explore and monitor the evolution of a system’s KPIs over time, whose perspectives would allow the aggregation of a system’s risk (and opportunity) management and performance management into a single space, in order to correlate risk management strategies and the achievement of performance objectives.

The Nobel Prize-winning economist Herbert Simon (H. A. Simon, 1955) proposes in his model of bounded rationality three essential steps for managing a system in an unstable environment (Cerabona et al., 2021a). The first step is *intelligence*, which aims to identify the problem and define the decision criteria through data collection and the creation of a conceptual workspace to define and understand the system under study (its KPIs, current and target performance, and internal potentialities) and its environment (external potentialities). The second step is *design*, which consists of building a reference model to model, analyse and understand the consequences of the different potentialities identified in the first step. The last step is *choice*, which consists of defining the mechanisms for selecting the best available options, *i.e.* choosing the potentialities whose impact is the most advantageous for the supply chain performance. Among the main tools and approaches existing in the literature and dedicated to decision support and performance management, none of them allows to consider the three previous steps at the same time (Benaben et al., 2021), which creates a gap between the needs of managers to have tools allowing them to navigate in instability and the tools currently at their disposal.

Considering the high level of complexity and unpredictability of future events (potentialities) that may impact a supply chain, traditional practices and tools do not seem to be effective anymore, which creates a need for dynamic models able to consider the maze

of interactions characterising supply chains and the sources of disturbances impacting it (Colicchia et al., 2012). According to Wieland et al. (2021) taking a complete inventory of risks as proposed by the transfer of traditional risk management processes from an organisation to the supply chain is illusory. This will only result in a substantial expansion of the list of risk sources, making any attempt at an inventory futile (Wieland et al., 2021). The most impactful events for supply chains are “*black swan*” events, risks that are difficult to predict and not included in the list of risk sources because they have simply been overlooked (Akkermans et al., 2018; Wieland et al., 2021), due to their low probability. The eruption of the *Icelandic volcano Eyjafjallajökull* in 2010 or the *COVID-19 pandemic* are glaring recent examples. Thus, traditional risk management approaches are not scalable enough to meet the risk management needs of such complex systems as supply chains (Wieland et al., 2021). These risk analysis and management techniques based on probabilistic methods have been widely exploited and particularly useful for dealing with predictable and calculable potentials (Linkov et al., 2014). “With the increasing level of volatility, the days of static supply chain strategies are over” (Simchi-Levi, 2010). It is important for managers to develop new mindsets on how to manage supply chains (Adobor et al., 2018; Christopher et al., 2011), and especially risk and instability, in order to fully appreciate the dynamism of supply chains, systems that are subject to constant change and evolution. In the age of turbulence proclaimed by Christopher et al. (2011) and Benaben et al. (2021), with increasing complexity and an unprecedented number of unforeseen threats, managers are required to make decisions in increasingly complex circumstances (rapidly changing conditions, a dynamic system, uncertain goals, tight deadlines, lack of information sharing among diverse stakeholders, limited resources, etc.), making traditional techniques less effective), which makes traditional and standard analysis and decision-making techniques too simplistic to cope with the complexity of modern problems (Zhengping et al., 2013). Therefore, there is a need to implement and develop innovative thinking, simulation models and new methods (Linkov et al., 2014).

The PoD approach, as an innovative decision support approach based on the laws of motion of physics, aims to address this need by providing innovative decision support tools in a context of instability and uncertainty (Moradkhani et al., 2022a). To do so, the PoD approach seeks to answer three fundamental questions (specified in the introduction to this chapter), which define a vision of decision making through the innovative management of performance and its dimensions. This requires: (1) understanding the *system* under consideration, its KPIs, its context, its current and target performance, (2) understanding the potential *changes* that this system and its environment may undergo, and (3) finding a way to *choose* among these changes the appropriate decisions to be taken based on their consequences on the performance of the system. This vision is in line with the theory of bounded rationality proposed by H. A. Simon (1955). Thus, the PoD approach seeks to respond in a single approach to the three steps proposed by Simon to support decision-making in an uncertain context. In the same way that today we take certain laws of physics for granted, such as gravity thanks to Newton’s work - *no one asks why an apple falls when we drop it anymore* - the PoD approach aims to determine the laws and dynamics (forces) governing complex and collaborative systems such as supply chains, using analogies with physics. Through its work, in the same way that gravity is adopted and understood by all as a law governing dynamics on Earth, the analogies used and developed will enable managers to have a set of fundamental laws that react to complex systems and thus greatly improve their management.

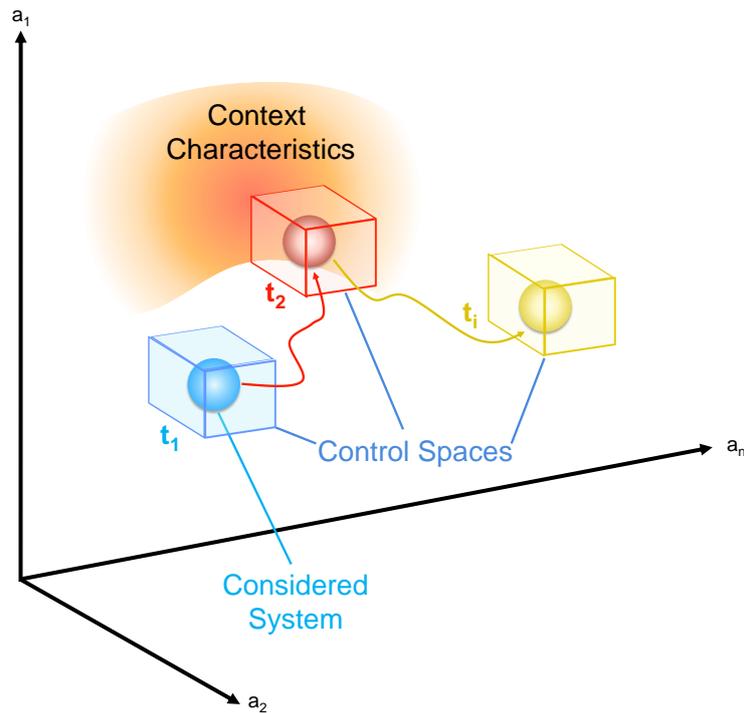


Figure 1.6 – Description space (adapted from Cerabona et al., 2023)

1.3.2 The description and performance spaces

To meet the two needs identified above, the PoD approach develops two complementary and connected modelling spaces: the description space and the performance space (Benaben et al., 2021). The **description space** is a multidimensional space where each dimension represents an attribute of the supply chain, *i.e.* a parameter that represents the characteristics and properties of the supply chain and its environment (Benaben et al., 2021; Cerabona et al., 2021b). In Figure 1.6, the supply chain is located in its description space by the different coloured spheres, representing at each moment its position with respect to the values of the supply chain’s attributes (*e.g.* customer demand, raw material price, production capacity, etc.) and its environment’s attributes (*e.g.* customs taxes, net minimum hourly rate, etc.), called characteristics. Each attribute has a certain degree of freedom, mainly due to the stochastic factors that may be associated with it (*e.g.* sales forecasts, transport times, etc.), but also their variations induced by the daily operation and management of a supply chain (postponement of an order, increase in production capacity, etc.). This degree of freedom is represented by the three coloured parallelepipeds in Figure 1.6. They model subspaces, called control spaces, in which the supply chain can move freely (Cerabona et al., 2021a).

The context features area represents parts of the space where the supply chain is more sensitive to certain hazards that may impact it (Cerabona et al., 2021b), *i.e.* its current state (current attribute values) makes it susceptible to certain potentials. It models and geo-locates the “risk” areas in the description space (orange area in Figure 1.6). It provides a dynamic representation of the three characteristic attributes of a hazard: its location (its position in the description space), its time window (the evolution of

its position and shape over time) and the impacted resources (materialised by the impacted dimensions of the space, *i.e.* the impacted attributes and their threshold values at which the hazard exists if the attributes of a supply chain approach it). The question of how to determine this zone is still open. It is certain that it can only be determined by a complete understanding of the supply chain and the determination of the relationships between the description and performance space. Some threshold values for certain attributes can be determined by studying the system, *e.g.* the threshold at risk of a company’s production capacity can be determined from the value of the various customer demands and the efficiency of its production lines. Conversely, for other attributes, determining the risk threshold for given situations will be much more complicated. In this case, the existing mathematical relationships between these two spaces will make it possible to determine them, based on the study of the zones of the performance space (in particular its resilience and robustness zones, the concepts of which are defined in Chapter 2).

The position of the supply chain evolves over time in its description space as a result of: its “natural” functioning (blue sphere at t_1 in Figure 1.6), the realisation of potentialities modifying the value of its attributes (red sphere at t_2 in Figure 1.6) and the decisions taken by managers to counter or favour potentialities according to their type (yellow sphere at t_i in Figure 1.6). Its position in the description space models its different states.

The **performance space** is dedicated to visualising and managing supply chain performance (Cerabona et al., 2021b). According to Bruneau et al. (2003), the actual or potential performance of a system can be measured at any time as a point in a multidimensional space of performance measures (based on the assumption that performance is only measured by quantitative indicators). The performance space takes up this principle by forming a multidimensional space, where each dimension is a supply chain KPI. This space thus responds to the needs of companies, which seek to measure, monitor and manage their performance across multiple dimensions built from a dynamic set of metrics supporting the decision-making process (Nudurupati et al., 2022). The KPIs used form a set of quantifiable measures used to evaluate the performance of supply chains according to their strategic and operational objectives (Graça et al., 2017). The notion of dynamism reflects the need to develop a performance measurement system capable of monitoring and evaluating the evolution of performance and its performance objectives at each moment and following changes related to events internal or external to a company or supply chain, requiring a revision of performance objectives (Taticchi et al., 2015). In this space, the evolution of the performance (the values of the KPIs over time) of a supply chain is modelled and visualised as a performance trajectory.

The value of the KPIs evolves following the realisation of potentialities. This evolution can be more or less abrupt depending on the impact of the potentialities. Abrupt changes in performance occur in the case of disastrous events or radical decisions, while “normal” fluctuations in the day-to-day management of supply chains result in minor variations in performance. These changes and variations in performance are generated by forces (coloured vectors in Figure 1.7), created by potentialities, which depending on their nature, move the supply chain and its performance trajectory away from (negatively deviate the trajectory) or towards (positively deviate the trajectory) its performance objectives (Cerabona et al., 2021a; Cerabona et al., 2021b). With this view, each force models the potential impact of each potentiality, which is reflected in

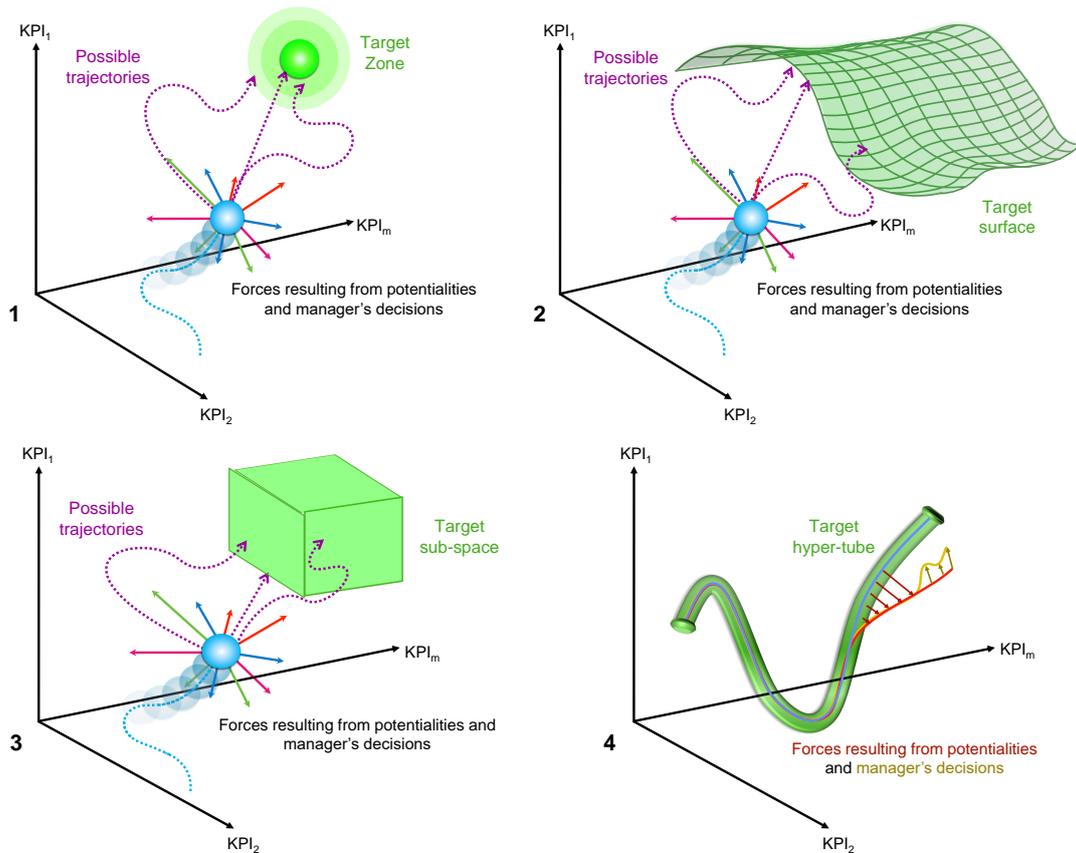


Figure 1.7 – Performance space (adapted from Cerabona et al., 2021a; Cerabona et al., 2023; Cerabona et al., 2021b)

the intensity of the deviation from the performance trajectory, thus materialising the displacement of the supply chain as a “physical object” in the multidimensional space of its KPIs (Cerabona et al., 2020).

Just as the position of the supply chain in this space, its objectives evolve over time and can be modelled according to different geometries: a point in space (*image 1* in Figure 1.7) or a subspace (*image 3* in Figure 1.7) to be reached, a hyper volume (*image 4* in Figure 1.7) in which to maintain the supply chain, or a hyper surface (*image 2* in Figure 1.7) representing a threshold of satisfaction between the different KPIs. Thanks to its concepts, the PoD approach thus makes it possible to reconcile risk assessment and supply chain performance objectives, two closely related concepts according to Heckmann et al. (2015).

This space is dedicated to support managers’ decision making (Cerabona et al., 2020), in particular by studying the best combinations of forces to select, in order to either reach the target areas with the least possible effort (the possible purple trajectories in *images 1, 2 and 3* in Figure 1.7), or to keep the system in the target hyper-volume (the green cube in *image 3* in Figure 1.7), seen as a “safe” subspace, or a space that needs to be traversed (the green hyper-tube in *image 4* in Figure 1.7). To support decision making, the main advantage of the performance space is the access to the performance trajectory of the supply chain, thus allowing to monitor and analyse the evolution of its performance, its position in this framework (Benaben et al., 2021). To apply the PoD

approach, the first trajectory to be modelled in this space is the *inertia trajectory* (blue trajectory in *image 4* in Figure 1.7). This trajectory models managers' expectations in terms of performance. Indeed, it is considered as the trajectory followed by the supply chain if it follows its "normal" behaviour (if it is not disturbed or disturbed only by expected forces), *i.e.* if it follows the predictions made by the managers. Ideally and most of the time, the *inertia trajectory* can be seen as the optimal trajectory to be followed to reach the performance objectives, *i.e.* the target zone to be reached (in the case of a supply chain, this target zone often corresponds more to a hyper volume to be maintained and/or followed, than to a zone to be reached). The *inertia trajectory* is used as a reference in the study of potentialities, each of its deviations is considered as the resultant of a force (the impact of the potentiality on supply chain performance). The activation of this resultant force (depending on its nature) generates two types of possible trajectories: the *passive trajectory* (red trajectory in *image 4* in Figure 1.7) and the *active trajectory* (yellow trajectory in *image 4* in Figure 1.7). In this approach, the *passive trajectory* is defined as the performance trajectory of the system following the realisation of a potentiality, without any corrective action having been taken to reduce its impact on the performance of the supply chain (Cerabona et al., 2023). It therefore combines the effects of both inertial forces and potentiality. This trajectory is generated by the variations of the system's attributes between the instants t_1 and t_2 (a change of state of the system materialised by its displacement between the blue and red spheres in its description space, illustrated in Figure 1.6). On the same principle, the *active trajectory* is defined as the performance trajectory of the system following the realisation of a corrective or preventive action, which has been implemented to minimise (respectively maximise) the impact of a risk (respectively an opportunity) on the system performance (Cerabona et al., 2023). The forces governing its motion and shape, correspond to the combination of the effects of the inertial forces, the disturbance and the corrective actions implemented. This trajectory is generated by the variations of the system's attributes between the instants t_2 and t_i (the displacement between the red and yellow spheres, illustrated in Figure 1.6). Based on the above, it is clear that these three types of trajectory (inertia, passive and active) are all similar in nature (Cerabona et al., 2023). Indeed, they all represent the performance of a supply chain in the face of different realities. However, they differ according to the meaning to be given to these actualities: *expected* for inertia; *expected and unexpected* for passive; *expected, unexpected and processed* for active (Cerabona et al., 2023).

It is important to consider that these two spaces are linked, as variations in the value of attributes as a result of a potentiality lead to deviations in the different performance trajectories considered, seen and measured in the performance space. Thus there are relationships between these two spaces, built from functions linking attributes to KPIs. Let us consider a supply chain (S) with n attributes (a_1, a_2, \dots, a_n) to describe its different states and parameters. S thus has an n -dimensional description space, which can be defined in the space \mathbb{R}^n . In the same way, S has m KPIs (p_1, p_2, \dots, p_m) to measure its performance. Its performance space is of dimension m and can be defined in the space \mathbb{R}^m . The relationship between its description space and its performance space can be defined as $\Psi : \mathbb{R}^n \rightarrow \mathbb{R}^m$. Thus for each of its states i , S can be modelled by the point $A_i = [a_{1,i}, a_{2,i}, \dots, a_{n,i}]$ in its description space, the corresponding performance P_i can thus be obtained through the relation $\Psi : \mathbb{R}^n \rightarrow \mathbb{R}^m$ as follows: $P_i = \Psi(A_i)$ and $[p_{(1,i)}, p_{(2,i)}, \dots, p_{(m,i)}] = [\Psi_1(A_i), \Psi_2(A_i), \dots, \Psi_m(A_i)]$. However, depending on the type of system studied and its complexity, these functions may be more or less difficult

to determine (Moradkhani et al., 2021). In the case where these relationships are too complex to determine (such as for supply chains), simulation models can be built and act as a “black box” to estimate the relationships between the attributes and the KPIs of the supply chain under study. Simulation campaigns can thus be carried out to determine the existing relationships between the attributes and the KPIs.

Summary of answers to the main questions related to the foundations of the PoD approach (developed in this section):

Q1. *How do you identify and model the system under consideration, its KPIs, its initial performance and its target performance?*

R1. Definition of an innovative formal theoretical framework, composed of two spaces (the description space and the performance space) for modelling the system and its performance.

Q2. *How do you identify risks, opportunities and potential changes in the system or its context?*

R2. Definition of mathematical relationships between the two spaces to support the identification and formalisation of potentialities (risks and opportunities), modelled as forces in the performance space.

Q3. *How can these potential changes be linked to changes in performance to make appropriate decisions?*

R3. Definition of the concept of performance trajectories and performance target areas.

1.3.3 The potential for SCR&OM

The two spaces defined in the PoD approach make it possible to cover the three stages of Simon’s reference framework (H. A. Simon, 1955), which are essential for navigating in an unstable environment. Figure 1.8 positions the contributions and concepts developed in the PoD approach in this framework. The description space and the performance space support the *intelligence* stage through their ability to describe and understand the evolution of the supply chain (its changes of state, potentialities internal to the supply chain) and its environment (potentialities external to the supply chain), from the point of view of its attributes and attributes specific to the potentialities, but also of its performance (the inertia trajectory offering an overview of the ideal performance, a reference trajectory serving as a comparison for the following stages, in particular that of the choice) The *design* stage is supported by the existing mathematical relationships between the two spaces, but also by the proposed analogy of measuring the impact of the potentials by forces and deviations of the different performance trajectories. These relationships can be determined by a detailed assessment of the supply chain under study through a sensitivity analysis (performed by simulations or neural networks), in order to deduce a correlation matrix between the system inputs (supply chain attributes and characteristics specific to each potentiality) and the measured KPIs. The performance space, by its definition, offers a performance visualisation and steering space dedicated to decision making. It is positioned as a reference framework for studying and modelling the consequences of the different potentialities, observed in the form of deviations of the different performance trajectories from the achievement of objectives following their realisation. It allows the study of different strategies (to stay in or reach the objective area at a lower “cost”) either through “*what if*” analyses or by using

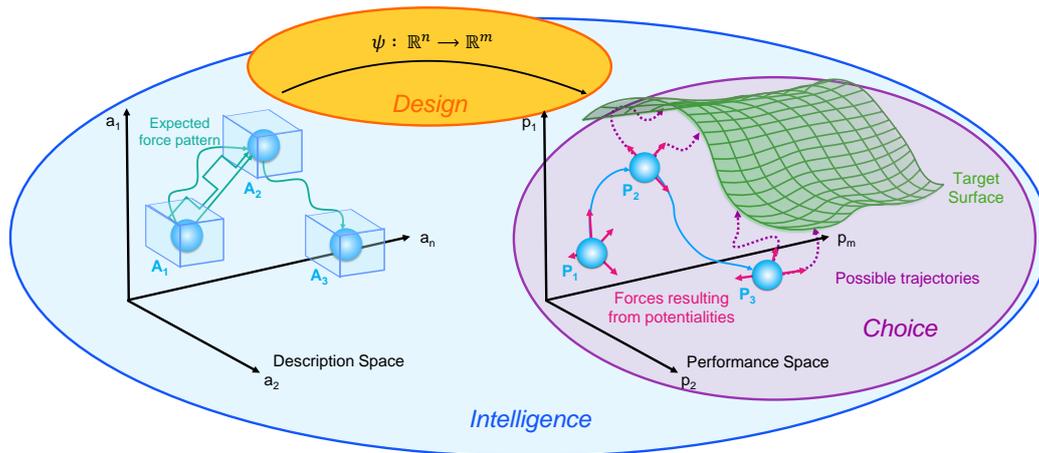


Figure 1.8 – Positioning of the PoD concepts in Simon's framework (H. A. Simon, 1955)

optimisation algorithms, such as the heuristic approach, in order to determine the best force selection (the most desirable decisions) to bring the supply chain towards its performance objectives. The performance space thus fully participates in the *choice* stage.

From the point of view of the risk and opportunity management process presented in section 1.1.2 and illustrated in Figure 1.9, the work presented in this manuscript on the PoD approach is essentially positioned on the last three stages of this process: *potentiality assessment*, *potentiality management* and *potentiality monitoring*. The *potentiality identification* phase will not be dealt with in this manuscript, whose work will apply the PoD approach to given and pre-identified potentialities. On the other hand, future work does not exclude work on this stage, which will be strongly dependent on the ability to master the performance space by studying these different zones (more or less favourable) and the description space by setting up mechanisms and techniques to efficiently determine the zone of context characteristics.

According to the causal chain, which is the basis of the notion of risk in the PoD approach, introduced in section 1.1 of this chapter and illustrated in Figure 1.2, the supply chain under study has to deal with one of these four potentials (Cerabona et al., 2021a):

- *Environment*: potentials related to the supply chain environment (a change in law impacting SMEs, a climatic event in a region, tax rules in a country, etc.), possibly due to the physical, social, political, legal or economic environment (Bogataj et al., 2007);
- *Expenses*: due to compulsory and incompressible costs (operating costs, salaries, maintenance costs, etc.) or revenues (rents, royalties, etc.) that must be taken into account at all times;
- *Innovation*: actions dedicated to the improvement of the supply chain or of a company (process improvement, purchase of new machines, etc.);

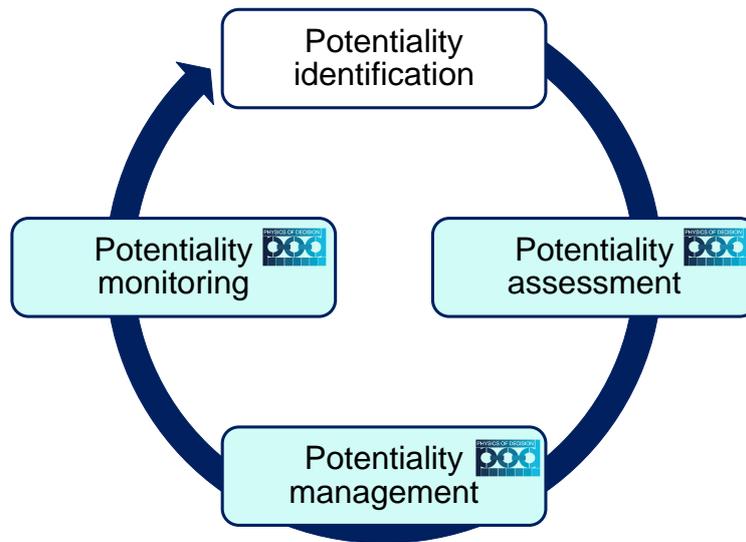


Figure 1.9 – Positioning of the PoD approach in relation to the risk and opportunity management process presented in Section 1.2

- *Interaction*: all the potentials created by the relationships between the different actors in the supply chain (information sharing, climate of trust between the actors in the network, etc.).

According to the causal chain mentioned above, potentialities (risks or opportunities) appear as a result of the sensitivity of the supply chain to some of these four types of potentials (Cerabona et al., 2021a). They come to life when certain conditions activate the potentials and thus become forces (the links between potentials and forces are illustrated in Figure 1.10). Therefore, several types of forces can be considered (Benaben et al., 2020). They are essentially divided according to their *internal vs. external*, and *inflicted vs. managed nature*. Basically, there are therefore four types of forces:

- *Contextual force*: corresponds to an *external* and *inflicted* force resulting from the potentials linked to the characteristics of the supply chain environment;
- *Natural force*: corresponds to an *internal* and *inflicted* force resulting from the inertial potential of the system, corresponding mainly to the operating costs of the supply chain, its compulsory and incompressible costs, which can be financial as well as temporal;
- *Autonomous force*: corresponds to an *internal* and *managed* force resulting from the innovation potential, mainly due to internal changes and decisions (continuous improvement processes);
- *Interface force*: corresponds to an *external* and *managed* force resulting from interaction potentials. Collaborative forces are due to the different partnerships (exchanges of goods and services) and relationships between the different actors in the supply chain (exchanges with suppliers, subcontractors, service providers

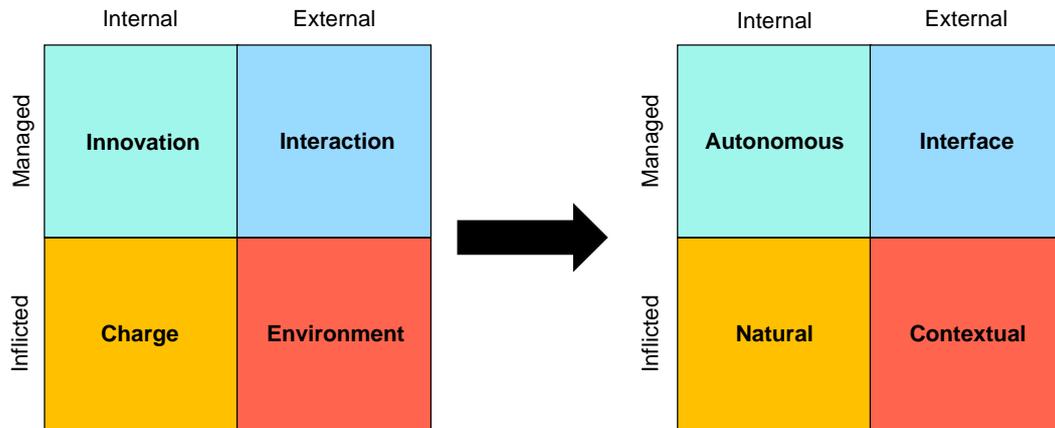


Figure 1.10 – System potentials in relation to existing forces

or customers). The nature of these agreements and relationships (trust, with common objectives, quality of information sharing between partners, etc.), but also their reactivity, cost and quality have a strong impact on the supply chain KPIs.

The notions of *inflicted* or *managed* force depend mainly on the position and displacement in the description space generated by the realisation of one or more potentials. A force is said to be *managed* when this variation of attributes is dictated by a decision of the managers (which corresponds to the activation of decision levers by the managers) or to variations included in the control space (described in the previous subsection), which correspond to variations linked to the daily management of the attributes of a company. Conversely, a force is said to be *inflicted* when it is triggered by a variation in attributes outside the decision space. It is important to consider that these two natures, *inflicted* or *managed*, are used for the purpose of categorising forces. In reality, for systems as complex as supply chains, the nature of a force is not completely binary, for example, a force may be partially managed.

The notions of *internal* and *external* force are close to the concepts identified in the analysis of supply chain risk classification. Basically, the terms *internal* and *external* are positioned at the level of the company but can easily be extended to the level of the supply chain as a whole. For contextual forces, the notion of *external* is found in the classifications of Trkman et al. (2009) in the form of exogenous risks, Samvedi et al. (2013) in the form of environment-related risks and Ho et al. (2015) in the form of macro-risks. These risks are both external to the supply chain and to the firm. For natural and autonomous forces, the notion of *internal* is found in the classifications of Trkman et al. (2009) in the form of endogenous risks, Samvedi et al. (2013) in the form of internal process risks and Ho et al. (2015) in the form of manufacturing micro-risks. The interface forces are external in the case where the system under study is a company. In contrast, in the case of a supply chain (seen as a network of interconnected firms), these forces are internal and correspond to the view of internal demand and supply risks defined by Samvedi et al. (2013).

In addition to their type and nature, forces have several properties and attributes. These properties need to answer four fundamental questions to be able to fully assess forces: (1) *how strong* is the force, (2) *how often* does the force occur, (3) *what pattern* follows the force, and (4) *when and for how long* does the identified force apply. These four questions highlight the properties of the forces and are consistent with the four attributes proposed by Macdonald et al. (2018) to define both positive and negative events responsible for supply chain disruptions, namely: magnitude, frequency, form and duration. The following points define the identified properties and their relationship to the causal chain concepts illustrated in Figure 1.2:

- *Force intensity*: measures the *actuality* (Figure 1.2) that follows the realisation of the identified force. The norm of the associated force vector (*i.e.* the absolute magnitude of the force) determines the magnitude of the concrete and geometric deviation of the system's performance trajectory from its expected trajectory (its inertia trajectory). Depending on the strategic, tactical and operational objectives defined for the system under study, this property makes it possible to specify the level of severity (or benefit) of the measured potentiality and thus to determine the room for manoeuvre that the system has (*i.e.* to choose which of the strategies defined in subsection 1.2.3 of this chapter to implement).
- *Force occurrence*: examines the probabilities of occurrence of the conditions (Figure 1.2) of activation of the different potentials, which activate the identified forces that may deviate the performance trajectory of the system.
- *Force model* (shown in Figure 1.9): refers to its mode of application, *i.e.* how the impact of the potentiality on the attributes of the system manifests itself (by which function could it be modelled): an impulse (*e.g.* a slap in the face, a strong abrupt impact), a continuous impact, a progressive (staircase) impact, dynamically changing impact over time (linear, sinusoidal, logarithmic, etc.), etc.
- *Time and duration of application of the force*: corresponds to the time of application of the force and its duration (the number of time periods over which it is active). Regardless of its source or nature, the importance of the time at which the force is applied will have a strong impact on the ability of the system to achieve its objectives (this also applies to its duration). This property highlights the importance of the notion of time in the performance space, a key component in risk analysis, which has not yet been addressed in depth in the supply chain risk management literature (Heckmann et al., 2015).

A first illustration of all the PoD concepts defined in this chapter is provided in Appendix A, in the context of a project on risk management in American voting centres.

1.4 Research questions formulation

1.4.1 Research Questions

Risk analysis is the dominant approach to failure prevention in engineering (Park et al., 2013), which includes different phases illustrated in section 1.2. However, for complex systems, risk analysis alone does not fully protect their functions and components

(Park et al., 2013). The classical risk analysis and management process starts with the identification of the different hazards that may impact the system, an exercise that is problematic for the management of complex systems operating in an unstable environment and with emerging threats that may be unknown (Park et al., 2013). Indeed, according to Wieland et al. (2021), the most impactful adverse events are risks that are difficult to predict (generally not included in the list of identified risks). Moreover, trying to draw up an inventory of all the hazards that can impact such systems is a futile task (Wieland et al., 2021). In these systems, risks emerge due to the non-linear relationships between system components and processes, the dependence of decisions and the non-stationary response of the system to a disturbance, the occurrence and impact of which on these systems are stochastic (Park et al., 2013). Thus the vulnerability of these systems evolves over time and in unexpected ways, with emerging hazards only being observed once they have occurred (Park et al., 2013). Therefore, the main reason for the ineffectiveness of traditional risk management is that it relies on the need for static information, whereas many risks are unpredictable and unknowable (Fiksel et al., 2015), especially in an unstable environment, in the age of turbulence (Christopher et al., 2011). Once the impacted component has been identified and the impact of the disturbance on the system functions during its realisation quantified, risk management techniques then focus on strengthening the system components impacted by these vulnerabilities, in order to increase their resilience to these events and avoid any overall system failure (Linkov et al., 2014). According to Linkov et al. (2014), two factors make this view of risk management unrealistic for many complex systems. Firstly, the hyper-connectivity between social, technical and economic networks creates complex systems where risk analysis by individual components becomes impossible in terms of cost and time. Secondly, the instability in which these systems evolve challenges our ability to understand and manage disruption. Attempts to combat disruption through traditional risk management approaches are therefore insufficient in the era of highly uncertain and dynamic environments (Chowdhury et al., 2017; Jüttner et al., 2011). Therefore, to combat the challenges arising from these unstable environments, organisations need to develop a resilient approach (Chowdhury et al., 2017).

Resilience is defined as the ability of an organisation to survive, adapt and grow in uncertain times (Chowdhury et al., 2017; Fiksel, 2006). Resilience is advocated in many fields as a remedy to cope with dynamic and uncertain situations (Gao et al., 2016; Wieland et al., 2021). It is thus evident that we are moving away from the traditional view of risk management seen as a reactive tactic in the face of disruptions towards more proactive strategies proposed by techniques for strengthening the resilience of supply chains, thus increasing their chances of maintaining their functions and some continuity in unstable situations (Katsaliaki et al., 2021). Linkov et al. (2014) propose to use traditional risk analysis to help prepare for and prevent foreseeable disruptions, and to focus on integrating and managing resilience to help systems recover and adapt quickly following the occurrence of disruptions. In contrast to traditional risk management approaches, resilience focuses on systemic features rather than on sources of risk (Wieland et al., 2021). Resilience has thus become extremely important in the field of supply chain management due to the increase in disruptions impacting them (Chowdhury et al., 2017). The estimation of resilience has become vital for making decisions based on the study of risks (Pant et al., 2014). Since its relevance to supply chain management was first identified (more than a decade ago), many methods dedicated to improving and assessing resilience have been developed (Wieland et al., 2021). However, this field has

not yet been fully explored (Pires Ribeiro et al., 2018), with researchers still debating how supply chain resilience should be conceptualised and measured (Chowdhury et al., 2017; Jüttner et al., 2011). The different interpretations of its concepts are the subject of long-standing debates within the supply chain management community (B. H. Walker, 2020; Wieland et al., 2021).

These different views of supply chain resilience are developed in Chapter 2 of this manuscript. Empirical research on this topic has been impacted by the lack of a valid (Chowdhury et al., 2017) and replicable measurement model. For the development of such a capability, therefore, specific methods to define resilience, quantitative models to comprehensively measure the resilience of a supply chain (not focusing only on a concrete part of a supply chain operation, but on the whole supply chain, providing a global view of the situation), as well as new modelling and simulation techniques need to be developed (Linkov et al., 2014; Pires Ribeiro et al., 2018). In these models, performance measures play a key role (Pires Ribeiro et al., 2018). This is an area in need of further research, as it plays a vital role in the study and application of models on supply chain resilience, but also for their importance in the decision-making process, providing a better understanding of the functioning of the supply chain as a whole (Pires Ribeiro et al., 2018). Given the challenge of managing and measuring resilience in risk management for complex systems operating in an unstable environment, the PoD approach needs to address the need to study resilience. Thus, Chapter 2 will aim to answer this research question:

Research Question 1 (RQ1)

How can we develop supply chain resilience capabilities (its management and measurement) using a kinetic approach such as PoD?

The PoD approach, presented in this chapter, is based on the ability to transform and evaluate the potentialities of a supply chain as physical forces in its multidimensional performance space. This space dedicated to decision making and the choice stage (proposed in H. A. Simon (1955)'s framework), offers perspectives to support the monitoring stage of the risk management process, much less studied in the literature than the other stages of this process (J. B. Oliveira et al., 2019). In particular, by providing a dynamic and interactive dashboard of the supply chain's status, risks, opportunities and performance, information that is essential for risk analysis. In order to provide decision-makers with such a performance visualisation and steering tool, two challenges need to be addressed.

In a purely theoretical case, where the aim of the approach would be only to select the "optimal" set of forces to be activated, in order to move the supply chain in its performance space in such a way that it reaches its predefined target area (objective) at the lowest cost, it is obvious that the use of optimisation algorithms would allow to achieve this result. Indeed, once the forces have been identified, characterised and evaluated, these algorithms (*e.g.* heuristics) could provide the "right" combination of forces to activate, without having to focus on the visualisation of performance trajectories and the resulting difficulties. However, the choices are usually more complicated than a combination of forces (potentialities) to be activated. There may be many external factors to consider, as well as human factors (personal reasons that may lead the decision maker to choose one potentiality or another). Supply chain risk management depends

on the quality of management in terms of knowledge, experience and skills (T. Wu et al., 2009). All of the concepts, tools and methods proposed over the last few decades certainly support decision makers in their decision-making, but they can never replace their judgements, which are required in most decisions made in a risky situation (T. Wu et al., 2009). Most approaches developed for supply chain risk management do not take into account the decision maker's attitude towards risk (Heckmann et al., 2015). Thus, the aim of the approach is to leave the decision maker with the final say and the choice of what decision to make. The decision-maker should thus be able to visualise and understand all components of the proposed decision set (Moore, 2017). This willingness also contributes to the decision maker's learning process in managing a set of decisions (corresponding to the fifth step of the risk management process proposed by T. Wu et al. (2009): organisational and personal learning, which seeks to capture, extract, distil and disseminate lessons and experiences within the organisation and the logistics network). Thus, the first challenge that this approach must meet is to be able to make all potential decisions and their combinations explicable and actionable for decision-makers.

In all the proposed representations of the performance space (Figures 1.7 and 1.8), in order to facilitate the visualisation of performance trajectories, this space has been limited to three dimensions, *i.e.* to the evaluation of the supply chain according to three KPIs. It is easy to imagine that for a system such as a supply chain, decision-makers will not limit themselves to observing three KPIs. Indeed, the management of a real system such as a supply chain quickly leads us to analyse more than three KPIs (Maestrini et al., 2017). In addition, as instability becomes the norm, the number of potentialities affecting supply chains is rapidly increasing year after year (Nakano et al., 2020), with each potentiality having an impact on one or more KPIs. However, being able to theoretically calculate the overall performance of the observed system as a trajectory impacted by any potentiality is one of the major contributions of the PoD approach. Thus, the second challenge is to manage the potentially large number of dimensions of the performance space, influenced by a potentially large number of potentialities to be considered. It is therefore imperative to find a way to make the performance space and the modelled performance trajectories manipulable for decision makers. The main question that Chapter 3 seeks to answer combines these two challenges:

Research Question 2 (RQ2)

How to represent, visualise and pilot the performance of a supply chain seen as a multidimensional trajectory (defined by numerous KPIs and impacted by numerous forces), in order to make it a decision-making tool that can be used in a relevant and ergonomic manner?

1.4.2 The Big Picture

This chapter provides a review of the literature on tools and concepts related to risk and opportunity management in the context of supply chains. This literature review highlights some of the weaknesses of current risk and opportunity management methods. The concept of opportunity has been overlooked in the majority of the methods studied. This is why it is important to propose an approach that meets the needs of managers in the management of potentialities and instability, *i.e.* an approach that responds at the same time and at a fairly high level to the three essential phases for the management

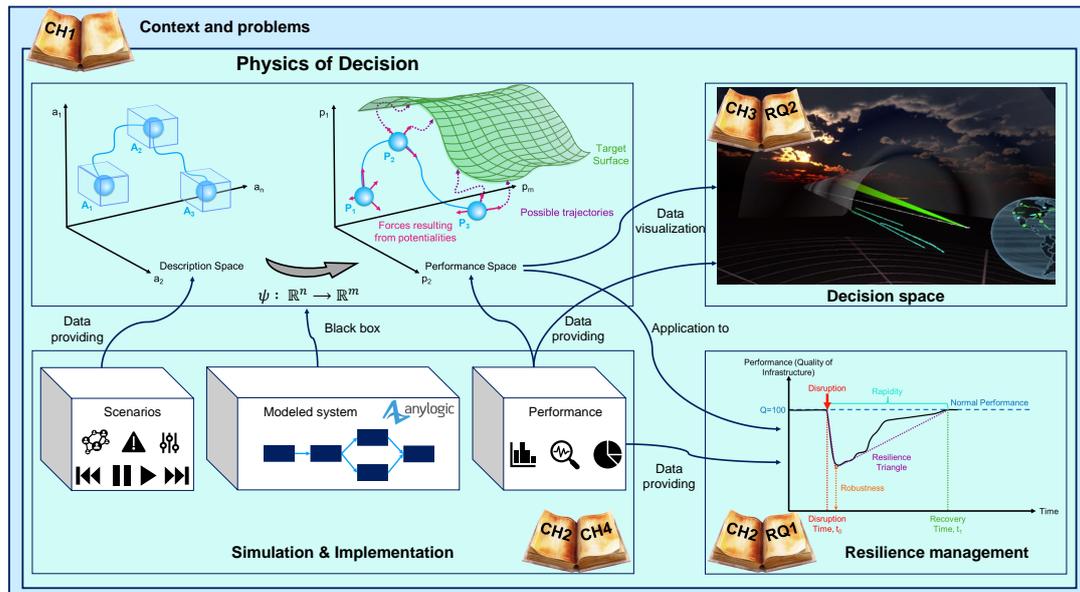


Figure 1.11 – Big Picture of the thesis

of instability put forward in Simon’s framework (H. A. Simon, 1955). The approach selected to address these shortcomings is the PoD approach. However, the PoD approach is a recent approach (the first works date from 2019) and requires many developments to benefit from its contributions. In the case of the study of its application to the management of potentialities impacting supply chains, these development needs are formalised in the form of the two research questions raised in this chapter. The work presented in this manuscript aims to answer these two questions. Firstly, Chapter 2, based on a state of the art on the concepts of supply chain resilience, including its definition and assessment, studies and illustrates the contributions of the PoD approach to the management and assessment of supply chain resilience. The proposed studies and scientific contribution will be used to answer RQ1. Then, Chapter 3 responds to RQ2 by presenting an application contribution related to the design of prototypes for the visualisation and steering of performance trajectories in a multidimensional repository. Finally, a concluding chapter, Chapter 4 summarises the contributions presented in this manuscript and presents perspectives for future work.

Figure 1.11 provides an overview of this manuscript, positioning the identified research questions in relation to the different chapters of the manuscript.

Application of the Physics of Decision approach to Resilience Management

Every once in a while, a new technology, an old problem, and a big idea turn into an innovation

Dean Kamen

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Introduction

As discussed in Chapter 1, current risk management strategies have focused primarily on reducing the probability of occurrence of disruptive events and their potential consequences. They have often focused on preventive and protective mitigation actions, designing systems to avoid or absorb disruptive events following their occurrence (Hosseini et al., 2016b). The main objective of protective strategies is to detect the disruptive event early enough to delay it long enough to act effectively (Hosseini et al., 2016b). While a protective strategy is essential to prevent disruptive events or their undesirable consequences, recent events such as natural disasters, man-made threats and the Covid-19 pandemic suggest that not all disruptive events can be prevented. Dealing with this instability and the resulting disruptive events is becoming a necessity for supply chain managers. Due to their unpredictable and unquantifiable nature, supply chains need to strengthen their ability to withstand the impact of disruptions and recover quickly (Brusset et al., 2017; Pettit et al., 2013; Pettit et al., 2010), *i.e.* build resilience. In the literature, supply chain resilience is seen as the ability “to both resist disruptions and recover its operational capability after disruptions” (Tan et al., 2020). Indeed, the term resilience is increasingly used because of its role in reducing the risks associated with unavoidable disruptions to systems (Hosseini et al., 2016a). Given its importance in supply chain management, there is a strong interest in resilience, as evidenced by the explosion of research on this topic, illustrated by Figure 2.1 which represents the number of annual results returned by the query “*supply chain resilience*”, performed on *Google Scholar* (on 02 February 2023). Understanding how to measure and manage the ability of a supply chain to prepare for, respond to and recover from disruption has become fundamental (Adobor, 2019; Pettit et al., 2010; Ponomarov et al., 2009). Despite this growing body of literature since the early 2000s, when the concept of supply chain resilience was first defined, there is still no consensus on its definition (Pires Ribeiro et al., 2018; Tukamuhabwa et al., 2015). Linkov et al. (2014) identify five key points for its development: (1) methods to define and measure it, (2) metrics to assess it, “that which isn’t measured isn’t managed” (Dalziell et al., 2004), (3) new modelling and simulation techniques, (4) the development of resilience engineering and (5) approaches for communication between stakeholders.

Given the need to define new methods for defining and measuring the resilience of supply chains, this chapter will seek to investigate the applicability of an approach based on analogies with kinetics and physics, seeking to address this issue:

Research Question 1 (RQ1)

How can we develop supply chain resilience capabilities (its management and measurement) using a kinetic approach such as PoD?

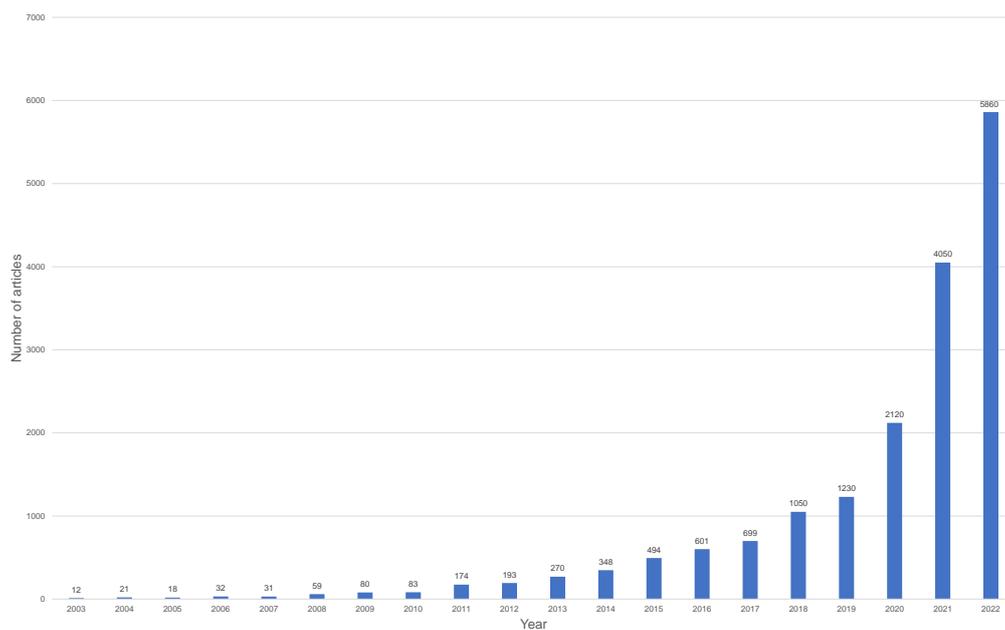


Figure 2.1 – Number of annual publications on supply chain resilience (data retrieved from *Google Scholar* using the query “*supply chain resilience*”)

The Physics of Decision Approach: a physics-based vision to manage supply chain resilience

Abstract. As instability becomes the norm, supply chain management is becoming increasingly complex and critical. As a result, supply chain managers must adapt to complex situations. Managing instability is a key expectation for these managers. One way to help them to manage this instability is to study resilience. Resilience is related to in the literature as the ability of a system to resist, adapt and recover from disruptions. Measuring and controlling supply chain resilience has therefore become a key issue for managers, especially in a context of instability. In 2013, the World Economic Forum (2013) highlighted in its study, this priority for the surveyed companies to master this concept of resilience. To address this need, this paper presents an innovative approach to disruption and resilience management based on physics principles. It considers disruptions as forces that impact supply chain performance. These forces are created as a result of changes in the internal or external attributes of the supply chain. In this approach, supply chain performance is represented and visualized as a physical trajectory modelled in the framework of its performance indicators. Thus, disturbances are considered as forces that displace and deviate the supply chain’s performance trajectory in its performance framework.

Keywords. Resilience, Physics of Decision, Performance Management, Supply Chain Management

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Publisher. International Journal of Production Research

Date of Publication. 18 April 2023

Reference. Cerabona et al., 2023

Online Access. [The Physics of Decision Approach: a physics-based vision to manage supply chain resilience](#)

To address this issue, this chapter is divided into four sections, which resume and extend the work presented in the journal article Cerabona et al. (2023). Section 2.1 defines the concept of resilience, particularly in the context of supply chains, through a state of the art on the definition of resilience and a study of the different techniques and measures developed to assess it (the question of how to measure the resilience of supply chains being still unclear, Kamalahmadi et al., 2016). Section 2.2 explores the contributions of the PoD approach to assessing supply chain resilience, in particular by highlighting the contributions of modelling performance as a multidimensional trajectory. Section 2.3 illustrates and applies the PoD approach and the concepts defined above to an illustrative supply chain case. Finally, Section 2.4 concludes this chapter with several perspectives and challenges for the PoD approach.

2.1 Concept of resilience and its assessment techniques

2.1.1 Resilience: theoretical foundations

The word resilience originates from the Latin *resiliere*, meaning to bounce back (Hosseini et al., 2016b). In common usage, the word resilience is used to define the ability of an entity or system to return to a normal state after the occurrence of a disruptive event (Hosseini et al., 2016b). This definition makes it a multidisciplinary concept studied and finding application in different scientific fields: engineering, ecology, materials science, social sciences, psychology, organisational management and economics (Hosseini et al., 2019b; Ponis et al., 2012). Each of these fields has developed its own definitions and research perspectives on resilience. The term resilience has its origins in the field of materials engineering, where it has been used for over a century. As early as the beginning of the 20th century, resilience was defined as the thermodynamic work required to cause elastic deformation in a solid material (Park et al., 2013). Resilience remained defined in this way until the 1970s, until Holling (1973) defined the concept of resilience as the ability of a system to adapt and cope with change while maintaining its original function and structure. Since then, based on the concepts defined by Holling, many definitions of resilience have emerged. Resilience has emerged as an important tool for managing the risks and vulnerability of supply chains to the unexpected (Adobor et al., 2018; Ponomarov et al., 2009), particularly for its ability to prepare for the unexpected, whereas traditional risk analysis methods assume that hazards and associated risks are identifiable (Park et al., 2013).

In the supply chain domain, the first definitions of resilience appear in the early 2000s. They emerge in 2003 (Kamalahmadi et al., 2016), with the work of Rice et al. (2003), who define resilience as the ability “to respond to an unexpected disturbance and then restore operations to normal”. Early research on supply chain resilience focused on using resilience as a means to reduce and overcome supply chain vulnerability (Christopher et al., 2004b; C. S. Tang, 2006a) and gain competitive advantage (Sheffi et al., 2005). Thus, a resilient supply chain is defined as one that is able to absorb or avoid disruption (Sheffi et al., 2005), or one that is able to recover much more quickly after a disruption (Zsidisin et al., 2005). Tables 2.1, 2.2 and 2.3 provide an overview of the many definitions of supply chain resilience found in the literature, demonstrating the lack of consensus and comprehensive definition to clearly understand supply chain

resilience (Kamalahmadi et al., 2016; Tukamuhabwa et al., 2015). An analysis of the selected definitions highlights commonalities between the definitions, through the six attributes of resilience identified: *event-orientation*, *anticipation*, *robustness* (resisting disruption), *time response*, *recovery*, and *performance* (measuring different states of the supply chain). The attributes identified are reflected in Linkov et al. (2014)'s definition of resilience, "the ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions", with the exception of the notion of performance. They also cover the four pillars introduced in the framework developed by Pires Ribeiro et al. (2018) to understand, evaluate and create definitions of supply chain resilience: (1) *adaptive framing or adaptive response*, (2) *speed*, (3) *performance level* and (4) *targeted event*. An event-oriented view of resilience is found in almost all definitions, as this is part of the nature of resilience, the ability to prepare for and withstand disruptions (Falasca et al., 2008; Hosseini et al., 2019a; Pettit et al., 2013; Sheffi et al., 2005; Wang et al., 2016), unexpected events (Golan et al., 2020; Ponis et al., 2012; Ponomarov et al., 2009; Roberta Pereira et al., 2014) and risks (Jüttner et al., 2011).

According to Pires Ribeiro et al. (2018), it is reductive to simply consider resilience as the ability to react or resist disturbances as defined by some authors. Resilience should be seen as a series of adaptive responses bundled into a multi-step approach to cope with disturbances. Closs et al. (2004) take such elements into account by stating that a resilient supply chain refers to: "the supply chain's ability to withstand and recover from an incident. A resilient supply chain is proactive: anticipating and establishing planned steps to prevent and respond to incidents. Such supply chains quickly rebuild or re-establish alternative means of operations when the subject of an incident". Ponomarov et al. (2009), based on a multidisciplinary study of resilience, define supply chain resilience as its ability "to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function". With this definition they illustrate the three essential steps of the resilience concept (defined in the next three paragraphs and found in the majority of the definitions in Tables 2.1, 2.2 and 2.3): *prepare*, *respond* and *recover*.

Preparedness is an essential step for supply chains in understanding their risk exposure. From this preparation step comes anticipation, supply chains must anticipate and prepare for any changes. The impacts of risks need to be fully understood and their likelihood of occurrence minimised (Kamalahmadi et al., 2016). Anticipation and preparation enable supply chains to strengthen themselves in the face of risk, in particular by taking advantage of their reactive (agility) and proactive (robustness) capabilities in order to reduce their probability of occurrence and their impacts (Chowdhury et al., 2017). The notion of robustness generally refers to the ability of a supply chain to withstand and maintain its operational state (Brandon-Jones et al., 2014) and expected performance (Ivanov et al., 2020; Nair et al., 2011), despite disruptions. Bruneau et al. (2003) define robustness as the strength of a system or its ability to withstand the impact of a disaster, either in terms of the amount of damage or loss of functionality resulting from that disaster. In their work, Dolgui et al. (2018) call this notion of robustness, resistance, to refer to this ability of the supply chain to withstand disruption. Thus with this view, increasing the robustness of a supply chain amounts to strengthening its resilience in order to counter and tackle the effects of the disruption, thus amounting to tackling more globally the vulnerability of the supply chain to these events (Hosseini

Table 2.1 – Definitions of supply chain resilience

Supply Chain Resilience Definition	Attributes					
	Focus Event	Anticipation	Robustness	Response Time	Recovery	Performance
“The ability to respond to an unexpected disturbance and then restore operations to normal.” (Rice et al., 2003)	✓				✓	
“The ability of a system to return to its original state or move to a new, more desirable state after being disturbed.” (Christopher et al., 2004b)	✓				✓	
“The firm’s ability to absorb disruptions or enable the SC network to return to state conditions faster and thus has a positive impact on firm performance.” (Sheffi et al., 2005)	✓		✓	✓	✓	✓
“Not only the ability to maintain control over performance variability in the face of disturbance, but also a property of being adaptive and capable of sustained response to sudden and significant shifts in the environment in the form of uncertain demands.” (Priya Datta et al., 2007)	✓				✓	✓
“The ability of a supply chain system to reduce the probabilities of a disruption, to reduce the consequences of those disruptions once they occur, and to reduce the time to recover normal performance.” (Falasca et al., 2008)	✓			✓	✓	✓
“The adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function.” (Ponomarov et al., 2009)	✓	✓			✓	
“The ability to react to the negative effects caused by disturbances that occur at a given moment in order to maintain the supply chain’s objectives.” (Barroso et al., 2011)	✓		✓			✓
“Supply chain resilience is concerned with the system ability to return to its original state or to a new, more desirable state.” (Carvalho et al., 2012)					✓	
“The ability to proactively plan and design the Supply Chain network for anticipating unexpected disruptive (negative) events, respond adaptively to disruptions while maintaining control over structure and function and transcending to a post-event robust state of operations, if possible, more favorable than the one prior to the event, thus gaining competitive advantage.” (Ponis et al., 2012)	✓	✓			✓	
“The ability to maintain and recover (adapt) planned execution, as well as to achieve planned (or adapted, yet still acceptable) performance.” (Ivanov et al., 2013)			✓		✓	✓
“The capability to anticipate and overcome supply chain disruptions.” (Pettit et al., 2013)	✓	✓			✓	

Table 2.2 – Definitions of supply chain resilience

Supply Chain Resilience Definition	Attributes					
	Focus Event	Anticipation	Robustness	Response Time	Recovery	Performance
“The ability of a supply chain to cope with change.” “A supply chain can, thus, be resilient if its original stable situation is sustained or if a new stable situation is achieved.” (Wieland et al., 2013)	✓				✓	
“The ability of a supply chain to return to normal operating performance, within an acceptable period, after being disrupted.” (Brandon-Jones et al., 2014)	✓			✓	✓	✓
“The capability of supply chain to respond quickly to unexpected events so as to restore operations to the previous performance level or even to a new better one.” (Roberta Pereira et al., 2014)	✓			✓	✓	✓
“The ability of the supply chain networked to withstand disruptions and return to a normal status quickly.” (Hohenstein et al., 2015)	✓		✓	✓	✓	
“The adaptive capability of a supply chain to reduce the probability of facing sudden disturbances, resist the spread of disturbances by maintaining control over structures and functions, and recover and respond by immediate and effective reactive plans to transcend the disturbance and restore the supply chain to a robust state of operations.” (Kamalahmadi et al., 2016)	✓		✓		✓	
“A resilient system is a system with an objective to survive and maintain function even during the course of disruptions, provided with a capability to predict and assess the damage of possible disruptions, and enhanced by the strong awareness of its ever-changing environment and knowledge of the past events, thereby utilizing resilient strategies for defense against the disruptions.” (Wang et al., 2016)	✓	✓	✓			
“The characteristics of a well-designed SC network with proactive and reactive capabilities, which enables the SC members to reduce the probability of disruptive events (or to reduce their impact) to take the organization to a stronger and more sustainable state.” (Chowdhury et al., 2017)	✓					
“Resilience is a complex, collective, adaptive capability of organizations in the supply network to maintain a dynamic equilibrium, react to and recover from a disruptive event, and to regain performance by absorbing negative impacts, responding to unexpected changes, and capitalizing on the knowledge of success or failure.” (Yao et al., 2018)	✓		✓		✓	✓

Table 2.3 – Definitions of supply chain resilience

Supply Chain Resilience Definition	Attributes					
	Focus Event	Anticipation	Robustness	Response Time	Recovery	Performance
“SC capability to utilize the absorptive capacity of SC entities to repulse and withstand the impacts of perturbations, to minimize the consequences of disruptions and their propagation by utilizing adaptive capacity and to recover performance level to normal operations in a cost-efficient manner using restorative capacity when absorptive and adaptive capacities are not sufficient.” (Hosseini et al., 2019a)	✓		✓		✓	✓
“The ability to recover from the negative impacts of unknown disruptions and adapt to uncertain future events. Resilience measures the ability to prepare for and perform essential functions during a disruption and then recover and adapt after the disruption in a form better suited to this new ‘present.’” (Golan et al., 2020)	✓	✓			✓	

et al., 2016a). Several researchers highlight this feature of supply chain resilience in their definitions (Hosseini et al., 2019a; Sheffi et al., 2005; Yao et al., 2018). Resilience therefore encompasses both the response and recovery of the supply chain after a disruption, but also its ability to withstand that disruption in the first place (Y. Li et al., 2020), serving as the supply chain’s first line of defence against disruption. The ability of supply chains to resist and absorb (deactivate) the effects of a planned or unplanned disruption before it spreads plays a vital role in ensuring the continuity of their operations (Kamalahmadi et al., 2016). A well-prepared supply chain traps disruption in this phase (Kamalahmadi et al., 2016). Indeed, robustness is seen as a proactive strategy to cope with change and disruption (Chowdhury et al., 2017; Wieland et al., 2013). To develop supply chain robustness, companies need to put in place measures to reduce the vulnerability of their supply chain, involving identifying its risks and addressing them before they occur (El Baz et al., 2021; C. S. Tang, 2006b). Developing robustness requires companies to carry out the preparedness stage. This stage allows firms to learn from their supply chain environment, including how to identify its threats, thus proactively building capabilities that improve their responsiveness to supply chain disruptions (Blackhurst et al., 2011; Bode et al., 2011; DuHadway et al., 2019; El Baz et al., 2021). This makes it easier for these firms to withstand the effects of disruptions and to recover (Ivanov et al., 2013).

All of the above points to the link between robustness and resilience in supply chain risk management practices. According to Ivanov et al. (2020), both robustness and resilience explicitly include performance in the analysis of the impacts of disruptions. The term robustness has often been used interchangeably with the term resilience in supply chain research (Spiegler et al., 2012). Asbjørnslett (2009) states that “a supply chain is robust, or resilient, with respect to a threat, if the threat is not able to produce any ‘lethal’ effects on the system”, meaning that both robustness and resilience imply

a recovery stage after a disruption. However, the definitions above and in Tables 2.1, 2.2 and 2.3, highlight that robustness is included in resilience. Resilience allowing the supply chain to bounce back from a disruption (Brandon-Jones et al., 2014), once it can no longer resist and absorb the effects of the disruption and therefore maintain its functioning. This view is confirmed by Christopher et al. (2004b), who state that a robust system is able to respond to reasonable variations whereas a resilient system can respond to major changes, thus a resilient supply chain will always be robust (the reverse not always being true). According to Asbjørnslett (2009) the main difference between resilience and robustness lies in the state reached after the disturbance: for robustness, it is identical to the pre-disturbance state due to its ability to resist, whereas for resilience, the supply chain can reach a new stable state due to its ability to adapt. Another difference lies in the changes and adaptations required of the supply chain. Ivanov et al. (2013) show that robustness analyses the ability of the system to resist a disturbance without any structural and parametric modification of the system, whereas resilience allows it to modify its structure and parameters in order to allow it to adapt and recover its level of performance (Ivanov et al., 2020).

Response implies the ability to react quickly to critical situations for the supply chain (Han et al., 2020). Indeed, when a supply chain is confronted with a change that impacts its mode of operation and its results, the notion of speed and time becomes crucial. Manuj et al. (2008) distinguish three forms of speed: (1) the speed at which a risk occurs, (2) the speed at which losses occur and (3) the speed at which the risk is discovered. To these three types of speed, Jüttner et al. (2011) add the speed of recovery of the supply chain following a disruption. This notion of speed of return to a state of equilibrium and therefore of response time is reflected in the definition of Hohenstein et al. (2015), who define resilience as “the ability of the supply chain networked to withstand disruptions and return to a normal status quickly”. Thus, time is a fundamental dimension for resilience, especially for its ability to respond to disruption. Without taking time into account, the concept of resilience cannot be fully explored (Behzadi et al., 2020). Brandon-Jones et al. (2014) indicate the need for a response within an acceptable time, “the ability of a supply chain to return to normal operating performance, within an acceptable period, after being disrupted”. This notion of rapid and efficient response requires key responsive capabilities for supply chains, one of which is agility. Agility is a key dimension of resilience (Wieland et al., 2013). Benaben et al. (2014) define agility as a purely schematic equation: $agility = (detection + adaptation) \times (reactiveness + efficiency)$. In this formula, sensing and adaptation are considered as its two main components. Thus, to be agile, a supply chain must be able to detect any (potentially unexpected) situation that involves changes in its initial and stable configuration (its structure and behaviour) and adapt to this situation (Benaben et al., 2014; Wieland et al., 2012). To be fully effective, detection and adaptation must be supported by two properties: responsiveness and efficiency. Indeed, the dynamics of agility are crucial, the concept of speed is inherent to agility (Prater et al., 2001), both in terms of rapid detection of changes, but also rapid adaptation to these changes, which corresponds to the speed of recovery of the supply chain (Tukamuhabwa et al., 2015). However speed is nothing without efficiency, the ability to detect any relevant change and adapt to it in a relevant way, wrong detection and/or adaptation could be fatal for the agility of a system (Benaben et al., 2014). To do this, a supply chain needs visibility, *i.e.* its actors need to have an overview of the supply chain, knowledge of its

environment and key assets; to enable better identification and awareness of ongoing changes (Christopher et al., 2004b).

Recovery refers to the aftermath of a disruption, *i.e.* the ability of a supply chain to restore itself and bounce back to a stable state of performance following a disruption, a normal state of performance (Falasca et al., 2008). For Carvalho et al. (2012), resilience is the ability to bounce back to an initial or more desirable state after experiencing a disruption. The authors thus add a notion of improvement and growth following a disruption, also called antifragility (Taleb, 2007; Taleb, 2014). This growth vision goes beyond the simple fact of recovering and allowing the supply chain to return to its initial state, *i.e.* before the disruption. It aims to take advantage of the disruption to position the supply chain at a higher, more advantageous and beneficial level than the initial state (Hohenstein et al., 2015), which can lead to competitive advantages through well-prepared responses (Kamalahmadi et al., 2016). More generally, resilience can be seen as the ability of a supply chain to adapt and reach a new steady state following a disruption. This new state of stability may be identical to the initial state of the supply chain, more favourable or conversely unfavourable for supply chain performance, in which case it is the notion of fragility. However, the response should not only reposition the supply chain to pre-disruption levels of performance, but also have the capacity to strengthen the supply chain to respond to future disruptions (Kamalahmadi et al., 2016).

Clement et al. (2021), based on these different notions, group the definitions of resilience into three categories, differing mainly on their concepts of absorption, response and return to a state of equilibrium. The first type of resilience (α) identified corresponds to Rice et al. (2003) definition of resilience, *i.e.* it is seen as the capacity to absorb the impacts of disturbance. Despite a potential loss of performance, the supply chain will have the ability to return to a level of performance equivalent to that which it had before the disruption. The second type of resilience (β) is very similar to the first one. In this view of resilience, the authors do not necessarily seek to achieve the initial level of performance, but rather seek to maintain or return the supply chain to a zone of resilience, corresponding to a zone of acceptable performance, as proposed in Ivanov et al. (2013)'s definition of resilience, or the zone in which it is feasible to maintain the supply chain to achieve its objectives despite the negative effects of a disruption (Barroso et al., 2011). This zone could also correspond to the balanced resilience zone, proposed by Pettit et al. (2013), corresponding to an optimal location for supply chains. This optimal location is determined by balancing the increase in a supply chain's vulnerability arising from its exposure to risk with the increase in its capacity to counter its vulnerabilities, which may lead to an erosion of its profits. This zone therefore amounts to modelling the ratio of vulnerabilities to resilience costs over time. The last type of resilience (γ) focuses primarily on the notion of adaptation. With this type of resilience, a supply chain is resilient if it is able to adapt to the disturbance with the aim of reaching a new stable steady state, as proposed in the definition by Wieland et al. (2013). Figure 2.2 illustrates all of this information and brings together in a single vision these three types of resilience, which is to maintain the supply chain in a resilience zone, one of whose limits is none other than its robustness. Once the recovery phase is over, the state of stability achieved can be negative (fragility), positive (antifragility) or equivalent in terms of the supply chain's pre-disruption performance.

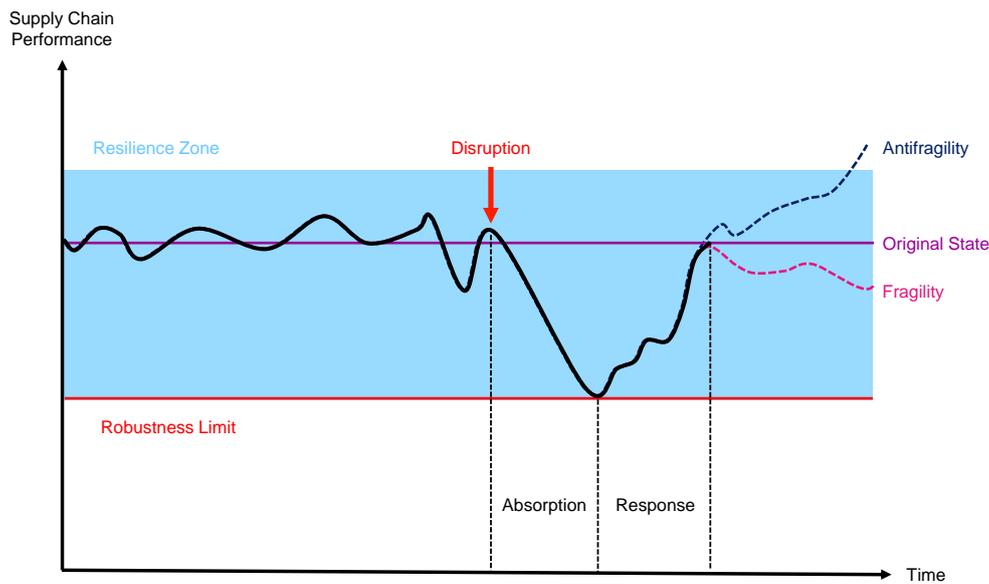


Figure 2.2 – Illustration of resilience concepts from the literature (adapted from Clement et al., 2021; Tukamuhabwa et al., 2015)

Christopher et al. (2004b) define resilience as “the ability of a system to return to its original state or move to a new, more desirable state after being disturbed”. In order to achieve the objectives set out in this definition of resilience, one of the most cited definitions in the literature (Adobor et al., 2018), different forms of resilience for supply chains need to be considered. Holling (1996) distinguishes two types: engineering and ecological, which differ in their design and management objectives. These two types of resilience emerge from his work in 1973, published in his book “*Resilience and Stability of Ecological Systems*”. His work popularised ecological resilience and has provided the basis for most studies of the concept of resilience. He defines ecological resilience as “the measure of persistence of systems and of the ability to absorb change and disturbance and still maintain the same relationships between state variables” (Holling, 1973). His work highlights how different views of behaviour within ecological systems create completely different approaches to resource management (Holling, 1973). He introduces two types of view: “*resilience*” and “*stability*”, which were later extended to give the terms “*ecological resilience*” and “*engineering resilience*” (Bhamra et al., 2011; Gunderson, 2000). These two concepts of resilience agree on the fact that the system is pushed out of its steady state by a disturbance, but differ on the mechanisms and strategies used by the system to return to equilibrium (Adobor et al., 2018). Indeed, these two views of resilience are based on two different views of stability, engineering resilience focuses on maintaining the effectiveness of the function, while ecological resilience focuses on the ability to absorb shocks and maintain the existence of the function (Brand, 2009; Ponis et al., 2012). Holling (1973) defines stability as the ability of a system to return to an equilibrium state after a temporary disturbance, the persistence of a system near or at a steady state (Gunderson, 2000). Holling makes the implicit assumption that without stability there could be no return to a pre-disturbance steady state (Ponomarov et al., 2009). Engineering resilience is defined as the time to return to a single, global equilibrium state, so the faster a system returns to its equilibrium state the more resilient it is, “stability near a stable steady state, where resistance to disturbance and speed of return to

equilibrium are used to measure the property” (Holling, 1996). This view of engineering resilience derives from engineering traditions, where the aim is to design systems with a single, mathematically representable and measurable operating goal (Gunderson, 2000). According to Ruhl (2010), “engineering resilience draws on reliability, efficiency, and quality control and similar strategies to pursue a single objective: return the system to equilibrium state”, thus making recovery an operating and design objective (Adobor et al., 2018). A key distinction between these two types of resilience is the assumption that there are multiple steady states (Gunderson, 2000). In the case where there is only one steady state, only near-equilibrium definitions and measures of resilience are valid, such as the return time characterising engineering resilience (Holling, 1996). In contrast, ecological resilience assumes that there are several states or domains of stability. The tolerances of the system to certain disturbances facilitate transitions and shifts between these different states. Thus ecological resilience can be seen as the limits and size of a stability domain. Gunderson (2000) proposes to measure ecological resilience as the amount of disturbance a system can absorb before a change in its structure occurs by altering the variables and processes governing its behaviour, *i.e.* the amount of disturbance a system can absorb before changing its state or domain of stability. Ecological resilience focuses on “persistence, change, and unpredictability—all attributes embraced and celebrated by biologists with an evolutionary perspective and by those who search for safe-fail designs” (Holling, 1996). Following this interpretation of ecological resilience, managers should therefore not seek to define a stable state of equilibrium, but accept that disturbances can generate changes that can shift a system from one behavioural regime to another (Folke, 2006). Carpenter et al. (2001) propose a definition of ecological resilience based on the work of Holling, “the magnitude of disturbance that can be tolerated before a socio ecological system moves to a different region of state space controlled by a different set of processes”. From this definition, the authors highlight three properties of ecological resilience: (1) the amount of change the system can undergo while maintaining the same controls on its structure and function, *i.e.* the amount of extrinsic forces it is able to withstand, (2) the system’s ability to self-organise following a disturbance, and (3) the system’s ability to learn and adapt. An important point arising from these two views of resilience is the concept of *adaptive capacity*, reflecting the ability of the system to learn from its behaviour in the face of a disturbance (Gunderson, 2000). According to Pettit et al. (2010), it may be beneficial for a supply chain not to revert to its original form after a disruption, but rather to learn from that disruption, as proposed by Yao et al. (2018) in their definition of resilience: “a complex, collective, adaptive capability of organizations in the supply network to maintain a dynamic equilibrium, react to and recover from a disruptive event, and to regain performance by absorbing negative impacts, responding to unexpected changes, and capitalizing on the knowledge of success or failure”. The supply chain can thus take advantage of this learning to adapt and develop a form better suited to this new “present” (Golan et al., 2020). Thus, through this adaptive capacity, the supply chain develops an ability to cope with unknown future circumstances (Bhamra et al., 2011). However, this capacity to adapt and reorganise requires a certain flexibility and “plasticity” of the system, as well as “driving” capacities to initiate and provide the energy for its redeployment.

In this section, following our review of the literature, two views emerge to characterise and define supply chain resilience: engineering and ecological resilience. This analysis, in Table 2.1, provides an overview of the range of definitions of supply chain resilience found in the literature. Although there is no consensus on its definition, all the definitions presented share several common properties: (1) the term resilience assumes the occurrence of a disruption, (2) resilience refers to the state of the system before, during and after a disruption, (3) it aims to implement strategies to make the best use of the proactive and reactive capabilities of supply chains, (4) after a disruption, the supply chain reaches a new, more or less favourable state of equilibrium, and (5) the deviation between these different states is compared in order to assess the ability of the supply chain to recover from a disruption. The gap between these different states is often assessed by measuring the gap between the pre- and post-disruption performance of the supply chain, the gap between target and disrupted performance (Hosseini et al., 2016b).

Now that the concept of resilience has been defined based on the state of the art, the question arises as to *how to measure the resilience of a supply chain*. It is important for supply chains and decision makers to assess resilience in order to facilitate and improve the analysis of supply chains' risk exposure, but also to evaluate the effectiveness of the different strategies implemented (Soni et al., 2014). The resilience metrics developed in the literature can be classified according to the quantitative model (the mathematical approach to measuring the metric) and the performance measure to be used in these quantitative models (Behzadi et al., 2020). The following section proposes to explore the methods and techniques proposed in the literature to measure supply chain resilience, and the indicators that are recommended to be measured to inform them.

2.1.2 Measuring resilience

Despite a growing body of literature on supply chain resilience and the many definitions that follow (as illustrated in the previous section), the literature on supply chain resilience management pays little attention to how resilience is measured and analysed (Han et al., 2020; Kamalahmadi et al., 2016; Spiegler et al., 2012). Most of the studies present in the literature provide a qualitative overview of the problem, focusing mainly on identifying sources of risk and determining strategies to reduce the likelihood of occurrence of disruptions and/or mitigate their effects (Spiegler et al., 2012), and thus do not seek to explicitly measure the resilience of supply chains (Cardoso et al., 2015). Without understanding the level of resilience of a supply chain, it is difficult to assess its response and reaction following disruptions (Kamalahmadi et al., 2016). It is crucial for organisations to conduct a resilience assessment of their supply chain, in order to understand its exposure to risk and be able to evaluate the resilience strategies in place (Soni et al., 2014). Ponomarov et al. (2009) see the search for measures of supply chain resilience as an important stream of research that can provide essential knowledge for its management. An essential part of resilience analysis is to identify and assess its different states (Carvalho et al., 2012). One method to monitor the evolution of these states is to define and measure the different efforts undertaken to achieve the objectives of a supply chain. Making these objectives representable is an important challenge (Franceschini et al., 2006). Typically, objectives are translated and associated

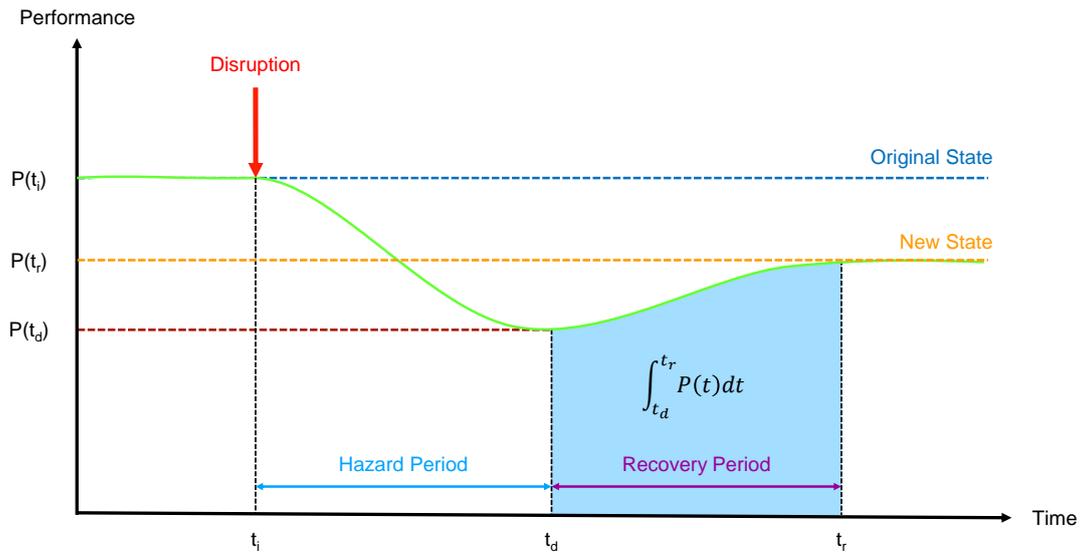


Figure 2.3 – Illustration of performance indicators used to quantify resilience (adapted from Cheng et al., 2022)

with performance targets, measured by a set of key performance indicators (KPIs) that represent the evolution of the state of the supply chain with respect to its identified objectives and represented as target values for these KPIs (Neely et al., 1995). Due to its complex nature involving different entities with objectives that may diverge, measuring the performance of a supply chain is not an easy task (Estampe et al., 2013). Neely et al. (1995) define performance measurement as the process of quantifying the efficiency and effectiveness of operations, identifying and measuring the gap between current performance and the desired level of performance, the objectives (Mani et al., 2014). Performance measurement is therefore a fundamental managerial mechanism for driving improvement (R. S. Kaplan et al., 1992), providing an indication of the evolution of the gap between the objectives and the actual performance of the supply chain, thus enabling the monitoring of progress in closing it.

Over the last two decades, many studies have proposed conceptual or quantitative models to address supply chain performance assessment, using: multi-criteria decision-making techniques, mathematical programming methods, statistical techniques, simulation and artificial intelligence models, to quantify supply chain performance against a set of performance parameters (Lima-Junior et al., 2019). However very few studies have attempted to create a quantitative framework to assess the resilience performance of supply chains (Spiegler et al., 2012). From an engineering perspective, quantifying the resilience of a system implies measuring its performance over time, with a particular focus on its performance during and after a disruption (Bruneau et al., 2003; Zobel et al., 2021). To date, no standard or common metrics have been developed to quantify resilience to different types of disturbance (Cheng et al., 2022). Most of the measures proposed in the literature are created from functions of one or more indicators from different phases of the system following a disturbance, as illustrated in Figure 2.3. These measures mainly include the recovery time, the lost and recovered performance over a period of time (*e.g.* the blue area in Figure 2.3) or at specific times ($P(t_i)$, $P(t_d)$ and $P(t_r)$) and the probability of recovering some or all of the lost performance (Cheng et al., 2022). According to Carvalho et al. (2007), the resilience of supply chains can only

Table 2.4 – Description of the performance indicators in the Figure 2.3 (adapted from Cheng et al., 2022)

Performance Indicators	Description
$P(t_i)$	performance level at time t_i (in this case equivalent to nominal performance)
$P(t_d)$	most degraded level of performance at time t_d
$P(t_r)$	performance level achieved at the end of recovery at time t_r
$t_d - t_i$	duration of the risk period
$t_r - t_d$	duration of the recovery period
$\int_{t_d}^{t_r} P(t)dt$	total performance over a given period of time (between t_r and t_d)

be measured after the occurrence of a disruption, usually by comparing its performance before and after a disruption (Hosseini et al., 2016b), based on two main aspects: the recovery time of the supply chain and the performance loss due to a disruption (Fattahi et al., 2020). Performance loss is generally defined as the difference between performance after a disruption and expected performance (Behzadi et al., 2020). The expected or baseline performance (*i.e.* the optimal performance in the absence of a disruption) is often used to compare solutions and measure resilience (Behzadi et al., 2020; Saghafian et al., 2016; Zobel, 2011). The performance indicators shown in Figure 2.3 correspond to those defined in the Table 2.4.

Several approaches have been developed to measure the resilience of supply chains as a time-dependent measure, either based on ratios of restored performance to lost performance, or based on modelling several possible performance trajectories that take into account the effects of uncertainty (Zobel et al., 2021), particularly related to the recovery process, which is inherently stochastic due to uncertainty about available resources and the severity of disruptions (Cheng et al., 2022). Of all the proposed methods, the resilience triangle (shown in Figure 2.4) developed by Bruneau et al. (2003) is one of the most recognised ways to measure the resilience of a system (Tukamuhabwa et al., 2015). Its simplicity, makes this method a solid basis for assessing resilience and developing new quantitative methods for assessing resilience (Zobel, 2011). This measure is based on the fact that at any point in time, the actual or potential performance of a system can be measured and characterised as a point or trajectory in the multidimensional space of its performance indicators (Bruneau et al., 2003). This measure takes into consideration the major concepts of resilience: performance level, loss estimation, robustness, recovery and speed (recovery time). They define speed as the ability to meet and achieve goals in a timely manner in order to limit losses (Bruneau et al., 2003), *i.e.* the speed at which a system can return to its initial state or

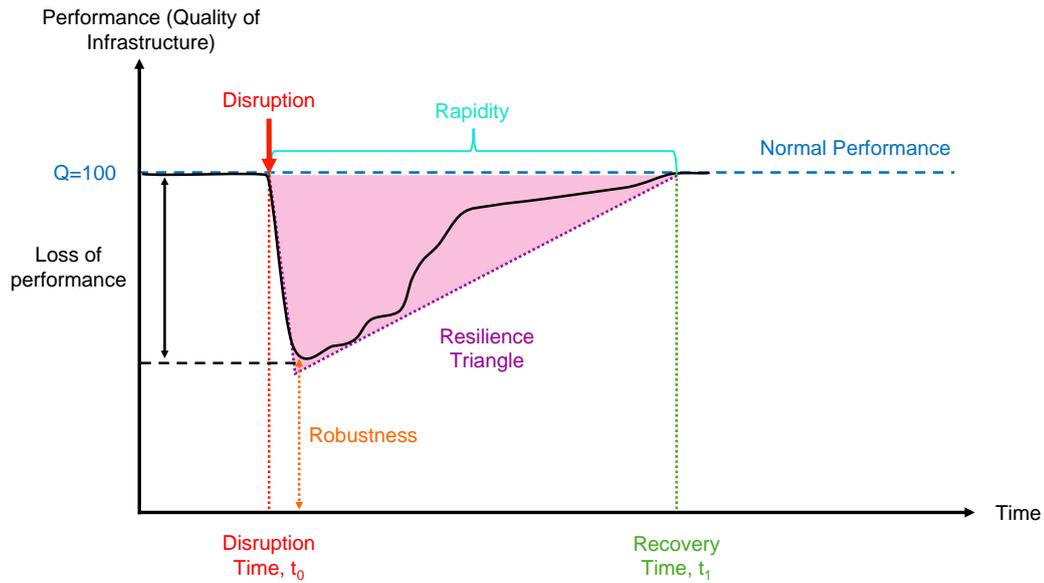


Figure 2.4 – Illustration of the resilience triangle concept (adapted from Zobel, 2010)

an acceptable state after a disturbance (Hosseini et al., 2016b). With this approach Bruneau et al. (2003) propose a deterministic measure of the loss of resilience R of a community following an earthquake, calculated by equation : $R = \int_{t_0}^{t_1} [100 - Q(t)] dt$. The integral is measured between the time t_0 , representing the beginning of the disturbance, and the time t_1 , representing the time taken by the community to return to an equivalent state before the disturbance. In this equation, $Q(t)$ measures the change over time in the quality of a community's infrastructure (in percent), which could represent for any system several types of performance indicators (Hosseini et al., 2016b). Thus this equation represents the area under the curve between the $Q(t)$ curve and the $Q = 100$ line, so it is possible to create a simple approximation on the area value, by calculating the area of the resilience triangle formed by the initial drop in functionality following the disturbance (the loss of performance) and the recovery time, the speed (Zobel, 2010). Considering a time series curve of system performance, the resilience triangle models both the immediate effect of a sudden impact disaster and its response behaviour (Zobel et al., 2021). Measuring the area of this triangle provides a static measure of resilience that can be applied to any type of system, including supply chains. Low values of the area of this triangle imply no significant consequences or rapid recovery.

Measuring the area under the curve to compare the responses of systems to disturbances is an approach that has been adopted by many disciplines (Macdonald et al., 2018): stock control theory (Whitin, 1955), psychology (Myerson et al., 2001), physiology (Pruessner et al., 2003) and information security (Kumar et al., 2008). Bruneau et al. (2003) were the first to apply this technique to measure the resilience of disrupted systems (Macdonald et al., 2018). Since then the concept of the resilience triangle has been applied and extended in many approaches. Zobel (2010) proposes to extend the resilience triangle concept to provide an analytical measure of the overall resilience level of a system in a given situation. While there are advantages to using and measuring

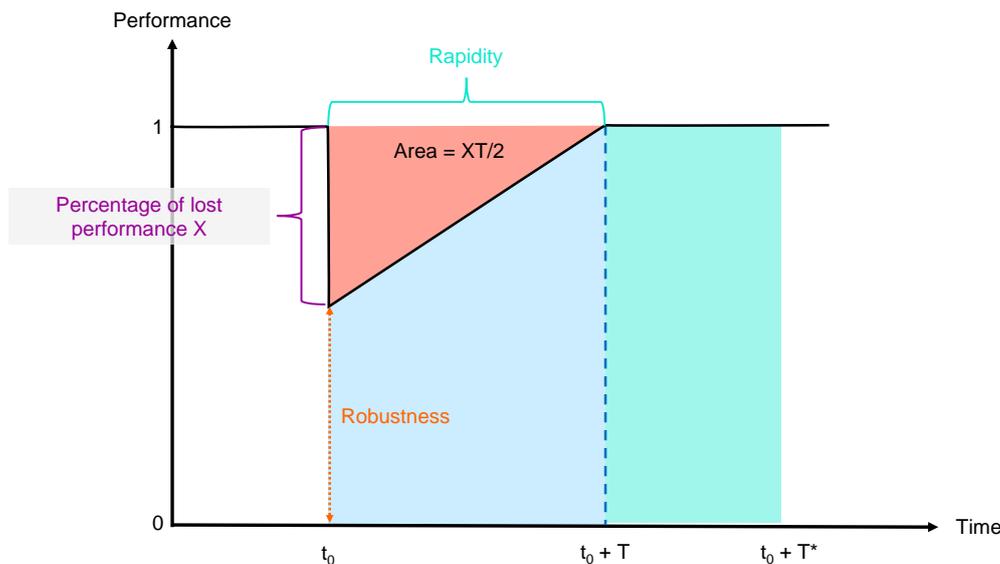


Figure 2.5 – Zobel’s reinterpretation of the resilience triangle (adapted from Zobel, 2010)

resilience from a single value, according to Zobel (2010), using the resilience triangle for this purpose may have some limitations. Indeed, very different combinations of performance loss and speed could correspond to exactly the same value of the area of the resilience triangle and thus to an equivalent level of resilience. With this measure of resilience, *Resilience triangle area* = $\frac{\text{Performance}_{\text{loss}} \cdot \text{Speed}}{2}$. For example, a system with little performance loss but a long recovery time could have the same resilience value as a system with high performance loss but a short recovery time. These two situations are very different, especially from the point of view of resource management, and decision-makers might therefore prefer one over the other (as for example in the management policies of Covid 19, which preferred to spread out the contaminations in order not to saturate the health system). Zobel (2010) defines the predicted resilience R (shown in Figure 2.5), as a function of the estimated initial expected loss $X \in [0, 1]$ (measured as the percentage of functionality lost as a result of a disturbance) and the expected and estimated time to recovery $T \in [0, T^*]$ (with T^* a sufficiently long time interval over which the loss of functionality can be determined, this value assumes that any system will return to its original state at before T^* ; R. Li et al., 2017), such that : $R(X, T) = \frac{T^* - \frac{XT}{2}}{T^*} = 1 - \frac{XT}{2T^*}$. With this equation, Zobel (2010) proposes to calculate the total possible loss as the area of the triangle $\frac{XT}{2}$ (illustrated by the red area in Figure 2.5), for a single perturbation.

To address the decision problems associated with the possible combinations of performance loss and speed that may correspond to identical values of the area of the resilience triangle, Zobel (2010) proposes to describe these combinations in the form of hyperbolas (illustrated in Figure 2.6). These hyperbolas are determined by the relationship between X and T (for a fixed resilience R and time T^*), provided by the equation of $R(X, T)$. This relationship is as follows: $XT = (X - 0)(T - 0) = M$ with $M = (2T^*)(1 - R)$, corresponding to the equation of a rectangular hyperbola centred on the point of coordinates (0,0) and whose asymptotes lie directly on the X and T axes

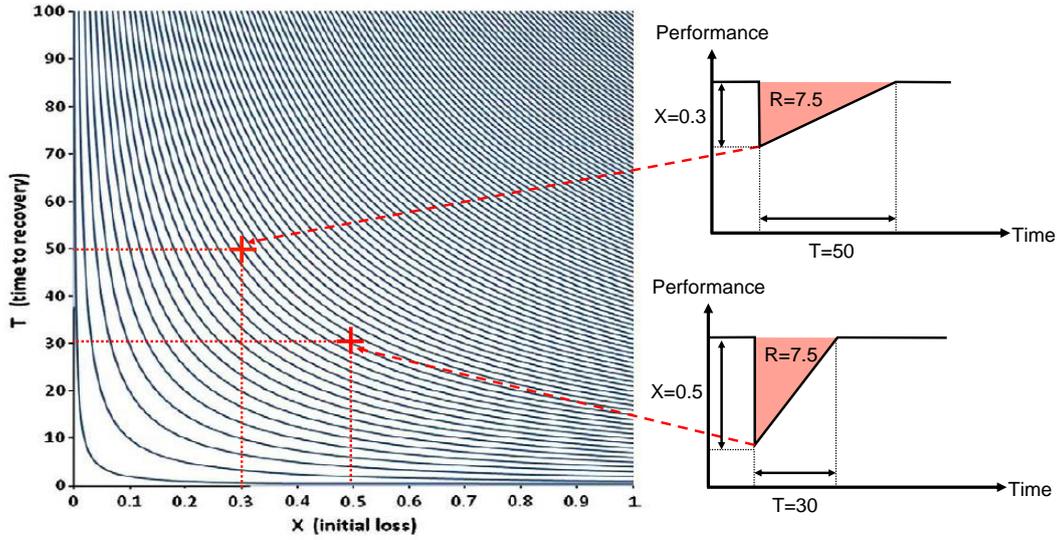


Figure 2.6 – Zobel’s proposed visualisation of expected resilience (adapted from Zobel, 2011)

(Zobel, 2010). With this representation (shown in Figure 2.6), the larger the values of R , the closer the system is to the origin. The proposed hyperbolas are equivalent to iso-resilience curves, as illustrated in Figure 2.6, by the two resilience triangles associated with two distinct points on a hyperbola.

Zobel et al. (2014) extend the measure of predicted resilience proposed by Zobel (2010), to be able to assess the resilience of a system subjected to multiple related events (sudden disasters followed by resulting disruptive events). They then define the overall resilience R for this type of event by the following equation: $R = 1 - \sum_i \frac{(X_i + X_i')T_i}{2T^*}$,

where i is the number of related events, X_i' is the performance lost by the system before event $i + 1$ occurs, and T_i is the amount of time it takes the system to move from the state represented by X_i to the state represented by X_i' . With this view (illustrated in Figure 2.7), the average performance loss over the time period T_i is measured by the formula: $\frac{X_i + X_i'}{2}$, and the area under this portion of the performance curve by the formula: $A_i = \frac{(X_i + X_i')T_i}{2}$ (Zobel et al., 2014).

These area-based resilience assessment methods proposed by Bruneau et al. (2003) and extended by Zobel (2010) and Zobel et al. (2014) have the advantage of proposing a simple assessment of resilience, approximating a linear recovery from one or more cascading disturbances. From the proposed illustrations of these methods (Figures 2.5, 2.6, and 2.7), they all tend to suggest an immediate degradation of performance after a disturbance (Hosseini et al., 2016b), which is not always the case depending on the type of disturbance (a dirac or a continuous and gradual impact in time) and the system in question. R. Li et al. (2017) identify some limitations for the previous methods: (Bruneau et al., 2003)’s measure cannot be used to compare the resilience of different systems because the time scale used is unbounded and has a variable recovery time (t_1) for each system; Zobel’s measures have a strict upper bound on the recovery time (T^*), thus making the proposed measures comparable. However, these measures do not consider the situation where the system could not return to a level of performance equivalent to its pre-disruption situation (in this case, the system is simply not resilient).

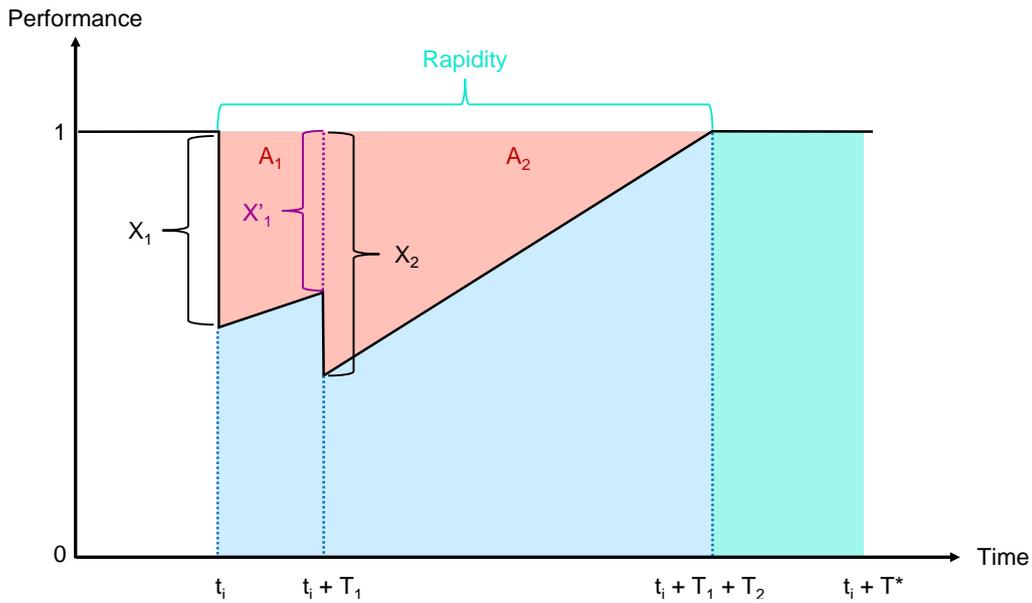


Figure 2.7 – Overall resilience for two related events (adapted from Zobel et al., 2014)

Based on these findings and their analyses of the literature, they establish that the resilience measure must meet several characteristics: (1) to be comparable, a fixed time interval must be defined (this interval must have an appropriate physical meaning for the system under study), (2) to reflect the ability of the system to recover after a disturbance, the moment when the disturbance occurs should be the beginning of the time interval considered for the measure, and (3) the measure can consider two situations a recovery or not of the system over the chosen time interval (R. Li et al., 2017). To address these characteristics, they propose to measure resilience over the maximum allowable recovery time interval (to be determined by the user depending on the system under study) and propose the following resilience measure:
$$R = \int_{t_0}^{T_a+t_0} \frac{Q(t)dt}{T_a}$$
 with t_0 the time when the system performance starts to decline following a disturbance, T_a the maximum allowable recovery time and $Q(t)$ the normalised system performance at time t (R. Li et al., 2017).

Other approaches, based on the resilience triangle, focus less on a direct measure of resilience, but more on factors that contribute to making the supply chain more resilient. Falasca et al. (2008) develop a decision support framework that aims to reduce the size of the resilience triangle proposed by Bruneau et al. (2003), by developing appropriate strategies for designing supply chain networks. They propose three measures: node density, complexity and criticality. They define supply chain density as the quantity and geographic spacing of nodes (actors) within a supply chain, measured as the number of nodes divided by the average distance between nodes (Falasca et al., 2008). The complexity of a supply chain is related to both the number of nodes in a supply chain and the interconnections between these nodes (Craighead et al., 2007; Falasca et al., 2008). It is measured in terms of the total number of nodes and the total number of direct flows. The criticality of a node is defined as its importance to the supply chain (Craighead et al., 2007). More difficult to characterise, node criticality is measured by a combination

of these three measures: (1) the relative importance of a node (manufacturer of critical products or with a very large production volume), (2) the number of non-redundant incoming flows, and (3) the number of non-redundant outgoing flows (Falasca et al., 2008).

These quantitative methods are dedicated to studying the resilience of supply chains in terms of their capabilities and the ability of the companies that make them up to return to a normal level of performance and operation after a disruption. This view of resilience requires the definition of performance indicators to measure and characterise their resilience capabilities (Zobel et al., 2021), measures capable of assessing the ability of these systems to prepare for, withstand, absorb the effects of unexpected hazards, maintain desired functionality, and recover quickly (Cheng et al., 2022). Indicators that consider the network of suppliers, businesses and customers in a supply chain can be particularly useful and important in assessing resilience (Zobel et al., 2021). Studies on the definition of resilience measures (metrics) are still quite rare (Han et al., 2020). Very few studies have explored the relationship between resilience and KPIs, as well as the benefits of KPIs for building more resilient supply chains (Hohenstein et al., 2015; Karl et al., 2018). Yet dedicated performance metrics for resilience assessment are needed (Sillanpää, 2015), especially to make full use of previous quantitative methods.

From an engineering perspective, the time to return to equilibrium is paramount in defining resilience. Simchi-Levi et al. (2018) propose two measures to quantify the resilience of a supply chain: *recovery time* (TTR) and *survival time* (TTS). *Recovery time* is defined as “the time for a facility to return to full capacity after a disruption”. *Survival time* is defined as “the longest time that customer service level is guaranteed if this facility is disrupted”. To avoid the recurrence of disruptions and to ensure the resilience of supply chain actors, the TTR must be lower than the TTS, a sine qua non condition for being able to deliver to a customer without interruption. The use of temporal indicators is also found in the study of Pant et al. (2014) who propose to measure the *time to full system restoration*, measuring the time between the total duration of recovery activities (whether parallel or serial); and the *time to full system service resilience*, measuring the total time between the start of recovery activities and the moment when the system functionality is fully restored. Carvalho et al. (2012) develop a discrete event simulation model to evaluate, compare and improve the resilience of supply chains through the study of different scenarios (applied to the design of supply chain networks in the automotive industry). To evaluate and compare the selected scenarios (supplier alternatives), they use two KPIs, the *lead time ratio* and the *total cost*. The *lead time ratio* is equal to the ratio between the actual lead time and the promised lead time. This performance measure assesses the ability of the supply chain to meet the agreed lead time with its first-tier customers (Carvalho et al., 2012). *Total cost* provides an assessment of all costs associated with each entity in the supply chain over a given period of time.

Priya Datta et al. (2007) propose an agent-based conceptual framework to study the operational resilience of complex (multi-product and multi-country) supply chains under constraints on production and distribution capacities. Supply chain resilience is assessed on the basis of the following KPIs (measured for each product in each distribution centre and company): *customer service level* (the total quantity sold to the final customer compared to the total quantity ordered), *production variation* (the number of changes and the average length of production cycles), and *average inventory* (at the level of

Table 2.5 – KPIs to be observed according to the different phases of a disruption for a supply chain according to Karl et al. (2018)

Level	KPI	Before the disruption	During the disruption	After the disruption
Company	Capacity utilisation	✓	✓	
	Quality of the products delivered	✓	✓	✓
	Order time	✓	✓	✓
	Delivery time	✓	✓	✓
	Orders delivered on time	✓	✓	✓
	Stock level	✓	✓	✓
Supplier	Supplier delivery efficiency	✓	✓	✓
	Supplier rejection rate	✓		✓
Customer	Customer satisfaction	✓	✓	✓
	Return rate		✓	

distribution centres and for the whole network). Spiegler et al. (2012) use the *temporal absolute error integral* to measure the resilience of supply chains (a measure used in control engineering to measure deviations in system performance). Based on their literature reviews, they propose to assess resilience in terms of *actual stock* or *time to cover* for firms operating on a make-to-stock basis and *lead time* or *order book size* for firms operating on a make-to-order basis. They also stress the importance of developing a single measure for resilience to ensure consistency and replicability (Spiegler et al., 2012). To do so, they propose to focus on the theoretical objectives proposed in Ponomarov et al. (2009)’s definition of resilience, namely (1) *readiness* (continuing to provide goods or/and services at reasonable costs in line with customer requirements, a reasonable minimum inventory or a reasonable minimum backlog may be appropriate measures), (2) *response* (minimising reaction time), and (3) *recovery* (returning to a “normal”, stable or permanent level of performance). Karl et al. (2018) explore through their literature review the influence of non-financial KPIs in creating more resilient supply chains. They construct six KPIs at the company level, two at the supplier level and two at the customer level. Table 2.5 positions the importance of these indicators for assessing performance in the pre-, during and post-disruption phases.

Han et al. (2020) divide the performance measures needed to assess the resilience of a supply chain into eleven categories: (1) *maintaining customer satisfaction* (maximising the customer service rate during the period of disruption), (2) *supply chain process completion efficiency* (relates to the time and efficiency between the initiation and execution of a process during the time of disruption), (3) *return to normalcy efficiency* (speed of full recovery of the supply chain), (4) *production and inventory performance* (measuring production capacity and inventory levels during disruptions, with a particular focus on critical products), (5) *relationship management* (measuring the quality and

flexibility of relationships between supply chain actors during disruption), (6) *financial performance*, (7) *monitoring of the supply chain situation*, (8) *ability to detect possible disruptions*, (9) *disruption damage* (measuring the performance lost as a result of a disruption), (10) *disruption response effectiveness* (how quickly the supply chain can identify a disruption and implement measures when the disruption occurs) and (11) *supply chain rebuilding* (reconfiguring and realigning resources after a disruption).

Rajesh (2016) proposes to measure resilience according to five major indicators: (1) *flexibility* (ability to handle changes quickly without excessive effort and loss), (2) *responsiveness* (speed of product delivery), (3) *quality*, (4) *productivity* (related to customer satisfaction) and (5) *accessibility* (network visibility and connections between network actors). Each of these major indicators is associated with several metrics to assess it, as defined in Table 2.6. The five major indicators proposed by Rajesh (2016) are very similar to, if not included in, the *performance attributes* defined by the SCOR model (more details on the SCOR model are provided in Appendix B). The SCOR model introduces five *performance attributes* (APICS, 2017): (1) *reliability* (ability to perform tasks as expected with a focus on predicting the outcome of a process), (2) *responsiveness* (speed of execution of a task), (3) *agility* (ability to respond to external disruptions), (4) *costs* (costs of operating the supply chain) and (5) *assets* (ability to use assets efficiently). The *performance attributes* represent the strategic performance characteristics on which to align the supply chain's performance to achieve its strategic objectives (Cerabona et al., 2023). APICS (2017) defines two types of *performance attributes* in its model: *customer-facing attributes* (reliability, responsiveness and agility) and *internal attributes* (assets and costs). By their definitions, the indicators proposed by Rajesh (2016) are *customer-oriented*. They can thus be integrated into the *performance attributes* defined by the SCOR model: *flexibility* in *agility*, *responsiveness* in *responsiveness*, and *quality*, *productivity* and *accessibility* in *reliability*. In addition, *agility*, defined as the ability of a supply chain to respond to external disruptions, thus measuring its ability and responsiveness to change (APICS, 2017). This performance attribute thus seems very promising and suitable for the assessment of resilience, especially in view of the definitions of resilience presented in Section 2.1.1. For each *performance attribute*, SCOR associates several KPIs, organised on several levels (for more information see Appendix B). Rajaratnam et al. (2021) support this idea of drawing on the KPIs proposed by the SCOR model to assess resilience, by proposing a hierarchical performance measurement framework based on 55 indicators proposed by SCOR to assess performance and diagnose problems in supply chains.

Table 2.6 – Lists and definitions of indicators proposed by Rajesh (2016) to assess supply chain resilience

Key indicators	Associated performance indicators
Flexibility	<i>Out-of-stock rate</i> : percentage of companies that experience an out-of-stock condition for one or more products they were supposed to deliver over a certain period.
	<i>Stock accuracy rate</i> : percentage of parts in physical stock for a product that corresponds to the computer stock for that product.
	<i>Number of small disruptions managed through supply chain flexibility</i> : counts operational incidents handled by process, product and production flexibility.
	<i>Percentage increase in sales due to design flexibility</i> : percentage of sales after a product has been modified to meet market requirements by adapting it due to the design flexibility of that product.
Reactivity	<i>On-time delivery</i> : ratio of the number of orders delivered on time to the total number of orders delivered.
	<i>Time to issue a contract</i> : average time between the decision to order and the purchasing department issuing the contract.
	<i>Contract approval time</i> : average time from the issuance of a purchase order to the award and signature of the contract by a supplier.
	<i>Storage time</i> : the ratio of the time it takes to unload a product plus the time it takes to store it at a designated location, to the total planned storage time for a product.
Quality	<i>Quality of forecasts</i> : percentage difference between forecasts and actual consumption over one year.
	<i>Quality test</i> : percentage of products tested per batch shipped over a given period.
	<i>Shipping quality</i> : percentage of products shipped without damage.
Productivity	<i>Order compliance</i> : percentage of orders for which the manufacturer does not have sufficient stock.
	<i>Fill rate</i> : ability of suppliers and manufacturers to fill orders in terms of quantity requested.
	<i>Storage space used</i> : percentage of total space used for storage out of the allocated space.
	<i>Units moved</i> : quantity of parts moved per hour and per person.
Accessibility	<i>Reseller accessibility</i> : percentage of resellers with direct access to manufacturers and suppliers.
	<i>Retailer accessibility</i> : percentage of retailers with direct access to manufacturers and suppliers.
	<i>Customer accessibility</i> : percentage of customers with direct access to manufacturers and suppliers.
	<i>Network intensity</i> : number of connections between suppliers, retailers and customers.

No agreement on a model for measuring resilience seems to have been found in the literature, the assessment of supply chain resilience performance has been studied structurally, using dimensions or phases of resilience (Cerabona et al., 2023). Most studies in the literature have focused more on developing their own measurement models (Han et al., 2020), rather than developing dedicated performance indicators for measuring resilience. Among the measurement models developed, one of the most recognised is the *resilience triangle* (Tukamuhabwa et al., 2015), a measure based on the fact that it is possible to represent the performance of the system at any point in time as a trajectory (Bruneau et al., 2003). The studies presented in this section (notably the various works on the *resilience triangle*) focus mainly on an assessment of engineering resilience (completely ignoring the assessment of ecological resilience).

Although supply chain management is strongly rooted in engineering and social sciences. The diversity offered by these two views of supply chain management is rarely found in the work and definitions of resilience offered in the literature (Wieland et al., 2021). Thus, some authors such as Wieland (2021) propose to reinterpret the supply chain, studying it as an organic system. Indeed, according to them, assuming that a supply chain behaves as a purely mechanisable system is an oversimplification in view of its complexity (Wieland et al., 2021). The idea behind this reinterpretation of the supply chain is not to reject the excellent work related to the technical interpretation of resilience that dominates much of the current work. Being able to stabilise a supply chain quickly after a disruption is essential for managers. But adding the concepts of ecological resilience to it, in order to benefit from their input to deal with the non-linear, uncertain and often surprising behaviour of supply chains (Wieland et al., 2021). Holling (1996) was the first to highlight the difference between engineering and ecological resilience. Engineering resilience focuses on constancy, predictability and efficiency, while ecological resilience focuses on change, unpredictability and persistence (Wieland, 2021). In other words, instead of measuring resilience as “resistance to disturbance” or “speed of return” to a steady state of performance, as engineers would do, ecologists measure resilience as the “magnitude of disturbance” that the ecosystem can absorb (Wieland, 2021). Only a few attempts have been made so far to study supply chain resilience through the lens of ecological resilience (Wieland et al., 2021). Despite this reinterpretation of supply chain management, it is important to retain the contributions of both types of resilience. However, to our knowledge, there is no approach that measures supply chain resilience by combining these two views of resilience, thus providing opportunities for the physics-based approach such as PoD to be studied. Let us see *how the PoD approach proposes to reconcile these two important views of supply chain resilience*.

2.2 Kinetic approach to risk and resilience management

Holling (1973) acknowledges the importance of classical physics in his definition, which he extends by redefining some concepts to fit the notion of systems ecology (Park et al., 2013). Classical physics is used to provide the essential concepts and intellectual background for defining his vision of resilience, including using its vocabulary: force,

equilibrium, magnitude, etc. This borrowing of terms from classical physics to define ecological resilience has been widely used in the literature on the subject. This is evidenced by the different components of ecological resilience identified by Ponomarov et al. (2009) from their literature reviews: *elasticity*, *magnitude*, *hysteresis*, *plasticity* and *damping*. *Elasticity* determines how quickly the system can be restored to a stable state after a disturbance (Orians, 1975; Westman, 1978). *Magnitude* is defined as the area of deformation at which the system will return to its initial state (Orians, 1975; Westman, 1978). *Hysteresis* is “the extent to which the path of degradation under chronic disturbance, and a recovery when disturbance ceases, are not mirror-images of each other” (Ponomarov et al., 2009). *Plasticity* represents the difference between the initial equilibrium state of the system and the equilibrium state reached and established after a disturbance (Westman, 1978). *Damping* represents changes in the system’s restoration path, modified and deflected by forces, which change its normal restoration strength (Clapham, 1976).

The analogies with physics used to define resilience make the PoD approach a prime candidate for its study. Indeed, the PoD approach models the realisation of potentialities as forces impacting on the performance of the supply chain (Benaben et al., 2019). This force view is fully in line with an important aspect of the definition of ecological resilience proposed by Holling (1973), who considers ecological systems to be systems subject to deterministic and stochastic forces, which evolve in time and space (Park et al., 2013).

Identifying the different states of a system is an essential component in the study and analysis of resilience (Carvalho et al., 2012). Its assessment requires a detailed understanding of the behaviour and functions of a system, especially during and following catastrophic events (Linkov et al., 2014). Indeed, as discussed above, the main difference between engineering and ecological resilience lies in the changes in state, including the number of equilibrium states attainable after a disturbance. The evolution of system states over time allows for the description of changes in system behaviour and conditions (Ferreira et al., 2009). Identifying these changes in state is central to systems diagnosis and requires the ability to characterise the system by assessing the various interactions between its attributes. The study of these relationships and their influence on the performance of the system is necessary to control it effectively and thus visualise and predict its changes of state.

The PoD approach, thanks to the two spaces developed, offers the possibility of following the evolution of the different states of the supply chain over time with the description space and the resulting impacts of these changes of state on its performance thanks to the performance space and the functions linking the two spaces developed (refer to the presentation of the PoD approach in Chapter 1 for more details). These two spaces therefore allow us to consider the dynamics governing the supply chain under study, whether linear or non-linear. Being able to consider the dynamics of a system is fundamental to the study of its resilience, as by definition resilience is a dynamic concept and a property of dynamic systems (Adobor et al., 2018). It is therefore crucial to be able to measure the resilience of a supply chain from its attributes and dynamics, the resilience of a system “needs to be considered in terms of the attributes that govern the system’s dynamics” (Adobor et al., 2018; B. Walker et al., 2004). To achieve this, it is essential to develop the capacity for visibility. Visibility is one of the five key capabilities proposed by Christopher et al. (2004b) to increase the resilience of supply chains: (1)

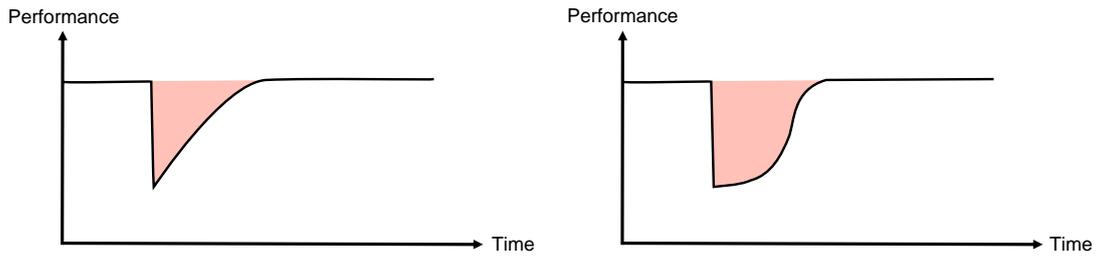


Figure 2.8 – Illustration of different absorption and response dynamics of a system following a disturbance

choose strategies that leave as many options as possible, (2) re-examine the trade-off between efficiency versus redundancy, (3) develop collaborative working, (4) develop visibility and (5) improve its speed and acceleration. According to Adobor et al. (2018), visibility is the ability to see the whole supply chain, *i.e.* to be able to see across its entire network and know its environment. To support this visibility capability, the PoD approach has developed the description space, which brings together all the information needed to monitor the evolution of the supply chain, its environment and its attributes. The latter capability offers very interesting perspectives in using the PoD approach to manage and kinetically improve the resilience of supply chains. Improving the speed and acceleration of a supply chain requires defining and visualising the objectives to be achieved, in particular by visualising, for example, its performance trajectory in a framework whose dimensions are its performance indicators.

In the light of all the above information, the interest in using an approach such as PoD lies in the objective of taking advantage of the two spaces developed and particularly the performance space to assess the resilience of supply chains from a kinetic point of view, the geometric definition of which has yet to be defined.

2.2.1 Kinetics concepts: a proposed application to supply chain resilience management

The principles of the PoD approach are directly derived from classical physics and in particular from concepts derived from the fundamental principle of dynamics. In this law, Newton states that the resultant of the forces exerted on an object (*i.e.* the force equivalent to the vector sum of all the forces exerted on that object) is directly proportional to the acceleration of an object produced by the resultant force and the mass of the object. Thus, from a kinetic perspective, the following points explain how to link supply chain resilience management concepts to physics concepts such as *displacement, velocity* and *acceleration*:

- *Displacement* corresponds to variations in a KPI's values, along the axis of the performance space with which it is associated (ΔKPI). Its study allows a problem to be identified quickly, particularly through the study of deviations in the performance trajectory of a supply chain, thus allowing appropriate corrective action to be taken before it worsens and spreads. For a view of α -resilience (ability to return to a state of performance identical to that before a disruption) or γ -resilience

(ability to adapt to reach a new steady state), displacement measures the gap between pre (*i.e.* no disruption) and post disruption performance trajectories. For β -resilience (which seeks to maintain the system in a resilience zone), displacement measures the gap between the boundary of the nearest objective performance zone (the resilience zone) and performance following a disturbance. The displacement therefore measures the performance lost or gained following a disturbance. This measure is very close to the concept of plasticity defined by Westman (1978). It is also very similar to techniques proposed in the literature to measure engineering resilience, namely the area calculation method, such as the *resilience triangle* presented in the Section 2.1.2. *Displacement* provides a dynamic measure of resilience at any point in time, while the area provides a measure of resilience over a selected time range (Cerabona et al., 2023). Low values of displacement mean no significant impact or quick recovery (Cerabona et al., 2023).

- *Velocity* is the derivative of the displacement over an interval δt : $\frac{dKPI}{dt}$. It measures the growth of the supply chain (Cerabona et al., 2023). Its sign indicates whether the growth is positive or negative from the point of view of the observed KPI. The evolution of its sign will allow a better understanding of its internal dynamics (illustrated in Figure 2.8), in particular how the supply chain is organised to best cope with any disruption (all the phases of change of sign of the *velocity*). It thus offers the possibility of tracking the progress or trend of the supply chain towards a given destination, usually its performance targets (which implies defining its targets, knowing the performance target area, in order to know whether the velocity is going in the “right direction”). Although resilience has been very well conceptualised in the literature with all the definitions present in terms of the capabilities of a supply chain to be ready, respond, recover and transform in the face of and following disruptions, very little information or techniques can be learned about its capabilities to manage growth and transformation phases (Adobor et al., 2018). *Velocity* therefore offers an interesting perspective in the study of resilience. To be fully effective, this measure requires observation over a longer period than displacement, to provide a more accurate picture of supply chain dynamics.
- *Acceleration* is the derivative of the velocity over an interval δt : $\frac{dv}{dt} = \frac{d^2KPI}{dt^2}$. According to *Newton’s second law*, its direction is always the same as the force resulting from the variation in supply chain attributes as a result of potentialities. The magnitude of the *acceleration* can reflect the strength or weakness of the fluctuation of a KPI in a positive or negative direction depending on its sign. Its norm, therefore, quantifies the magnitude of the potentiality that a supply chain can tolerate (Cerabona et al., 2023). Being able to quantify it is very important for measuring resilience from an ecological point of view, defined as the amount of disturbance that can be tolerated by a system, *i.e.* the amount of extrinsic force that the system can withstand (Carpenter et al., 2001). Looking at this definition of resilience through the lens of physics, and more specifically kinetics, we can define resilience as the amount of force generated by a potentiality that the system can absorb before it moves from one stable equilibrium state to another. In physics, the concept characterising the resistance to movement of an object is mass. The *Encyclopaedia Britannica* (2023) defines physical mass as the resistance that a body (made of matter) offers to a change in its velocity or position when subjected

to a force. Furthermore, according to the principle of dynamics (*Newton's second law*), the intensity of a force is proportional to the mass of the system on which it is applied and the acceleration of the system produced by that force. Given the number of actors, relationships and attributes that characterise a supply chain and its environment, estimating its mass is not an easy task (and it cannot be excluded that the mass of such a system varies over time). In order to measure ecological resilience, it is therefore necessary to quantify the capacity of a supply chain to resist a potentiality by measuring its *acceleration* as a result of this potentiality (considering its mass constant and neglecting it as a proportionality factor).

Displacement, velocity and *acceleration* are equally important, they simply provide different information for different purposes. In the proposed study, the calculated *velocities* and *accelerations* will be local velocities and accelerations, calculated as follows:

$$Velocity = \left[\frac{x(t) - x(t - \delta t)}{\delta t} \right] = v_x(t) \quad (2.1)$$

$$Acceleration = \left[\frac{v_x(t) - v_x(t - \delta t)}{\delta t} \right] = a_x(t) \quad (2.2)$$

The PoD approach, through its proposal to model system performance as a multi-dimensional trajectory and its foundations based on analogies with physics (and associated concepts such as force, displacement, velocity and acceleration), links the two important views of resilience for supply chains: engineering and ecological. This approach allows both views of resilience to be assessed - *to our knowledge no other approach assesses both types of resilience for a supply chain* - and to assess them in a single approach.

2.2.2 Distance: a proposed measure of engineering resilience inspired by the resilience triangle

Based on the information from the literature review proposed in section 2.1.2, quantifying engineering resilience involves measuring the evolution of system performance before and after a disruption, thus making the loss of performance due to a disruption an important measure to quantify it. Behzadi et al. (2020) define performance loss as the difference between performance after a disturbance and expected performance. Based on the concepts of kinetics presented in the previous section, this performance loss can be measured by the concept of *displacement* and *distance* (Cerabona et al., 2023). By analogy with the *resilience triangle* (illustrated in Figure 2.4) and the measure of resilience proposed by calculating the area of this triangle, the idea is to approach resilience by summing the distances between performance trajectories (as proposed in the article Cerabona et al., 2023). In particular, by summing the purple distances (illustrated in Figure 2.9) between the *inertia* (*i.e.* undisturbed) and *passive* (*i.e.* disturbed and without corrective action) trajectories, it is possible to estimate the area between these two trajectories, provided that the time intervals between each distance measure are sufficiently small depending on the system under study and the KPIs considered. In order to make the proposed measure comparable for different systems, the time interval between each distance measure could be calculated as a fraction of a maximum allowable recovery time (as proposed by R. Li et al., 2017; Zobel, 2010), to

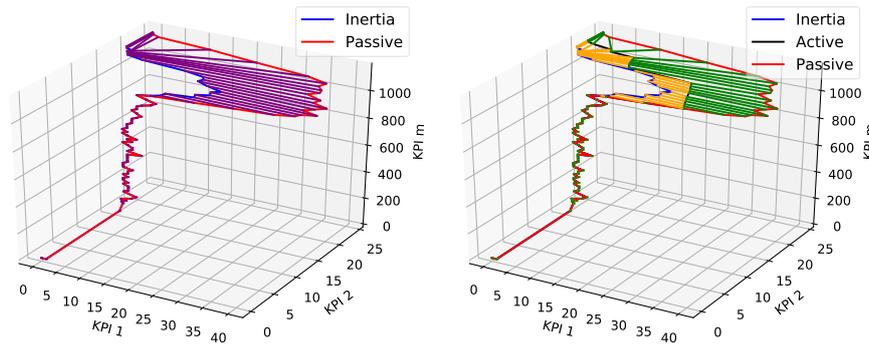


Figure 2.9 – Distances for each time step between the trajectories: inertia, passive and active

be defined depending on the system under study (*e.g.* one hundredth of the maximum recovery time). The definition of a maximum allowable recovery time should allow, according to R. Li et al. (2017), to be able to consider two situations: a recovery or a non-recovery of the system, *i.e.* a situation in which it could not return to a level of performance equivalent to the one before the disturbance (in this case, the system is simply not resilient).

The proposed measure also addresses another weakness of the resilience triangle, the failure to consider the multidimensional aspect of resilience. Although, “some studies have addressed the multidimensional nature of resilience by aggregating the magnitude of deviation from equilibrium and the time to recovery of the performance profile to capture resilience” (Munoz et al., 2015), through the use of the *resilience triangle*. Its use both favours the use of aggregation indices over “more direct” measures of performance, in order to consider the multidimensional aspect of resilience. However, the use of such an index (*aggregation function*) does not allow for a precise characterisation of resilience. Indeed, with the *resilience triangle*, the only way to increase the number of dimensions, *i.e.* to measure a single value of resilience from the results of the impact of a disturbance on several KPIs of a system, is to use aggregation functions, which are relatively complicated to implement and validate, as they rely heavily on the human factor for the evaluation of the different weights to be applied to the KPIs measured. In this case, the proposed measure makes sense. Indeed, it allows us to measure the distance between multidimensional performance trajectories, represented in a performance space, which has the capacity to be composed of as many dimensions as the number of KPIs to be studied. This capacity thus allows us to evaluate the distance between the inertia and passive trajectory whatever the number of KPIs to be studied (even if it is not possible to visualise these trajectories and this space beyond three dimensions).

As proposed in Cerabona et al. (2023), with this method, three types of distance will be used to calculate three different surfaces. The first distance calculated is used to measure *degradation*. It is used to measure the *natural resilience*. The *natural resilience* is the area between the *inertia trajectory* and the *passive trajectory*, in the case of α -resilience (ability to return to the post-disturbance performance level) and γ -resilience (ability to adapt in order to reach a new equilibrium state of performance). In the case of β -resilience (ability to maintain the system in a resilience zone), it corresponds to the area between the nearest boundary of the target zone and the *passive trajectory*. It is calculated by summing the purple distances in Figure 2.9. The second distance

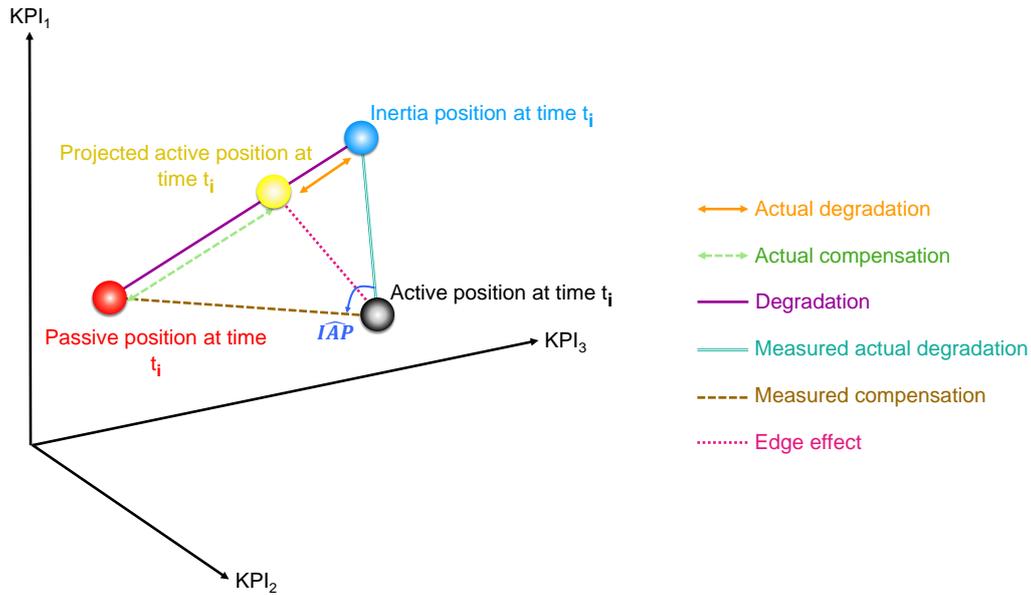


Figure 2.10 – Illustration of concepts related to the geometry of resilience: distances (adapted from Cerabona et al., 2023)

calculated measures the *actual degradation*, allowing the *corrected resilience* of the supply chain to be measured. The *corrected resilience* is the area between the *inertia trajectory* (for α - or γ -resilience, or the boundary closest to the target area for β -resilience) and the *active trajectory*. It is calculated by summing the orange distances in Figure 2.9. The last distance considered measures the *actual compensation*, which is used to measure the *resilience gain*. The *resilience gain* is the area between the *active* and *passive trajectory*. It is calculated by summing the green distances in Figure 2.9.

However, not being in a two-dimensional framework, limiting oneself to these formulae for the calculation of distances is not entirely accurate. It is important to take into consideration the value of the angle \widehat{IAP} between the inertia (I), active (A) and passive (P) trajectories, point by point, *i.e.* for each instant t_i considered. Two values for the angle \widehat{IAP} are of particular interest to us: 0° and 180° . When the angle \widehat{IAP} is 0° , the three points coincide at the time t_i . When the angle \widehat{IAP} is 180° , the three points are aligned on the right (IP). The values of the two previous distances will be all the more valid as the value of the angles measured at each instant t_i will be close to 180° or strictly equal to 0° . Thus, in these two cases, the *real degradation* (orange distance in Figure 2.10) is equal to the *measured degradation* (turquoise distance in Figure 2.10). Indeed, the active position (black dot in Figure 2.10) is thus confused with the projected active position (yellow dot in Figure 2.10).

If the value of this angle is too far from 180° , additional calculations will have to be made. A new distance will then have to be considered, the *edge effect* (dotted pink line in Figure 2.10), which is the distance between the real active position at time t_i and its projected position on the right (IP). These projection calculations will become mandatory, if the majority of the measured angles \widehat{IAP} are less than 90° , the edge effect is no longer negligible and projection calculations become mandatory. In this case, the corrected resilience can be calculated as the sum of the *real degradation* distances

(orange distance in Figure 2.10) at each time t_i . This manipulation will result in a new trajectory, the *projected active trajectory*, obtained from the set of real active positions projected on the right-hand side (IP). This manipulation also involves measuring the *edge effect* as the sum of the distances between the set of points of the *active trajectory* and their corresponding projections on the line connecting all *inertia* and *passive positions* at the same time t_i . If the *edge effect* is too significant, the study of resilience will then be limited to comparing the sum of the purple distances and the sum of the green distances (illustrated in Figure 2.9), in order to know whether the *active trajectory* (the corrective solution) is interesting or not.

2.2.3 The resilience cone: a proposed measure of ecological resilience through the PoD paradigm

In addition to this first way of assessing resilience, accessing measures of engineering resilience, the paradigms and concepts of the physics of motion on which the PoD approach is based can also be used to assess the ecological resilience of supply chains, making a real contribution to the gaps in the literature on this subject as illustrated by the literature review in this chapter. In the same way that Holling (1973) recognises the importance of physics in his definitions of resilience, the physics underpinning the PoD approach is directly relevant to the notion of ecological resilience. Indeed, Carpenter et al. (2001) define it as: “the magnitude of disturbance that can be tolerated before a socio ecological system moves to a different region of state space controlled by a different set of processes”. Thus the amount of extrinsic force that the system can withstand, *i.e.* the amount of change it is able to absorb without altering its control over its structure and functions, is one of its properties (Carpenter et al., 2001). From the perspective of the PoD approach, this property translates into the resulting strength of a disturbance that can be withstood by a supply chain without it becoming unable to meet its performance objectives. As presented in Figure 1.7, *image 3*, describing the performance space, the hyper-tube can be considered as the part of the space in which the supply chain (more precisely its performance trajectory) must be maintained, in order to ensure that it responds to and achieves the set objectives. Based on the definition of the hyper-tube and by extension its properties, ecological resilience could be defined as the set of forces that the supply chain is able to resist without leaving the target area, modelled by a hyper-tube (Cerabona et al., 2023). The shape of the hyper-tube is clearly time dependent. It varies according to the supply chain’s objectives and its ability to meet them. Indeed, past results will impact future results, yesterday’s objectives are not today’s, or even tomorrow’s. The less efficient the supply chain is, the more the volume of this hyper-tube will shrink, until it disappears if the target can no longer be reached. Let us take the example of a person who has to plant 90 trees in 10 days to illustrate this idea. This person is able to plant 15 trees per day. Initially, the hyper-tube is quite large, so this person can choose to plant between 0 and 15 trees on the first day and so on for the other days. He may even decide not to plant any trees until the fifth day. However, if he makes this choice, he will have no choice but to plant 15 trees per day between days 5 and 10 to achieve his objectives. This reduces the hyper-tube to one line. If during these six days of intensive work he finds himself unable to plant 15 trees, there is no solution and no more hyper-tube. Defined in this way, the evolution of the shape and volume of the hyper-tube over time is very similar to the notion of a critical path in project management. From a physical point of view, the hyper-tube could be compared to certain materials, whose physical properties allow

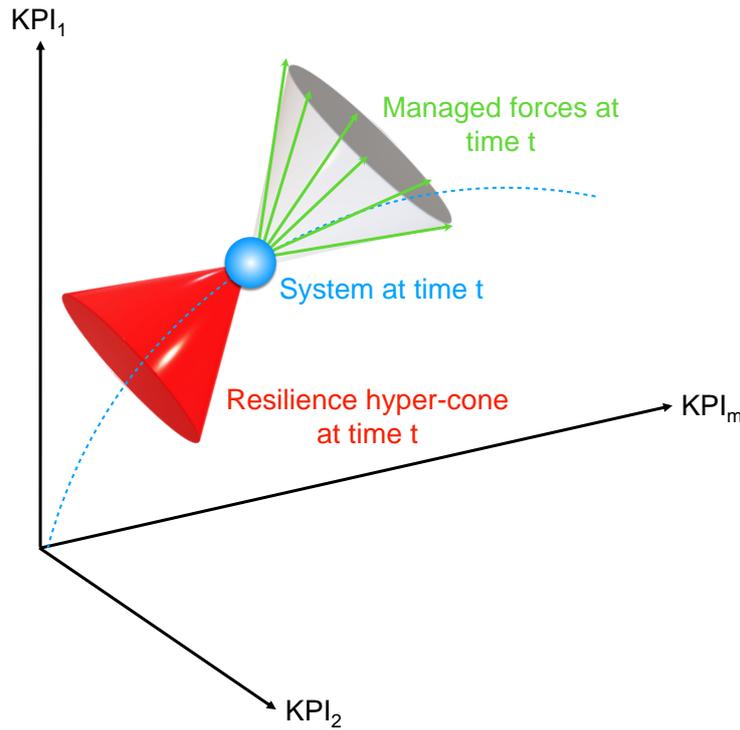


Figure 2.11 – The resilience cone (adapted from Cerabona et al., 2023)

them to absorb shocks and impacts, to accumulate them up to a certain level, from which they break at the slightest shock (Cerabona et al., 2023).

In the light of the above points and the framework set by the PoD approach, supply chain resilience, according to its ecological vision, can then be defined as the set of forces for which the supply chain is capable of activating one or more levers, *i.e.* counter-forces, which will allow its performance trajectory to remain within a realistic and achievable target hyper-cone (Cerabona et al., 2023). A measure of the ecological resilience of supply chains could thus be calculated from the volume of the red hyper-cone, illustrated in Figure 2.11. This red hyper-cone is the symmetrical of the grey hyper-cone (from which the force vector required to move through the hyper-tube will be removed). The grey hyper-cone models the space defined by the set of counter-forces (corrective actions and managers' decisions) that can be activated at each time t (illustrated in Figure 2.11). Thus, the red hyper-cone models the space in which each force vector represents the impact of one (or more) disturbance(s) on the supply chain, which could be countered by corrective forces managed by the managers (green vectors in Figure 2.11), in order to maintain the supply chain in its target zone (its hyper-tube). The supply chain cannot therefore absorb a disturbance whose force is greater than those contained in the red hyper-cone. With this new vision of resilience, it is no longer necessary to wait for a disturbance to occur and for a return to a stable state of performance before resilience can be assessed, unlike previous methods. However, to be applicable and robust, this measure of ecological resilience requires: (1) a high level of knowledge of the system and its environment, in order to be able to identify all the (corrective) forces that are manageable at any given time; (2) the ability to estimate their impacts as accurately as possible (probably for most forces from previous or simulated data); and (3) the ability

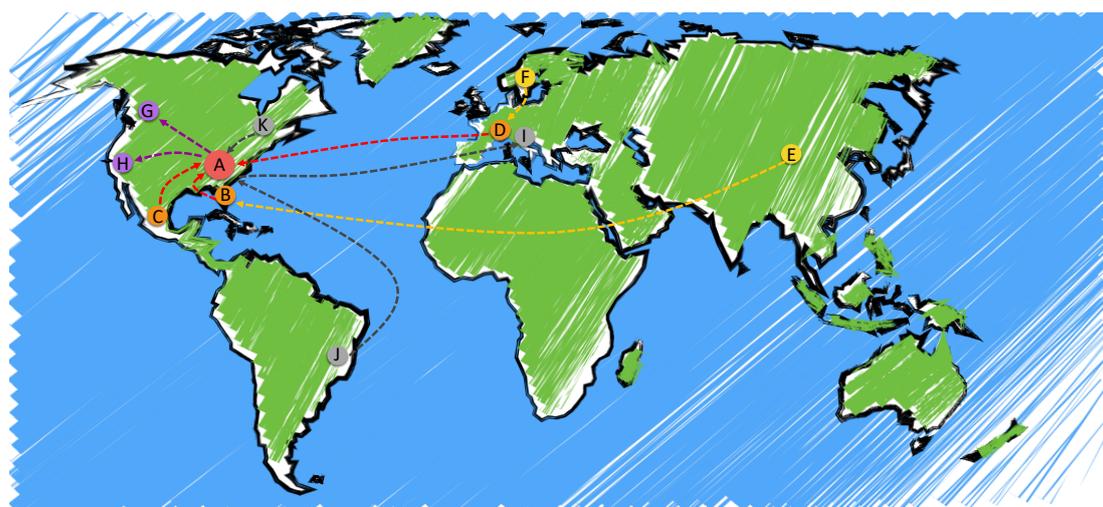


Figure 2.12 – Location of Rich Kids supply chain actors (adapted from Cerabona et al., 2023)

to define and measure the overall volume resulting from these forces (which in a space of more than three dimensions requires further development). These needs, to make this measurement effective, also raise the question of the independence of the forces and their summability criteria, two points at the heart of this approach, which are not currently resolved.

2.3 Physics of Decision approach: application to the measurement of supply chain resilience

2.3.1 Case study presentation: Rich Kids supply chain

The case study selected to illustrate the contributions of the PoD approach to the development of supply chain resilience capabilities deals with a supply chain of electric skateboards. This case study was created in 2019, as a purely fictional case illustrating the beginnings of the PoD approach. The motivations around the name of this case study, “Rich Kids”, mainly stem from the product developed and the initial idea, which was that end users do not buy, but rent skateboards according to the different places they go on holiday (from surfing to skiing resorts). So instead of moving their own skateboard, they rent one of equal quality wherever they go. This type of offer is mainly aimed at wealthy children. Since then, some liberties have been taken from the original case, *e.g.* in the case presented in this manuscript, we will not be interested in how and by whom the skateboards are used, once purchased by the dealers. Different actors are considered in this logistic network. Table 2.7 briefly describes the role of each actor and possible new partners. Figure 2.12 shows the geographical position of all actors in the network.

Despite its simplicity, this case study offers a large potential for evolution in terms of complexity and scenario studies. In order to collect the necessary material for the application of the PoD approach, *i.e.* the data related to this case study, a simulation model was developed on AnyLogic© software, based on the discrete event simulation method (see Appendix C for more information on this simulation method).

Table 2.7 – Description of Rich Kids supply chain actors

Company	Description	Location
A	manufactures electric skateboards, steered by an application	GA. USA
B	sources the electrical components (battery and motor) from E, develops the control application and sells the package to A.	Fl. USA
C	manufactures synthetic wheels sold to A.	Mexico
D	makes the boards sold to A (from wood purchased from F).	France
E	manufactures the engines and batteries sold to B.	China
F	supplies wood to D.	Sweden
G	skateboard dealer in a ski resort.	Canada
H	skateboard dealer in a seaside resort.	CA. USA
I	skateboard dealer in a ski resort (potential).	Italy
J	supplier of synthetic wheels (potential).	Brazil
K	supplier of wooden boards (potential).	Canada

2.3.1.1 The value of simulation

In the literature, simulation is indeed advocated as a methodological approach for theory development (Davis et al., 2007; Harrison et al., 2007; Nair et al., 2009), notably for its ability to provide test support for theories (Groff, 2007; Mosler et al., 2001; Neufeld et al., 2010; Serrano et al., 2005). According to Davis et al. (2007), simulation is recommended when “the theoretical focus is longitudinal, nonlinear, or processual, or when empirical data are challenging to obtain”.

Simulation is also a particularly effective tool for studying the dynamic behaviour of a system (Albores et al., 2006). Ball (1996) defined it as “the technique of building a model of a real or proposed system so that the behaviour of the system under specific conditions may be studied. One of the key powers of simulation is the ability to model the behaviour of a system as time progresses”. Simulation can also be defined as the process of designing an abstract model from a real system (which may be complex and with random behaviour, such as a supply chain). This abstract model is built with the aim of conducting experiments, in order to understand the behaviour of the modelled real system, for a set of criteria and appropriate input data sets, modelling its operating range, limits and constraints (Stefanovic et al., 2009). Simulation thus provides the flexibility and agility to consider all arbitrary stochastic elements (uncertainty factors in demand, delivery time, etc.), allowing the full complexity and dynamics of supply chains to be modelled, without resorting to oversimplifying assumptions (Ben Jbara, 2018; Cope et al., 2007). It thus provides the essential level of realism and utility required to accurately model a supply chain and its dynamic environment (Cope et al., 2007).

The relative uncertainty associated with the notion of risk makes simulation a very appropriate tool for its analysis (D. Wu et al., 2015), thanks to its ability to consider and model stochastic factors that influence the real world (Stefanovic et al., 2009).

“Simulation allows a dynamic consideration of randomness in disruption and recovery policies, real-time analysis, real problem complexity, inventory control policies, dynamic recovery policies, gradual capacity degradation and recovery, impact of changes in sourcing, transportation and production policies [...] and operational parameter dynamics in time” (Ivanov et al., 2017). Simulation therefore allows the development of virtual and artificial environments in which the dynamic behaviour of risks can be assessed (Singhal et al., 2011), as well as the response of the system to these risks, through various tests and experiments, before the risks are realised in the modelled real system. Through simulation, these tests are carried out without interrupting the real system, so experiments can be carried out without disruption and without significant investment (Stefanovic et al., 2009). It may be impossible or too expensive to observe certain processes (network reorganisation or strategies) in the real supply chain (Campuzano et al., 2011). Simulation allows to study and analyse the behaviour and the different state changes of a system when it is impacted by risks or decisions. Simulation also provides a better understanding of how system attributes influence its behaviour. Simulation thus provides visibility into the understanding of the evolution of a system and its performance (including the cause and effect relationships influencing its performance) over time. It also offers a very interesting support for the prediction of the evolution of the performance of a system (Hermann et al., 2003). Monitoring the evolution of its performance over time is the major objective of using simulation for supply chains (Thierry et al., 2008). Simulation models thus facilitate decision-making, thanks to a better understanding of the system and its modelled processes (Neu et al., 2002). Of course, the quality of the decision support provided will depend on the quality of the simulation model built.

In the context of supply chain management, simulation has been particularly applied when the environment is affected by variance associated with risks and uncertainties, facilitating, for example, the analysis of various assumptions and the assessment of the benefits and impacts of risks and instability (J. B. Oliveira et al., 2019). It has also been used to develop and test different improvements and decision-making alternatives (Campuzano et al., 2011). The analysis of risks and their numerous mitigation strategies is carried out through the definition and study of scenarios (Singhal et al., 2011), which are sufficiently detailed and are usually constructed from data on previous disturbances. The study of these scenarios makes it possible to identify and understand the causes and effects of the simulated potentialities on the system, particularly on its performance (Campuzano et al., 2011). Indeed, the simulation allows measuring the gaps between the supply chain performance for each scenario studied and the desired performance (Carvalho et al., 2012), thus allowing testing and analysing the contribution of the strategies implemented to close the performance gaps, by adjusting or deactivating structural elements of the supply chain and the parameters selected (the operational attributes of the supply chain) to achieve the desired objectives (Ivanov et al., 2021). Simulation therefore provides a systems approach to understanding the relative impact of factors (simulation model parameters) for the different scenarios studied (Ghadge et al., 2012). Simulation also allows for the study of one of the key aspects in the management of potentialities, time. The modelled system can thus be studied either in real time (Katsaliaki et al., 2021) or in accelerated time, thanks to its ability to “compress” time (Stefanovic et al., 2009). This ability to simulate a system in accelerated time makes it possible to obtain the results of a scenario in a short period of time, in the case of a strategic decision, the effects of which would not have been observed and measured in

the real system until several months after its implementation. This ability to obtain the impacts of many scenarios almost instantaneously allows, thanks to optimisation techniques or “what if” analyses, to access the best response strategy to a disturbance almost in real time (*i.e.* before it occurs). Simulation is thus applied in many fields for its ability to address critical issues before they become problems and risks (Müller et al., 2008). The developed simulation models thus offer support for decision making and deployment of contingency plans (Ho et al., 2015; Ivanov et al., 2021; Lückner et al., 2019). Simulation is therefore proving to be a particularly effective tool in the study of strategies to improve the resilience of supply chains to risks (Carvalho et al., 2012; Falasca et al., 2008).

A tool recommended in the literature for theory development, simulation offers a technique for modelling and analysing the full range of issues involved in managing supply chain instability. Simulation is the combination of: (1) a virtual model of the system (a space for experimentation), (2) input sets for the model (sufficiently representative to take into account all the stochastic dimensions of a system such as supply chains), and (3) an execution layer that allows the model to be stressed with appropriate input sets and scenarios modelling the different potentialities impacting the system. Its ability to capture the dynamics of a system perturbed by various potentials makes it a particularly interesting technique to support the study of the applicability of the PoD approach, in particular to make the link between the description and performance spaces (as specified in Chapter 1).

2.3.1.2 Assumptions associated with the Rich Kids case study simulation model

Using the discrete event simulation method, the processes and laws governing the operation of the *Rich Kids* supply chain were modelled, in particular to carry out the tasks of procurement, production and shipping. Through these processes, different entities circulate and exchange, which possess certain attributes, state variables essential for exchanging information between the different actors (quantities ordered) or measuring certain performance indicators (delivery times). These state variables thus make it possible to collect or assign data to the different entities used as flows in the different processes modelled.

The model is based on several general operating principles:

- Global:
 - Suppliers and Company A operate on a make-to-stock basis.
 - Triangular distributions were used to model the duration of the different operations and transport times, in order to mimic the probabilistic nature of the modelled supply chain (Carvalho et al., 2012).
- Procurement and supply planning:
 - A continuous daily review of the level of raw material stocks is implemented, according to a min-max policy (s, S), illustrated in Figure 2.13, with S fixed and $s = \lfloor \text{average consumption} \cdot (\text{delivery time} + \text{safety stock}) \rfloor$ with the safety stock corresponding to a coverage period.

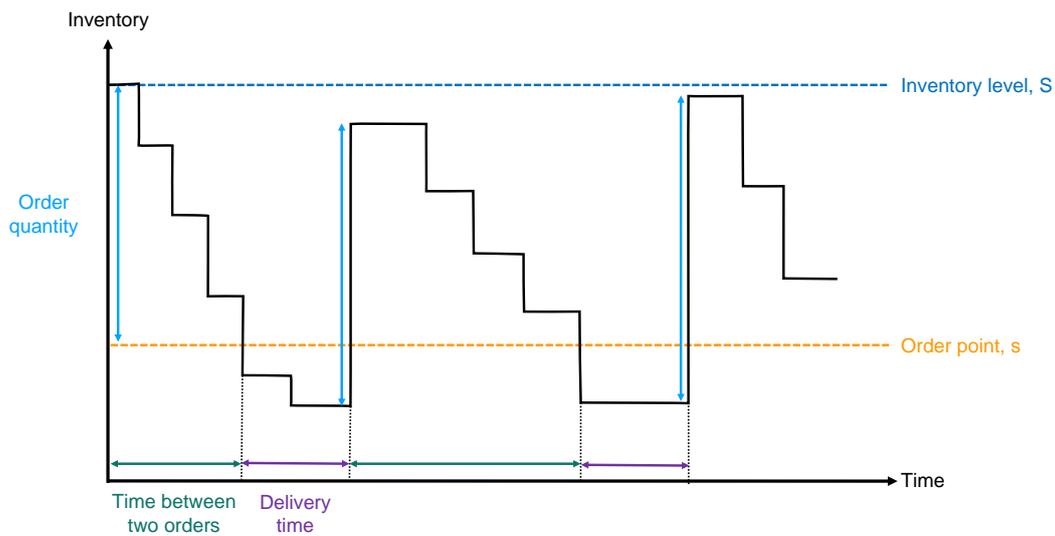


Figure 2.13 – Illustration of the (s,S) inventory management policy

- To regulate the number of orders placed with suppliers, once an order is placed, the cyclical event used for the daily stock review is stopped until the goods are received.
 - If a raw material order cannot be delivered in full, then it can only be delivered partially if a certain volume of the order can be covered (50%). Otherwise, the order is put on hold until the supplier’s stock allows the entire order to be shipped.
- Delivery and creation of sales orders (only for company A):
 - Fixed and weekly customer orders.
 - Company A has a time limit (equal to the difference between the delivery time and the transport time), to fulfil the order (before it becomes overdue), *i.e.* to ensure that it has the required quantity of parts in stock.
 - Manufacturing (only for company A):
 - The quantity of skateboards to be produced daily is calculated from the net requirement (NR), with $NR = \max(0, \lfloor \text{daily demand} + \text{safety stock} - \text{inventory} \rfloor)$.
 - In the event of a shortage of raw materials, the volume of skateboards awaiting production may not exceed four times the weekly demand.
 - The opening time is 50 hours per week (Monday to Friday).
 - Manufacturing (for suppliers):
 - The suppliers’ inventory levels are updated daily according to their production capacities (production is stopped if the inventory level reaches a fixed maximum value).

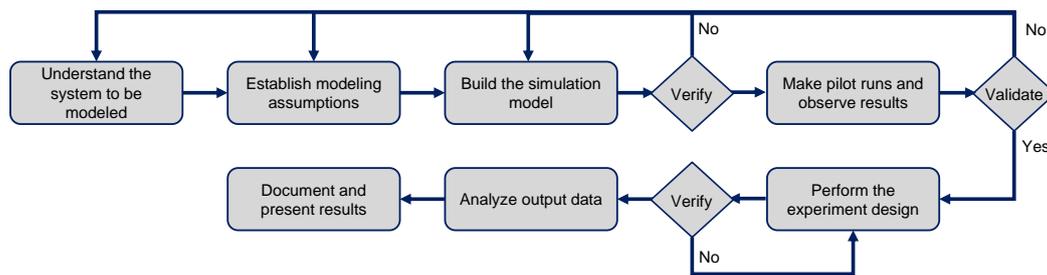


Figure 2.14 – Creation and validation framework for simulation models (adapted from Grest et al., 2021; Law, 2013)

2.3.1.3 Methodology: validation of the simulation model

Once the processes have been modelled and the assumptions defined, it is essential to ensure the validity of the simulation model developed, which is one of the most difficult problems for the person responsible for its analysis and development (Law, 2013). This is a critical point for any simulation model, if it is not valid it cannot be used for decisions and especially to determine the impact of those decisions. Law (2013) defines validation as the process of determining whether a simulation model is a correct and accurate representation of the real system being modelled, for specific objectives particular to the study being conducted. The difficulty of this process depends on the complexity of the system being modelled. In order to ensure the reliability of the results of the developed models, a functional framework for the creation and development of the simulation has been followed and adapted for our experiments. It takes up and adapts the framework linking the validation and credibility building steps of simulation models proposed by Law (2013) and extended by Grest et al. (2021). It consists of seven steps (illustrated in Figure 2.14): (1) understanding the system to be modelled (data analysis and understanding), (2) making the modelling assumptions, (3) building the simulation model to be verified, (4) pilot testing and observing the results to be validated, (5) conducting the experimental design, (6) analysing the output data and validating it, and (7) documenting and presenting the results. This framework is not necessarily a sequential process, it may be necessary to revisit certain steps as the simulation model develops (increasing complexity and understanding of the operation of the real system being simulated and/or the associated model). It is rare to build a simulation model (for complex systems such as supply chains) in one go, generally the model is built brick by brick, which must be validated.

2.3.2 Preliminary application of the PoD approach

For this case study, the simulation¹ is used to capture and model the uncertainty related to each potentiality or decision studied, thus providing a correct representation of the

¹In this study, simulation is used to generate the data needed to apply the two proposed resilience measures (distances and the resilience cone), in the absence of access to real data (but also to have more freedom in the study of the different potentialities). The necessary data correspond to time series of KPIs evolution (taken at regular time intervals), illustrating the evolution of KPIs when a supply chain is functioning normally and when it is disrupted (which can be obtained from past disruption data). Thus, the proposed measures are fully applicable for real and not simulated supply chains, according to the same principle as the one proposed in this purely illustrative case.

Rich Kids supply chain response dynamics over time. In particular, it was used to measure the performance gaps between the actual state of Company A and its objectives (represented in this study by its initial performance, *i.e.* when it is not subject to any potentiality), following the realisation of different scenarios (potentialities and corrective solutions). The scenarios studied allow the generation of the different forces, the “*inflicted*” forces are generated from scenarios modelling disruptions impacting the raw material supply flows of company A. Conversely, the “*managed*” forces are generated from scenarios aimed at improving Company A’s capabilities, notably by creating new partnerships.

The collection of data related to the realisation and study of the different scenarios considered was carried out at regular time intervals during the different simulation runs, according to a standard procedure widely used in the simulation field. This procedure consists of running the simulation over a fixed period of time, in order to obtain time series of sampled data for analysis (Macdonald et al., 2018). In this study, the data (time series of changes in measured KPIs) were collected on a daily basis over a whole year. In order to identify and collect only the effects attributed to the experimental factors, *i.e.* the inertia of the system and the potentialities impacting it, it is important to clean up the effects of the so-called “extraneous factors” (Macdonald et al., 2018), mainly due to the stochastic factors introduced in the simulation model. The results presented in this chapter were obtained from so-called “compare run” simulations. With this type of simulation, the AnyLogic© simulation software generates the random factors from identical seeds, allowing to collect only the effects related to the experimental factors. Thus, with this type of simulation, the variability related to stochastic factors disappears. This method allows to recover after each simulation run and thus for each simulated scenario, consistent and comparable results.

As described in Chapter 1, the PoD approach proposes to study three different types of performance trajectories. The first trajectory to be observed is the *inertia trajectory*, obtained by measuring the natural evolution of the system’s performance (when it is not subjected to any unanticipated potentiality). This trajectory is considered as a reference trajectory for the study of potentialities, any deviation from this trajectory is considered as resulting from a potentiality and can be modelled by a force. The second trajectory to be observed is the *passive trajectory*, which corresponds to the evolution of the performance of the system subjected to a disturbance and without measures implemented by the managers to correct the situation. It combines the force of inertia of the system and the forces due to the disturbances. In this study, we are dealing with a hurricane in the Gulf of Mexico, impacting companies B and C (the evolution of its impact on the supply chain attributes are referred to in Table 2.8), activated 150 days after the beginning of the simulation (starting on 1st January, over a period of one year) and for a duration of 150 days (its activation range is materialised by the orange zones in Figures 2.16, 2.18, 2.19 and 2.20). The second trajectory to be observed is the *active trajectory*, which corresponds to the evolution of the system’s performance when it is faced with disturbances and when specific measures are put in place by the system’s managers to reduce the consequences of the disturbances. It combines the forces measured by the passive trajectory and those resulting from the measures taken. In this study, the aim is to sign a partnership (30 days after the onset of the hurricane, shown as a green line in Figures 2.16, 2.18, 2.19 and 2.20) with a new available supplier, Supplier J, and thus double the sources of supply for the wheels of the skateboards, in order to respond to the impacts of the hurricane on Company

Table 2.8 – Descriptions of the scenarios studied (adapted from Cerabona et al., 2023)

Name	Short description	Force pattern		Force onset time and duration	Force type
Passive	Hurricane in the Gulf of Mexico	Continue		From day 150 to day 300	Inflicted
		Company B	Company C	Different phases of disruption	
		Quality: -20% Lost stock: 50% Production capacity: -70% Lead time: $\times 3$	Quality: -20% Production capacity: -80% Lead time: $\times 2.5$	From day 150 to day 270	
		Quality: -5% Production capacity: -40% Lead time: $\times 2$	Quality: -10% Production capacity: -60% Lead time: $\times 2$	From day 270 to day 300	
		Production capacity: -14%	Production capacity: -40%	From day 300 to day 365	
Active	Double sourcing	Punching		From day 180 to day 365	Managed

A's performance. This new supplier should be able to supply 40% of Company A's skateboard wheel requirements (until the end of the simulation).

Table 2.8 summarises all the information for the two scenarios studied. This study assumes that the forces occur instantaneously (at the times specified in Table 2.8), so no work will be done on the occurrence of the two forces generated by these two disturbances (only the time period chosen for the occurrence of the hurricane corresponds to the hurricane season in the Gulf of Mexico). The impacts of the hurricane on the system attributes (in the column) correspond to the impacts relative to the initial situation.

In order to be able to visualise the different performance trajectories, the performance space of company A has been limited to three KPIs: *profit* (in hundreds of thousands of euros), *finished goods inventory* (the stock of skateboards) and *lead time*. Equivalent to the lead time ratio measure (introduced in Section 2.1.2) proposed by Carvalho et al. (2012), the lead time indicator is calculated according to this formula: $delay = \frac{\text{waiting time} + \text{delivery time}}{\text{expected lead time}}$, with the *waiting time* equivalent to the waiting time to have the finished products in stock and the *expected lead time* equivalent to the maximum delivery time agreed between company A and its different customers. Figure 2.15 shows the three types of trajectories proposed by the PoD approach, represented in the performance benchmark composed of the three KPIs described above.

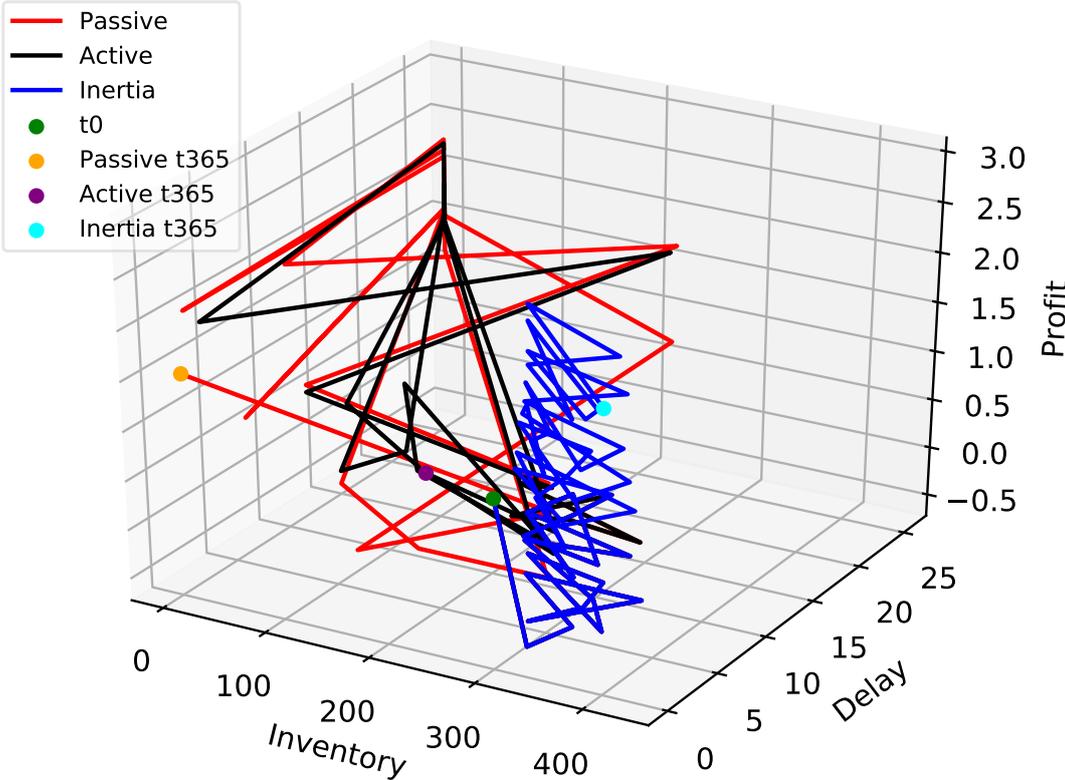


Figure 2.15 – 3D performance trajectories for the Rich Kids case study (over 365 days)

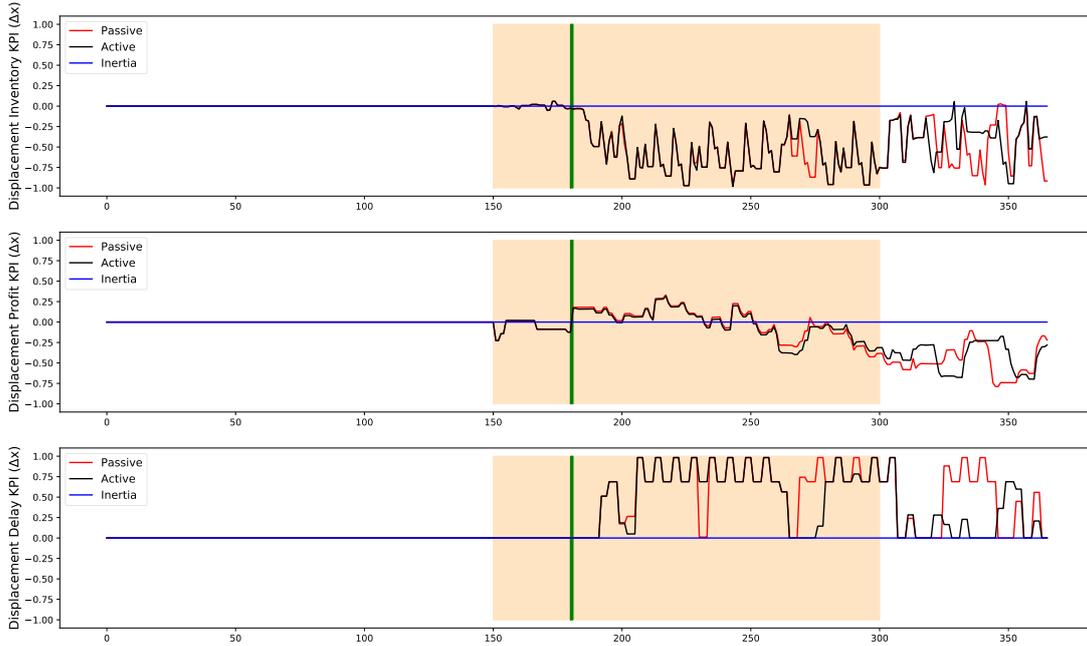


Figure 2.16 – Displacements for the three KPIs studied

For the rest of the study, in order to make it possible to compare the different KPIs selected with regard to their deviations and variations, all the KPI values obtained for each scenario were normalised (to obtain values between $[-1, 1]$) according to the following formula: $KPI_{norm} = \frac{KPI}{\max(KPI_{max}, |KPI_{min}|)}$.

2.3.2.1 Application of the proposed engineering resilience measure

A first analysis, purely graphical in Figures 2.15 and 2.16, shows that following the hurricane, the performance of company A is strongly degraded. The corrective action, aiming at sourcing part of the supply from a new supplier while the current supplier recovers from the consequences of the hurricane, reduces the impact of the disruption on performance (mainly after t_{300}).

From the different measured displacements (illustrated in Figure 2.16), the three types of distance (*degradation*, *actual degradation* and *actual compensation*) mentioned in Section 2.2.3 can be measured. Based on these distances between the multidimensional performance trajectories of Company A, according to the three proposed resilience measures (*natural resilience*, *corrected resilience* and *resilience gain*), let us extend the notion of the *resilience triangle* and calculate these measures. The first proposed resilience measure is the *natural resilience*, which is the sum of the *degradation* distances (distances between the blue and red curves in Figure 2.16) over the chosen time interval (in this example t_{150} the date of the hurricane and t_{365} the maximum allowable recovery time). Thus in this example, the natural resilience = $\sum_{t=150}^{365} \sqrt{(inertia(t) - passive(t))^2}$. In the case of a hurricane in the Gulf of Mexico, the *natural resilience* of Company A is 173.71. The second proposed resilience measure is the *corrected resilience*, which is the sum of the *actual measured degradation* distances (distances between the blue and black curves in Figure 2.16) over the time interval $[t_{150}, t_{365}]$. Thus in this example, corrected resilience = $\sum_{t=150}^{365} \sqrt{(inertia(t) - active(t))^2}$.

Table 2.9 – Distribution of angles \widehat{IAP} (inertia - active - passive) t_{150}

Angle value	Equal to 0°	Lower than 90° (and different to 0°)	Greater than 90°	Greater than 130°
Percentage distribution	14%	27%	59%	7%

However, as mentioned in Section 2.2.2, not being in a two-dimensional framework, limiting oneself to this formula for the measurement of the corrected resilience is not entirely accurate. It is important to take into consideration the value of the angle \widehat{IAP} between the inertia (I), active (A) and passive (P) trajectories, for each time t_i considered. Table 2.9 shows the different distributions of values for the angles \widehat{IAP} measured for this case study. Although the majority of the measured angles are greater than 90°, only 21% of them correspond to the range of values sought (equal to 0° or strictly greater than 130°). In this case, let us calculate the *edge effect* (pink dotted line in Figure 2.10) to ensure that we can estimate or not the *corrected resilience* by the previous formula. Over the period t_{150} to t_{365} , the *edge effect* has a value of 30.76. Following projection calculations aimed at determining the coordinates of all the points of the *active trajectory* projected onto the line connecting all the *inertia* and *passive positions* at the same time t_i (illustrated in Figure 2.10), it is possible to calculate the *real degradation* by the following formula: $\sum_{t=150}^{365} \sqrt{(\text{inertia}(t) - \text{projected active}(t))^2}$. For this example, the *real degradation* is 142.19 (*i.e.* a gain of 18.1%), very close to the *measured degradation*, equal to 153.94 (*i.e.* a difference of 8.2%). Finally, in this case, it would have been possible to approximate the *real degradation* by the *measured degradation*.

Discussions

The previous sections illustrate how the PoD approach can be used to measure the engineering resilience of a supply chain. Of course, the same type of reasoning could be applied to any other socio-economic system (*e.g.* US polling stations, as illustrated in Appendix A), whose performance can be assessed by quantitative indicators. The proposed measure is inspired by the *resilience triangle* (illustrated in Figure 2.4), by assessing the area between multidimensional trajectories of expected performance (*i.e.* the *inertia trajectory*) and the actual performance trajectory (*i.e.* the *passive* and *active trajectories*). Following the same principle, the *resilience gain* is evaluated by the area between the *passive* and *active performance trajectories*.

Drawing on the *resilience triangle*, it is important to discuss and observe whether the limitations of the *resilience triangle* apply to this measure. Based on their reviews of the literature on the *resilience triangle* and the different measures inspired by it, R. Li et al. (2017) establish that a resilience measure must meet three characteristics: (1) to be comparable, a fixed time interval must be defined (this interval must have an appropriate physical meaning for the system under study), (2) to reflect the recovery capacity of the system, the lower bound of the time interval under consideration must correspond to the moment of activation of the potentiality, and (3) the proposed measure can consider a recovery or not of the system over the chosen time interval.

Thus, like the *resilience triangle*, the measures proposed in this manuscript are highly time-dependent, in particular the activation range of the different resilience measures, *i.e.* the fixed time interval over which it makes sense to perform these measures. Theoretically,

this time interval should be defined from the moment when the potentiality is realised to the moment when the *passive trajectory* (the perturbed performance trajectory) joins the *inertia trajectory* (the initial performance trajectory). In the proposed illustrative example, this criterion of convergence between the trajectories is not met, as shown in Figure 2.15, at t_{365} , the points of three trajectories shown are distinct. Thus, this example basically shows no resilience, the magnitude of the hurricane, and/or the maximum allowable recovery time chosen (215 days), and/or the ineffectiveness of the countermeasure (the intensity of the force linked to the *active trajectory*) does not allow the *inertia trajectory* to be reached over the duration of the experiment performed. Nevertheless, it illustrates how from the calculation of the distance between multidimensional performance trajectories proposed by the PoD approach, it is possible to extend the theoretical vision of the *resilience triangle*.

Another time-related criterion to be considered is the number of measurements needed to estimate a surface between two performance trajectories from distances. In the proposed example, the measurements were made on a daily basis, thus representing $1/215^e$ of the fixed time interval per calculated distance.

Apart from time and its impact on the proposed measures, the implicit weight of the measured KPIs has not been discussed. In the proposed example, each KPI has been normalised to values in the range $[-1, 1]$ and no weights have been assigned to them, so each KPI is assumed to have the same theoretical impact on the proposed resilience measure. However, as illustrated in Figure 2.16 (and also in Appendix A), the variations caused by the hurricane on each KPI are not equal. Thus, the choice of KPIs measured according to the type of potentiality studied will have a significant impact on the resilience values of the system.

2.3.2.2 Application of a kinetic approach to measure ecological resilience

As discussed in Section 2.2.3, the measurement of ecological resilience (through the resilience cone) relies on a different set of challenges: the knowledge of the system and its environment to be able to identify all the manageable forces at any given time, and the ability to estimate their impacts as accurately as possible through the kinetic concepts on which the PoD approach is based. Thus, with the support of the PoD concepts, it is essential to be able to assess the significant forces impacting a supply chain, namely: (1) the *disturbance force* (the forces generated by disturbances) and (2) the *corrective force* (the forces generated by the corrective actions applicable at each moment).

In order to be able to estimate these two forces, the PoD approach relies on two strong assumptions: (1) neglecting the mass of the system and (2) the summability of the forces. These two assumptions are related to *Newton's second law*, which defines a simple relationship between the acceleration of an object of mass m and the resultant of the forces acting on this object: $\vec{F}_{net} = m\vec{a}$. Neglecting the mass (considering it to be constant over time) of the system makes it possible to approximate the resultant of the forces applied to the system under study by its global acceleration (with a constant proportionality factor, which will be neglected in this study). On the basis of this hypothesis, the forces will be estimated from the different local accelerations, measured in equation 2.2, for a daily measurement from the time t_{150} , date of the hurricane.

In the same way that the PoD approach defines three different performance trajectories, three accelerations are to be calculated to estimate the perturbation and correction forces. The first acceleration to be obtained is the reference acceleration, corresponding

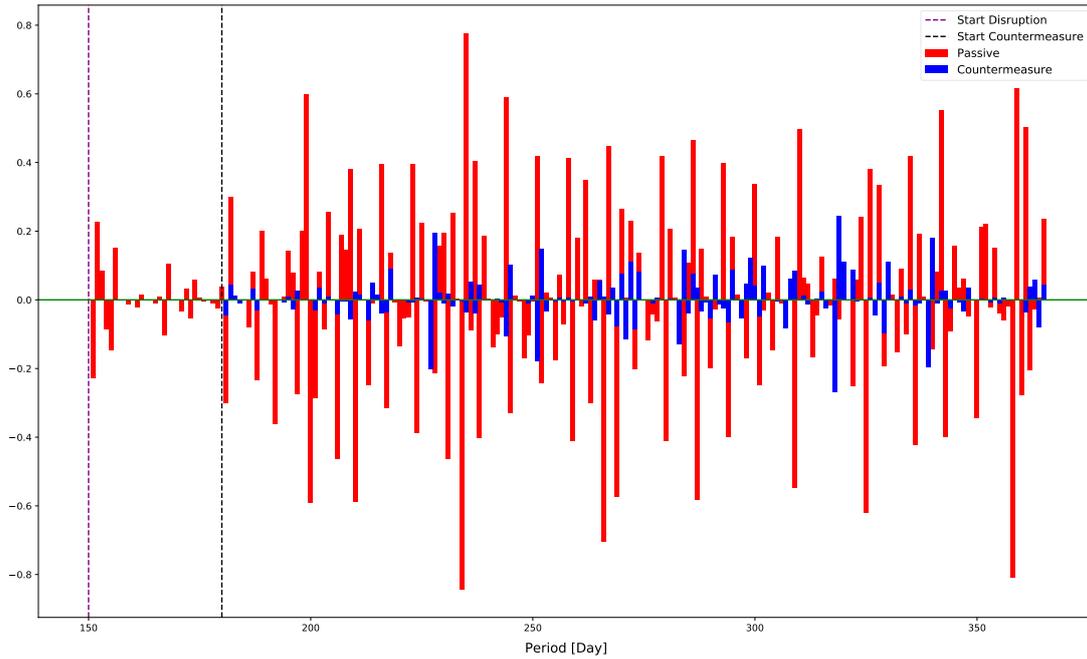


Figure 2.17 – Resulting accelerations over the period t_{150} to t_{365}

to the *inertia acceleration* (the local acceleration of the *inertia trajectory*). The second acceleration corresponds to the *perturbation acceleration*, obtained by calculating the difference between the local acceleration of the *passive trajectory* and the *inertia acceleration*. The third acceleration corresponds to the *corrective acceleration*, obtained by calculating the difference between the local acceleration of the *corrective trajectory* (which, unlike the *active trajectory*, only combines the changes due to the forces resulting from the corrective actions) and the *inertia acceleration*.

In this study, the *perturbation* and *corrective accelerations* were calculated by 3D vectors of the considered performance space. In order to assess the impact of each potentiality, it is important to consider these two elements: (1) the *intensity* of the force (approximated by the norm of the different acceleration vectors) and (2) the *contribution* of the force (its direction). The *contribution* of the force amounts to determining its direction, *i.e.* whether the force pushes or pulls the system away from its expected situation (the *inertia trajectory* for α or γ type resilience, or the nearest boundary to the target zone for β -resilience). The contribution will be approximated by calculating the scalar product of the acceleration vector (perturbation or corrective acceleration) with the vector relating the position of the system at time t_i in its performance space and the expected position at this time t_i (*i.e.* the position it should have had with respect to its *inertia trajectory*). This scalar product will provide a value of the cosine of the angle between these two vectors, whose product with the intensity of the force will give the resultant force with respect to the expected performance, *i.e.* the actual impact of the potentiality on the performance trajectory of the system. Figure 2.17 illustrates this notion of resultant force for the two scenarios studied.

Consistent with previous analyses, the proposed remedial action appears to correct the impacts of the hurricane only slightly. However, being able to assess the resulting force is not sufficient to apply the proposed measure for ecological resilience. Indeed, in the

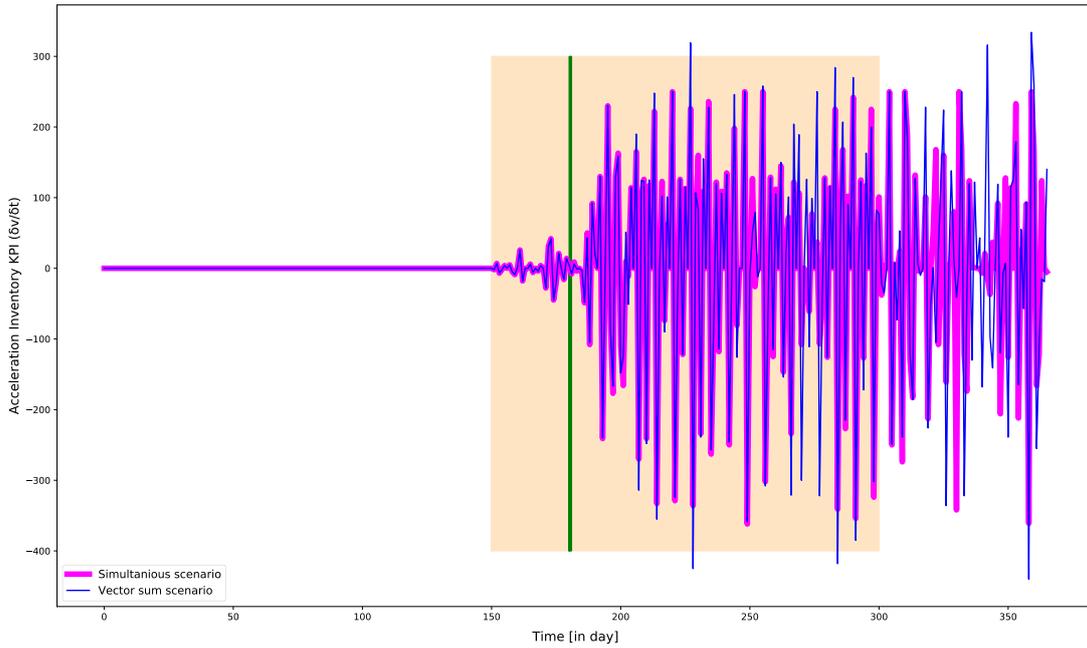


Figure 2.18 – Simultaneous acceleration and sum of individual accelerations for the finished goods inventory level KPI

case of several potentialities and corrective actions, to ensure that the resilience cone is meaningful, once the forces have been identified and their resultants calculated, it is necessary to be able to sum them. This means checking the summability of the forces and the assumption of constant mass (two points at the heart of the PoD approach), which is the subject of the next section.

2.4 Discussion of the challenges to be met in exploiting the PoD approach

The work presented in this chapter does not attempt to resolve the issue of force independence and their summability criteria. This discussion section aims to highlight the challenges that need to be addressed to make the approach fully exploitable and to take advantage of its potential for resilience management and measurement (particularly the proposed measure of ecological resilience), illustrated in this chapter. We are fully aware that the PoD approach is a recent and developing approach, with the first work on the approach dating back to 2019, when it was introduced by Benaben et al. (2019). As it stands, the PoD approach relies on two strong assumptions to approximate the forces: neglecting the mass of the system and the summability of the forces. By neglecting mass (and considering it constant), *Newton's second law*, the relation $F_{net} = m\vec{a}$, takes the following form in the case where the system is subject to p potentialities: $F_{net} = \sum_{i=1}^p F_i$. This formula, by *Newton's second law*, is therefore equivalent to: $a_{net} = \sum_{i=1}^p a_i$. The overall acceleration of the system would thus be equal to the sum of the accelerations generated by each potentiality.

Let us then check whether the summability assumption is verified with the *Rich Kids* supply chain use case, using the same scenarios and KPIs as in Section 2.3.

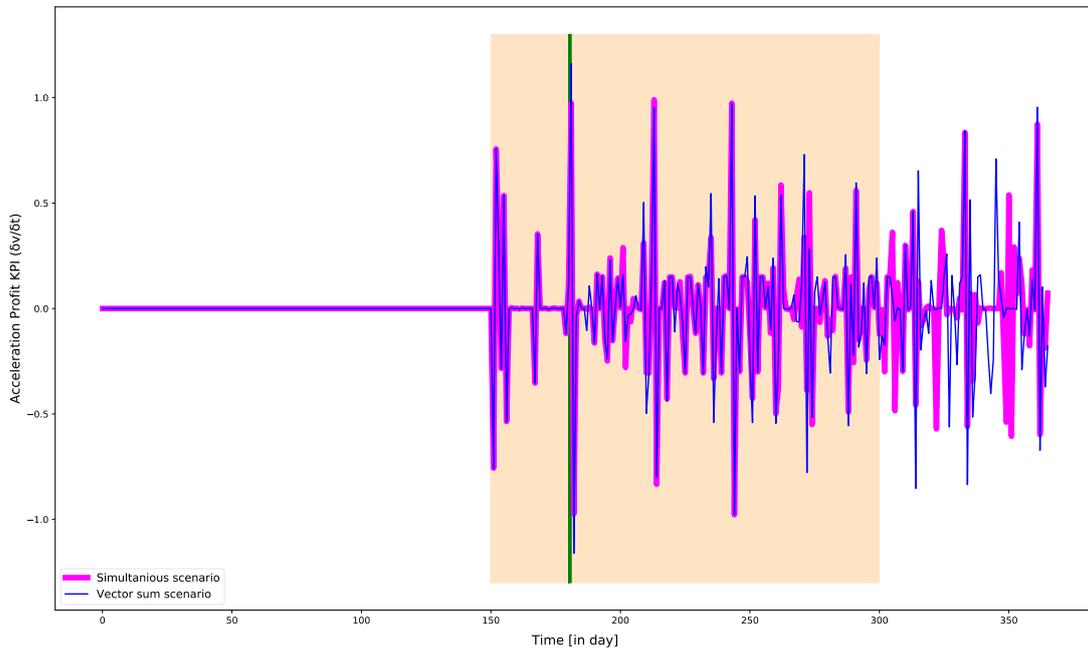


Figure 2.19 – Simultaneous acceleration and sum of individual accelerations for the profit KPI

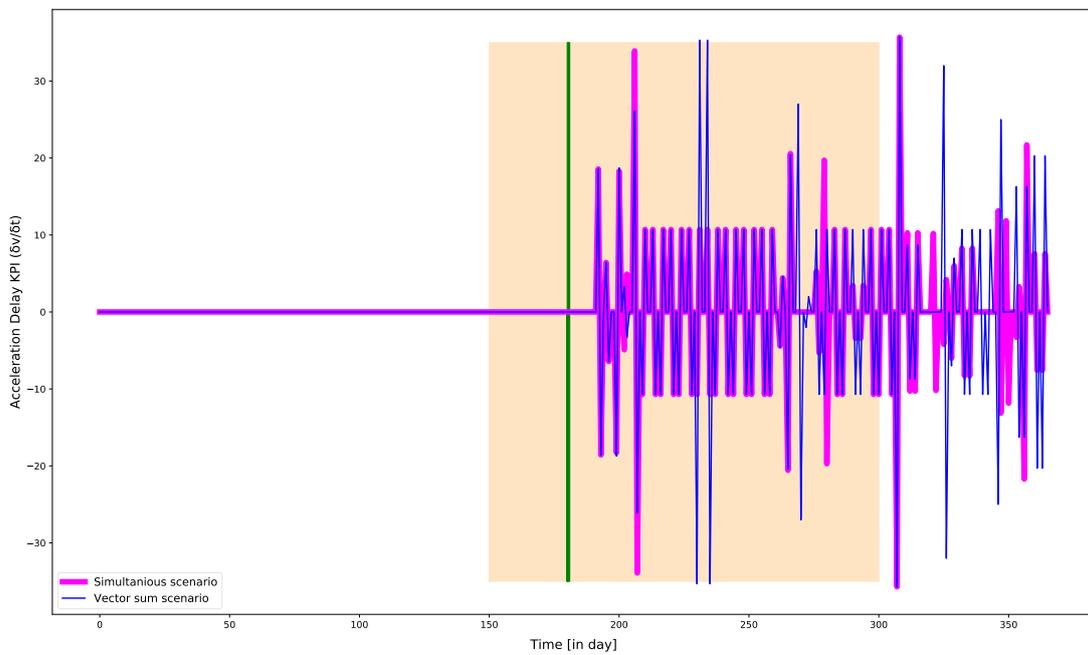


Figure 2.20 – Simultaneous acceleration and sum of individual accelerations for the lead time KPI

The associated simulation model will be used to calculate the accelerations for the simultaneously simulated scenarios (pink curves in Figures 2.18, 2.19 and 2.20) and to simulate the two scenarios (a hurricane in the Gulf of Mexico and doubling the supply sources for skateboard wheels) separately. In the case where the scenarios are simulated separately, the accelerations obtained for each separate scenario are then summed to obtain the overall system acceleration, illustrated by the blue curves in Figures 2.18, 2.19 and 2.20. These scenarios were chosen to consider the simultaneous effect of the potentialities, *i.e.* to ensure that there is an interaction between the forces associated with these potentialities. They are observed over a relatively long range, the hurricane has an activation period that extends over the whole orange range and the scenario to double the number of suppliers starts from the green line and only ends at t_{365} (see Figures 2.18, 2.19 and 2.20), in order to avoid any brief shock effect on the system and not being able to observe what we are trying to verify.

The comparison of the results between the “simultaneous” and vector sum of the accelerations and thus of the forces applied to the system, shown in Figures 2.18, 2.19 and 2.20, proves that the summability assumption is false. In no way do these results call into question the equations and relations defined by *Newton’s second law*. These results simply point out that we should be interested in the criteria for which this hypothesis is true and the corrective factors to be determined when it is not verified. The fact that this assumption is false can be explained by several factors (at a minimum): (1) the mass of a supply chain is variable; (2) the plasticity of the system (absorption or amplification of forces), which deforms like a solid physical object; and (3) the existing conflicts between forces.

For a system such as a supply chain, the concept of mass is not clearly defined and no equation to our knowledge has been proposed in the literature to evaluate it. Its network structure, based on evolving relationships between different actors (and potentially new actors), leads us to believe that its mass varies over time and certainly according to the impacts of disturbances on its attributes and environment, in this study the gain of a supplier. The observed deviations confirm that *Newton’s second law* is not suitable for systems with variable mass. Wieland et al. (2021), in their paper reconsidering the supply chain and putting forward two perspectives of supply chain resilience, mention in their hypotheses that if the supply chain is defined through the prism of engineering, it will be seen as a closed system, conversely if it is defined through the prism of socio-economic systems, then it will be seen as an open system Moradkhani et al. (2021) propose to treat such a system as a rocket burning fuel and ejecting the burnt gases. To treat such a system, it is necessary to use an extended version of *Newton’s second law*, in order to consider the mass variation in time of the object by ejection or mass increment. *Newton’s second law* for such systems takes the following form: $F + u \frac{dm}{dt} = m \frac{dv}{dt}$, with u the velocity of the mass escaping or being added to the object (MacCready et al., 2010; Moradkhani et al., 2021).

In the absence of having been able to establish and develop a clear concept of mass for a system such as a supply chain. These differences can perhaps also be explained by the criteria of summability of the forces. Indeed, on the one hand, in the case studied, the two forces are not independent. On the other hand, in reality, are the acts really summable? For example, in the case where a person slaps another person who tries to block the blow with his arm in order to minimise the impact of the slap. Does it make sense to sum up the measures of the impact of the slap and the defence separately

on the integrity of the person hit? What we are interested in is the impact of the combination of these two actions on the integrity of the person hit. Thus, a great deal of work remains to be done on the criteria for the summability of forces.

2.5 Conclusion of the chapter

This chapter illustrates the first applications of the PoD approach to the management and measurement of the two types of supply chain resilience (engineering and ecological), through initial, highly conceptual results on a kinetic view of resilience measurement. The consequences of the studied scenarios (a disruption or a decision) on the performance of the supply chain are predicted by associating a simulation model with the decision framework of the PoD approach (represented by trajectories in its performance space). The simulation thus makes it possible to transform the micro-impacts of the potentialities (the internal dynamics of the system, the estimation of which is not an easy task following a disturbance such as a hurricane Linkov et al., 2014) into macro-impacts (its impacts on the performance of the supply chain), *i.e.* to make the link between the *description* and *performance spaces*. Modelling from a “what if” approach, the impacts of potentialities (risk, opportunity or decision) are seen as deviations from the different performance trajectories modelled. Following this principle of modelling impacts by trajectory deviations, this chapter proposes to measure engineering resilience by calculating the surfaces between the expected trajectory (the *inertia trajectory*, seen as the “target” trajectory to be followed in order to achieve the set performance objectives) and the disturbed trajectory (with or without corrective actions).

Combining a simulation model with the PoD decision-making framework also allows the forces responsible for deviations in performance trajectories to be estimated. Simulation is used because of its ability to consider all the stochastic factors associated with each potentiality (its onset date, duration and the resulting variations in supply chain attributes). Being able to estimate the forces reacting to the behavioural laws of a supply chain allows us to propose a measure of ecological resilience, in the form of the volume of a hyper-cone (illustrated in Figure 2.11), modelling the space defined by the set of *counter-forces* (corrective actions and decisions) that can be activated at each moment. With this new measure of resilience, decision-makers will no longer need to wait for a disruption to occur and the supply chain to return to equilibrium before being able to assess its resilience. However, the application of such a measure implies solving certain challenges concerning the obtaining and estimation of forces, which are essential for the future results and developments of this approach, especially for a system with more than three KPIs or a very large number of potentialities (especially in the case of a cascading effect). This chapter thus highlights the challenges to be met in order to be able to estimate the forces as accurately as possible.

Furthermore, in order to facilitate and enable the visualisation of performance trajectories, all the performance spaces illustrated in this chapter have been limited to three dimensions. However, it is easy to imagine that supply chain managers will not limit themselves to observing only three KPIs. However, being able to theoretically calculate the overall performance of the observed system in the form of performance trajectories impacted by various potentials is a major contribution of the PoD approach. It is then mandatory to find a way to make these results, these multidimensional performance trajectories, manipulable for decision makers. The following chapter presents the research

work carried out to transform the performance space into a relevant and ergonomic decision support tool, in which decision makers could visualise, experience and interact effectively with the performance trajectories.

Immersive and virtual decision support tool

Look carefully because what you are about to see is not what you have just seen.

Leonardo da Vinci

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Introduction

In Chapters 1 and 2, the importance of measuring supply chain performance was clearly highlighted, particularly in relation to managing instability, potentialities and resilience. The state of the art on potentiality management in Chapter 1 has demonstrated the need to develop a space for exploring and monitoring performance, the inputs of which should allow the combination of capability and performance management of supply chains in a single space, in order to correlate potentiality management strategies with the achievement of predefined performance objectives. This space should thus fully contribute to the *choice* stage (defining the mechanisms for selecting the best available options), as proposed by Herbert Simon (H. A. Simon, 1955) in his model of bounded rationality. To do this, the PoD approach proposes and develops the performance space, a visualisation space (a key element for decision-makers) and a performance management space dedicated to decision-making. It is positioned as a reference framework for the study and modelling of the consequences of the various potentialities, in the form of physical forces, deviating the multidimensional performance trajectory of a supply chain (the theoretical calculation of which is one of the major contributions of the PoD approach), with respect to the achievement of its objectives. Given its high potential, the objective is to support managers' decision making and risk management process, using this performance space to provide them with a dynamic, interactive and immersive performance dashboard for managing supply chain instability.

In the literature, a performance dashboard is defined as a multi-layered system, capable of disseminating information and generating insights and alerts, for effective management and monitoring of business performance (Abdelfattah, 2013). Thus, in general, the objective of a dashboard is to collect, summarise and present information from various sources to allow the decision maker to have a quick and comprehensive view of the evolution of the observed KPIs (Yigitbasioglu et al., 2012). The use of dashboards is expected to improve decision making, in particular “by amplifying cognition and capitalising on human perceptual capabilities” (Yigitbasioglu et al., 2012). As it has emerged as an important management tool, interest in dashboards has increased and is an important area of research (Abdelfattah, 2013), as evidenced by the existence of many dashboard solution providers in the market (Yigitbasioglu et al., 2012). The majority of studies on performance dashboards present in the literature have mainly focused on what motivates their adoption (Pauwels et al., 2009), the implementation steps of dashboards (Pauwels et al., 2009) and the selection of measures (Pauwels et al., 2009), thus leaving the question of their design unanswered (Abdelfattah, 2013; Yigitbasioglu et al., 2012). This lack of work on their design tends to make current dashboards complex, with many numerical elements that only few people know how to interpret. The choice of the right design and architecture relies heavily on the needs of the users and how to convey the complexity of the performance measures they need to support (Abdelfattah, 2013), to support users in their decision making.

In order to fully exploit the potential of the performance space and make it the performance dashboard of the future for decision making in a context of instability, several challenges need to be addressed: (1) to make potential decisions explicable and actionable for decision makers, *i.e.* to find a solution that allows decision makers to manipulate and interpret the abstract concepts related to the application of the PoD approach; and (2) to find a solution to abstract from the visualisation limits of the performance space (a solution to overcome our visualisation limits to more than three

dimensions), in order to be able to handle the potentially huge number of dimensions related to the measurement of supply chain performance (influenced by a potentially huge number of potentialities to be taken into account). Taking into account these two needs in terms of interpretation of abstract concepts and visualisation, this chapter will focus on proposing a solution to meet the expectations regarding the construction of performance management dashboards with a high visual quality (dynamic visualisation of the state of the supply chain and its potentialities) and with a high capacity of interpretation of abstract concepts (interactive management of potentialities, through action levers induced by their physical representation in the performance space). This chapter will thus seek to answer the following question:

Research Question 2 (RQ2)

How to represent, visualise and pilot the performance of a supply chain seen as a multidimensional trajectory (defined by numerous KPIs and impacted by numerous forces), in order to make it a decision-making tool that can be used in a relevant and ergonomic manner?

To address this issue, this chapter is divided into three sections. Section 3.1 studies the state of the art solution for abstract concept visualisation and decision making. Section 3.2 presents our vision of an immersive performance dashboard. Section 3.3 presents its concrete implementation and evaluation. Finally, Section 3.4 concludes this chapter with several perspectives and developments to make the work undertaken more exploitable.

3.1 Use of virtual reality as a decision support tool

Faced with the observation that instability is the norm (Benaben et al., 2021), supply chain managers are particularly interested in developing decision support systems, especially to support the identification of disruptions (monitoring and recognising them in real time), to understand the network's predispositions (*i.e.* its resilience) to disruptions, and to determine the best actions to take during the absorption and recovery phases following disruptions (Ivanov et al., 2021). These needs therefore place decision support systems as devices at the heart of risk and opportunity management (Fang et al., 2012). (Druzdzal et al., 1999) define them as “interactive, computer-based systems that aid users in judgment and choice activities”. These systems are essential tools for dealing with complex situations in which decision-makers have to analyse multiple sources of information (Conges et al., 2020; Martinsons et al., 2007), linked to the interconnection between the system components and their environment, generating a massive amount of data. The implementation of such systems has been a long-standing challenge in the field of performance management, especially for its use as an informative tool to support decision makers in their decision-making processes, linking strategies to operations (Bititci et al., 2012) This information system is none other than the performance dashboard, which is used “to translate the organisation's strategy into objectives, metrics, initiatives, and tasks for each group and individual in the organisation; however, many organisations have been unable to implement dashboards successfully” (Bugwandeem et al., 2019). Performance dashboards are an integral part of company information systems (Bugwandeem et al., 2019). They should thus

contribute to the achievement of the organisation's strategic objectives (justifying its activities, existence and defining its performance standards), in particular by measuring, monitoring and managing its key activities and processes (Eckerson, 2010). They should therefore provide decision-makers with the appropriate information to support decisions, optimise them and increase the benefits of organisations (Bugwandeem et al., 2019). However, despite their strong appeal, some business leaders question the return on investment of such systems (Bugwandeem et al., 2019; Lederer et al., 1990), pointing to software capabilities, lack of automation and lack of a holistic view as obstacles to such systems (Bugwandeem et al., 2019; Eckerson, 2010; Yeoh et al., 2014). Yet, according to the literature review conducted by (Heckmann et al., 2015), the supply chain's risk assessment and risk exposure are closely related to the objectives it needs to achieve, making the use of effective performance dashboards of paramount importance for risk management.

Furthermore, the work of Wieland (2021) on the reinterpretation of supply chains and the extension of the concepts of panarchism ("a structure of adaptive cycles that are linked across different levels on scales of time, space, and meaning", Wieland, 2021) to its management, prompts the review and proposal of new solutions for creating the dashboards of tomorrow. Wieland (2021) proposes to reinterpret the supply chain as an organic socio-ecological system, whose management objective would no longer be to maintain the supply chain in a fixed optimal state, but rather to guide it through its changes along desirable trajectories, in order to develop a more contemporary vision of "dancing the supply chain" (Wieland, 2021). "Dancing represents the human ability to foresee the next steps while acknowledging that '[a]ctor bonds and resource ties are contexts which may both shape the dancing and be shaped by the dancing' (Wilkinson et al., 1998) and, therefore, require the dancer to improvise, experiment, and innovate" (Wieland, 2021). This concept of "dancing" views disruptions as "windows of opportunity" to transform the system into a more desirable, or even radically different, trajectory (Davoudi et al., 2013; Wieland, 2021) With this view, supply chain management becomes about "dancing", navigating along trajectories and experimentation, making the decision-making process even more subjective than it already was. Indeed, many external factors, as well as personal reasons, may push the decision-maker to choose one option (a potentiality or a corrective action) over another. The many tools and methods developed over the last few decades, despite their contribution to supporting the decision-maker in his/her decision-making, cannot replace his/her judgements, especially when making decisions in risky situations (T. Wu et al., 2009). Of all the approaches developed for supply chain risk management, few take into account the decision maker's attitude towards risk (Heckmann et al., 2015). In order to be able to give the decision maker the final say, it is essential for him/her to be able to visualise and understand all the components relating to the various possible choices and decisions (Moore, 2017). However, in recent years, the exponential increase in the amount of (digital) data collected and stored makes this task more complex and requires finding ways to make sense of it, making the development of visualisation tools a priority (Cavallo et al., 2019) According to (Bryson, 1996), decision-makers are more interested in the induced behaviour of data ("such as streamlines in a vector field") than in the given values.

Virtual reality via the development of immersive analysis solutions could be the solution to these needs. "Virtual reality is an immersive, synthetic or computer-generated environment that provides the experience of 'being there'" (Beroggi et al., 1995). "Virtual reality is a powerful technology for creating a sense of immersion", especially through the

use of virtual environments, which “allow trainees users to gather all the necessary visual and auditory contextual information to make the necessary decisions” (Dugdale et al., 2004). “Virtual reality is a three-dimensional user interface in which the user can perform actions and experience their consequences” (Louka et al., 2001), greatly enhancing the decision maker’s ability to analyse and remember information. Visualisation-based technologies help to improve the appropriation and understanding of large amounts of complex (qualitative or quantitative) information, through the abstraction of a large information space (Jain et al., 2006), capable of presenting the decision-maker with a large amount of spatial and temporal data (Louka et al., 2001). Immersive environments have become the standard for the analysis and visualisation of large amounts of data and complex, extremely difficult or impossible to study and explore using other computing devices (Cavallo et al., 2019). Indeed, virtual reality technology offers a great deal of freedom to the user to explore and interact with a virtual environment, in which he/she has the possibility to observe, manipulate and evolve among various objects, observable from different angles and points of view, as in the real world (Conges et al., 2021; El Beheiry et al., 2019). The use of such an environment “engages the user to interact with the data” (El Beheiry et al., 2019), allowing him/her to immerse himself in the data, to the point of “viscerally understanding them” (Conges et al., 2021), thus greatly supporting the decision-making process (Congès, 2022; Dwyer et al., 2018). Immersive analytics can thus transform virtual environments (the space surrounding the decision maker) into a canvas for decision making and data analysis, in particular by stimulating and supporting the cognitive abilities of the decision maker (Batch et al., 2020). Although data exploration in virtual reality is more demanding for users than 2D data, it is nevertheless much more satisfying due to the possibility of interacting with it and exploring it in 360° (Andersen et al., 2019; Congès, 2022; Millais et al., 2018). Interactions with data in virtual reality are much closer to the natural movements of the human body, than manipulations with a mouse or keyboard (Congès, 2022). This interaction also makes it easier to position information using “human metaphors”, for example by placing important predictions or information in front of the user and past or less important events behind them (Conges et al., 2021; McCormack et al., 2018). Virtual reality also offers the possibility for the decision-maker to no longer just look at data, but to be virtually surrounded by data, which they can touch, hear or even smell (Conges et al., 2021; McCormack et al., 2018), thereby increasing the engagement of their different sensory channels (something that “traditional” dashboards could not offer). Virtual reality therefore offers new means of visualisation aimed at eliminating “barriers between people, their data, and the tools they use for analysis by developing more engaging, embodied analysis tools that support data understanding and decision making everywhere and by everyone, either working individually or collaboratively” (Dwyer et al., 2018).

In addition to visualisation and interaction with massive and complex data, virtual reality also offers another interesting perspective through the development of multi-player virtual environments: collaboration. Indeed, it “can provide an easy and natural path to a collaborative data visualisation and exploration, where scientists can interact with their data and their colleagues in the same visual space” (Donalek et al., 2014), regardless of the distance between users, thus offering interesting perspectives for the management of networked systems of actors located in different countries, such as supply chains, and even more so in crisis situations where information sharing is paramount. In the case of group decisions, the use of virtual reality could improve communication and

the choice of appropriate strategies, thus enabling faster and more consensual decisions. This collaborative aspect could also greatly contribute to visibility capability (the ability to see the whole supply chain (Adobor et al., 2018), one of the five key capabilities proposed by Christopher et al. (2004b) to increase the resilience and agility of supply chains.

Finally, virtual reality also allows for participation in the process of learning by the decision maker in managing a set of decisions (which corresponds to the fifth stage of the risk management process proposed by T. Wu et al., 2009, Table 1.3). T. Wu et al. (2009) define this stage as organisational and personal learning, seeking to capture, extract, distil and disseminate lessons and experiences within the organisation and the logistics network. In virtual reality environments, “players are encouraged to learn by trying different strategies, succeeding and failing as they would in an entertainment game” (Saunders et al., 2019), the virtual aspect of which allows decision-makers to try (different strategies or scenarios) and make mistakes at lower cost (security risks and hardware costs are much lower in virtual environments) and without consequences for the real system. The use of such a system could be relevant to support the choice step proposed by Herbert Simon (H. A. Simon, 1955), in his model of bounded rationality. Indeed, decision-makers could test a multitude of decisions before implementing them in the real system. Moreover, once the virtual environment has been constructed, each scenario could be repeated countless times, until the process is mastered (Conges et al., 2020). As all manipulations can be replayed, monitored and analysed, the risk management skills of the decision-makers can be assessed, thus contributing to their learning and also allowing for a more general improvement of risk management.

From this analysis of the literature, immersive analytics, through the use of virtual reality, seems to be a relevant solution to build the performance dashboard of tomorrow and to meet the two needs of the PoD approach in terms of visualisation and meaning to be given to decisions. Although augmented reality could offer a better solution, the lack of maturity of its technologies (too small a field of vision) undeniably rules it out.

Virtual reality allows the decision-maker to be immersed in all the data and strategies to be analysed, notably in the form of manipulable floating objects (for which the use of spatial metaphors could reduce their degree of abstraction). The creation of a virtual space will make it possible to represent all the data (the performance of a supply chain) and choices in a multidimensional environment dedicated to decision making, in which the decision makers can experiment at leisure to find the best possible response to a potentiality among a selection of available scenarios and seek to achieve the performance objectives set. In this type of virtual environment, the addition of time (*e.g.* on the Y-axis) will allow to represent the different situations (*past, present* and *future*) and to be able to follow the evolution of the performance trajectory of the supply chain and its potentialities. The high level of interaction offered between the decision-maker and the modelled objects should allow him/her to fully appreciate the manipulation of the performance trajectory and potentialities, which he/she will be able to observe from different angles and points of view. The decision-maker will thus be able to become fully aware of the impact of a potentiality on the performance trajectory and the associated objectives.

We are fully aware that in this section the limits and obstacles to the application of virtual reality in industry, linked in particular to the costs and equipment required, have not been mentioned. However, the aim of this chapter is to lay the foundations for our vision of the performance dashboard of the future. We see analogies in virtual reality with the development of computers and computing. In the 1950s, the size, price and capabilities of computers limited any industrial application. However, once the size of the computer was reduced (to fit on a desk), its computing and storage capabilities increased and software such as Word and Excel (to name but a few) were developed, the computer became widely available to industry. We believe that the same will be true for virtual reality, thanks to the work on the metaverse, which will lead to a democratisation of its use and the development of equipment. Thus, the objective of this work is to start thinking about the decision support tool of tomorrow, as virtual reality has become one of the fundamental technologies of Industry 4.0 (Alejandro Huerta-Torruco et al., 2022).

3.2 Towards an immersive experience for steering the performance of a system in an unstable situation

To meet the two challenges presented in the introduction to this chapter and to build the performance dashboard of tomorrow (dynamic and immersive), the initial idea is to use virtual reality technologies to propose an immersive cockpit, the main objective of which is to focus on the management of a system (in this case, a supply chain) by visualising and manipulating its performance trajectory. In this context, virtual reality is used for its ability to abstract from reality and its usual limitations, while keeping the user in a familiar environment. This ability is supported by the virtual environment, which has the major advantage of mobilising and stimulating the user's senses as in reality. The user can perceive the notions of distance and positioning in relation to space, and is able to see where an object is located in relation to him/her (close, in front, behind, etc.). This use of virtual reality also makes it possible to transform abstract concepts into concrete objects that can be manipulated by the user.

In this immersive cockpit, the decision-maker will be immersed in a virtual environment, representing the performance space (introduced in Chapter 1, in Section 1.3) and surrounded by the various abstract elements related to this space. Imagine projecting the decision-maker into a virtual environment, in which the abstract concepts related to unstable situations (risks or opportunities) are represented in the form of red spheres, more or less large and coloured, orbiting a purple timeline, as shown in Figure 3.1. The closer these red spheres are to the timeline, the more likely the potentiality they represent. The larger they are, the greater their range. The redder they are, the more dangerous they are. This way of representing risks is much more meaningful than diagrams or matrices.

Like performance dashboards, which in the organisational context have their origins in the design of car dashboards, which contain the key metrics that the driver needs to

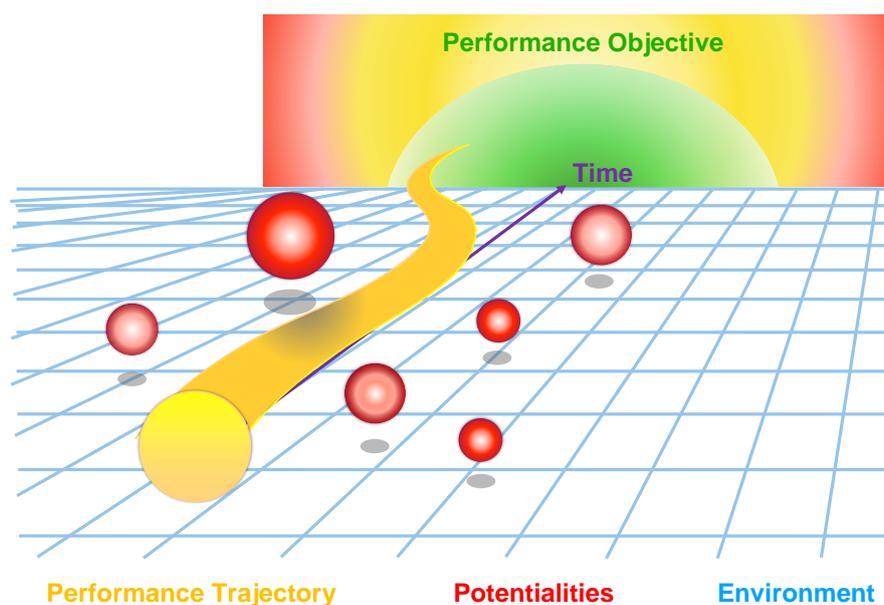


Figure 3.1 – Initial vision of the immersive cockpit for decision making

track in order to drive a car (Lempinen, 2013; Pauwels et al., 2009; Yigitbasioglu et al., 2012). The whole abstraction present in the developed virtual environment is based on the proposal to place the driver (the decision-maker) in a cockpit surrounded by black tinted windows, whose objective is no longer to optimise a trajectory, consisting of sequences of turns, climbs and descents to be managed, but to keep the car (the managed system) on an optimal straight line (modelled as the timeline), in order to reach its performance targets (distant and predictive goals). This reduction in dimensions is only possible through the work presented in the previous sections (the computational tools used to create the straight line), plus those presented in this chapter, which will act as “interpreters” to transform the turns, climbs, descents, braking and acceleration into simple and interpretable movements for decision makers.

Thus, in this virtual environment, the dimension facing the user is time. The other two dimensions are used to visualise deviations from the performance trajectory (yellow trajectory in Figures 3.1 and 3.2), by selecting one or more potentialities (activable by touching the different red spheres, as illustrated in Figure 3.2). It is important to consider that the deviation generated has no real meaning. Indeed, in this virtual space, two dimensions are used to visualise the deviations of a multitude of KPIs, aggregated into a single performance trajectory. Thus the decision-maker should not try to interpret and relate the observed deviation as the impact of a potentiality on a single KPI, *e.g.* a deviation of the performance trajectory resulting in a shift to the left does not mean a loss of profit and an upward shift does not mean an increase in average lead time. The deviation shows whether the performance trajectory is moving towards or away from the ideal trajectory (the purple timeline) as a result of the realisation of potentialities. The real qualitative and quantitative interpretation of the deviation between the purple timeline and the yellow performance trajectory will have to be measured with other tools, once the different manipulations have been carried out. However, the more the performance trajectory deviates from the ideal trajectory, the more there is indeed a significant quantitative gap.

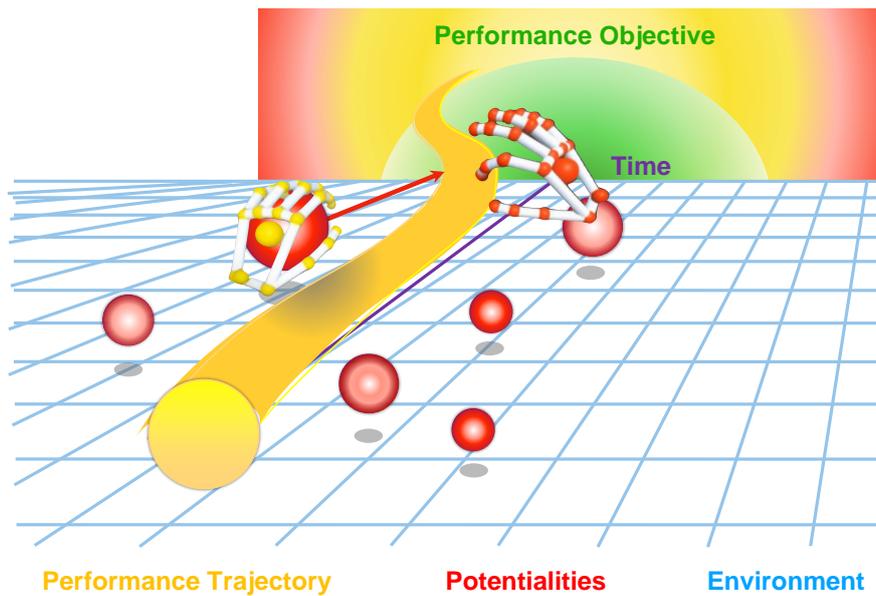


Figure 3.2 – Initial vision of the immersive cockpit for decision making

3.3 Application of an immersive experience to manage the performance of a supply chain in an unstable situation

Based on the previous concepts and the two challenges presented in the introductory section of this chapter, this section presents our technical contribution in terms of a performance dashboard for the management of supply chains (called decision space) through the presentation of two prototypes of the decision space using virtual reality (our contribution focuses on the second version of the prototype, the first version having been realised during work initiating the PoD approach). The presentation of these two prototypes allows us to highlight the design and development directions taken to make these prototypes increasingly complete and functional. These two prototypes were developed using the Unity® framework, in partnership with the company *Immersive Factory*. The use case used to illustrate the functionalities of these two prototypes is the one introduced in Chapter 2, namely *Rich Kids*. Each of the potentialities (risks and opportunities) studied was modelled in terms of micro-events, which were simulated using simulation models developed on Anylogic© (for the first version based on a model not presented in this manuscript, for the second version based on the model presented in Chapter 2, these two models use the same simulation technique, *i.e.* discrete event, more information on this technique in Appendix C), in order to collect their real consequences. Both prototypes aim to make a theoretical approach (the PoD approach), which produces results that are very difficult to understand and manage, comprehensible and actionable. In both prototypes, the user is immersed in virtual environments whose concepts are highly abstract.

These are the first two usable prototypes that demonstrate the benefits of using virtual reality to visualise and drive the performance trajectory of a supply chain in an unstable environment. These results were presented to various industrial and academic partners

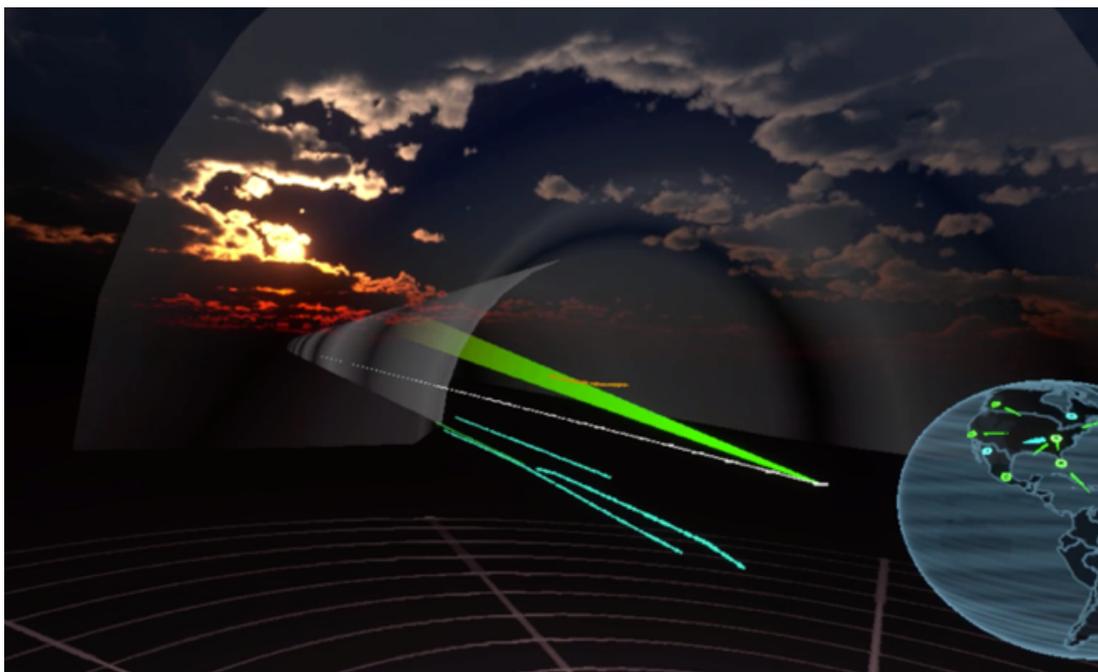


Figure 3.3 – Global environment of the first version of the PoD prototype

(from different fields of activity), during different demonstration and hands-on sessions. They all approved the great interest of the approach and the indisputable benefit of using virtual reality to facilitate its use.

3.3.1 Version 1 of the virtual reality prototype

Introduced in Benaben et al. (2023), Figure 3.3 illustrates the virtual environment proposed in the first version of the prototype, in which the user is required to make decisions. The organisation of the *Rich Kids* supply chain network can be observed in a very artificial way from a globe, located in the bottom right corner of Figure 3.3.

The white line represents both the timeline and the ideal trajectory, *i.e.* the optimal performance trajectory, which is potentially unattainable. The green conical trajectory represents the actual performance trajectory of the supply chain with respect to the selected set of KPIs. In this prototype version, it is calculated from distances to the target trajectory in the multidimensional theoretical performance space. The shape of this trajectory is conical, in order to consider the uncertainty in the prediction of the KPI values. A grey, semi-transparent vortex surrounds these two trajectories in the upper semicircle. It represents the survival zone, *i.e.* the target performance area in which to maintain the green conical trajectory in order to satisfy performance objectives that ensure the survival of the system. It is defined by arbitrary limits for the measured KPIs.

Around the white timeline, different coloured flows gravitate, modelling the different types of potentialities impacting this supply chain (illustrated in Figure 1.10). The orange flows represent environment-related (external risks). Green flows represent potential innovations. Blue flows represent potential new interactions (opportunities).

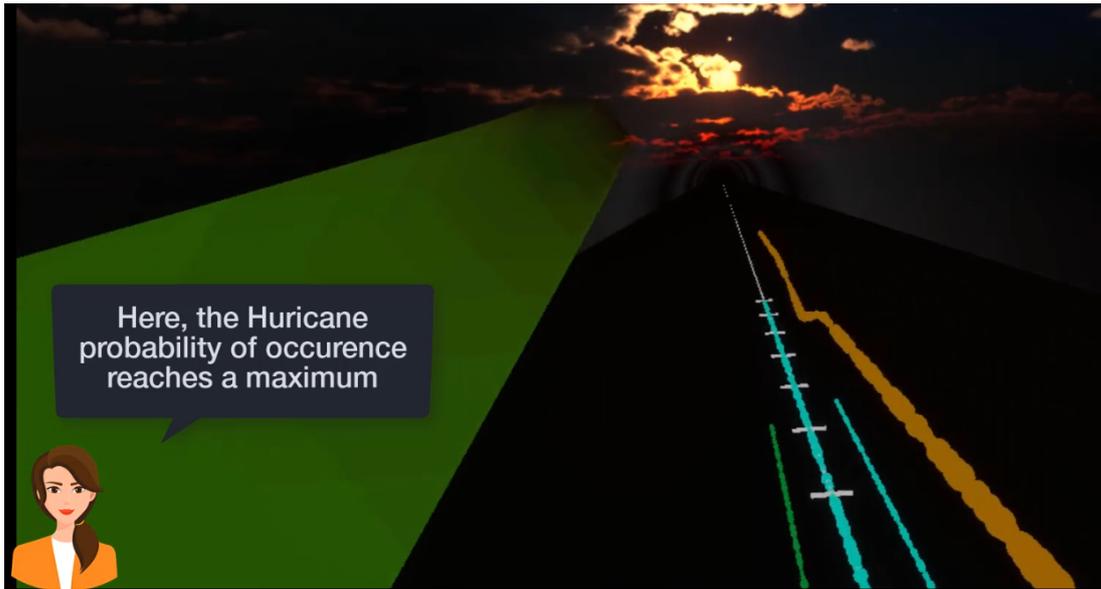
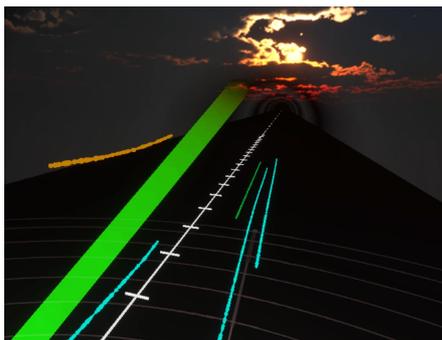
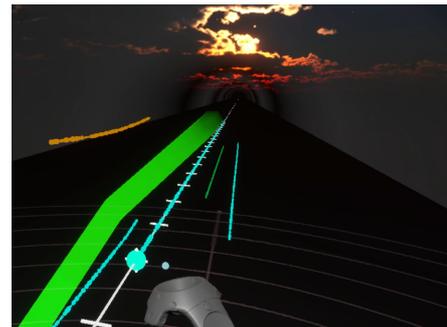


Figure 3.4 – Abstract view of the probability of occurrence of the activation conditions of a potentiality

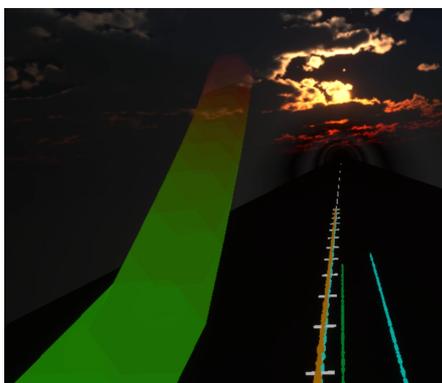


(a) Before movement

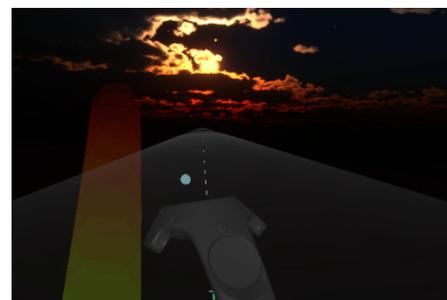


(b) After movement

Figure 3.5 – Manipulation of potentialities in the proposed virtual environment, left the initial situation and right the situation after activation of an opportunity



(a) Overview of a colour change



(b) Zoom in on a colour change

Figure 3.6 – Change in colour of the performance trajectory as it leaves the acceptable area

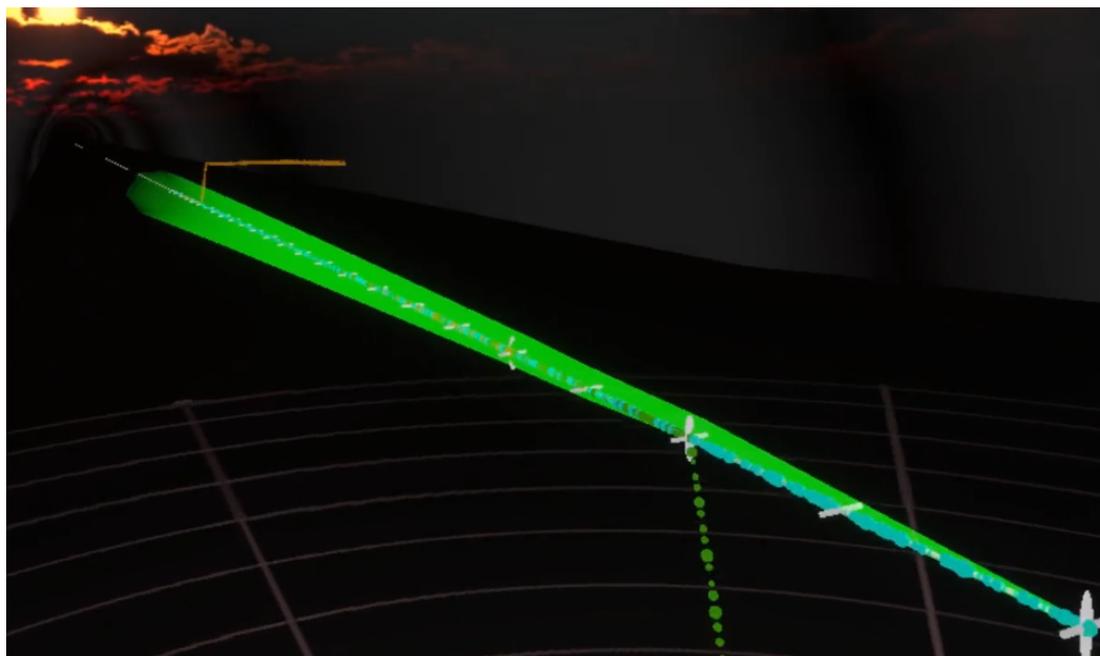


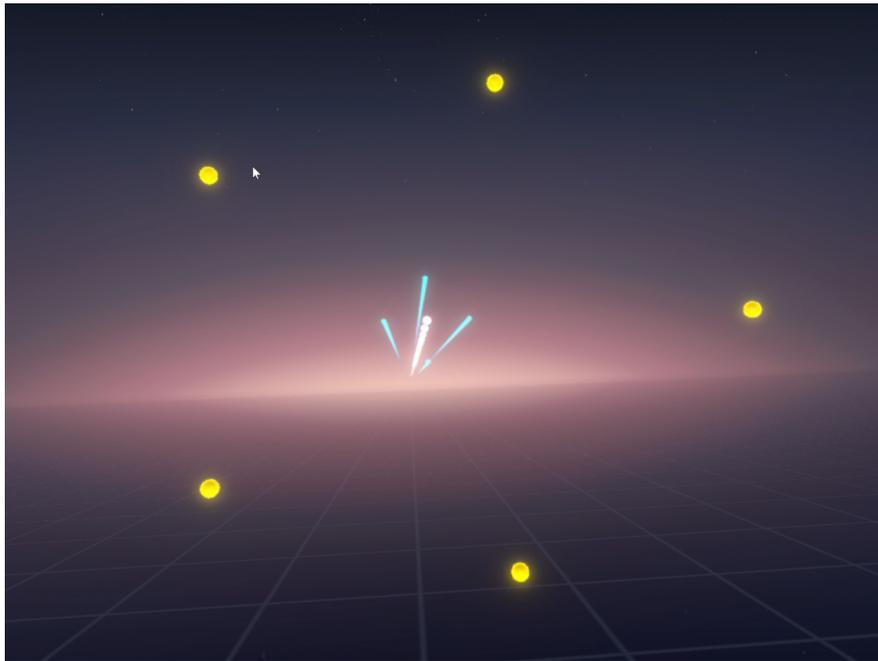
Figure 3.7 – Final result of several iterations

Unlike the white timeline, the coloured flows are not infinite lines, they can only be activated during the potential period of realisation of the potentialities. This activation period, via the temporal evolution of the probability of occurrence of the different activation triggers of the potentialities will shape their trajectories and their distances from the timeline. Basically, the higher the probability of occurrence, the closer the trajectory of the coloured flow will be to the timeline. Let us take the example of the hurricane risk to illustrate this notion of distance. In the geographical area under consideration, the risk of a hurricane is seasonal, from mid-May to the end of November, with a maximum probability of occurrence between August and September. Consequently, the hurricane flow is closer to the timeline over this period (as illustrated in Figure 3.4). By moving the joystick over the coloured streams, it is possible to access the probability of occurrence of the event.

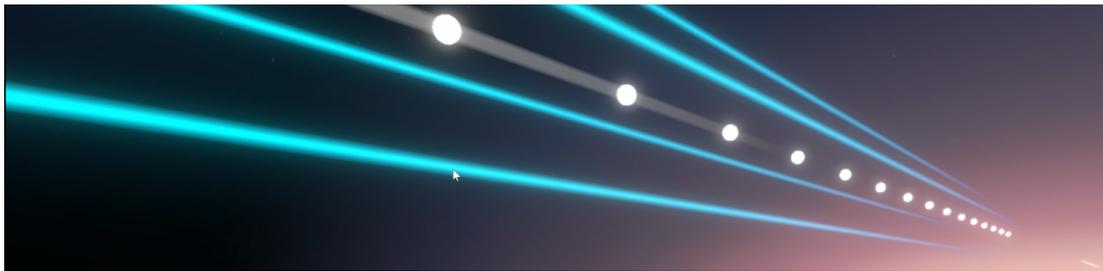
In this virtual environment, the principle is to see the timeline as the direction to be followed by the user. Then, using a “what if” method, by selecting one or more potentialities (one or more coloured streams), dragging and dropping them onto the timeline with the joystick, the user can observe their impacts in the form of deviations of the performance trajectory (the green conical trajectory), bringing it closer to or further away from the timeline, which represents the perfect situation (as shown in Figure 3.5).

When the green conical trajectory is brought out of the vortex (the zone of acceptable performance) following the realisation of a potentiality, its colour changes to red (as shown in Figure 3.6). In this version of the prototype, it is important to note that the deviation itself has no real significance. Instead, the more the performance trajectory deviates from the ideal trajectory, the more significant the quantitative deviation is.

From the set of potentialities proposed (proposed scenarios), the user is free to make and test the decisions he/she wishes, in particular by activating at specific times the



(a) Front view



(b) Side view

Figure 3.8 – Global environment of the second version of the PoD prototype

different possible strategies (selection of the various green and blue flows) to deal with the risks (orange flow). Thus, by learning and following several iterations, it is possible to obtain an optimal solution, illustrated in Figure 3.7.

A video illustrating the operation of this prototype is available [here](#) (last access on 19 December 2022).

3.3.2 Version 2 of the virtual reality prototype

This second version of the virtual reality prototype, unlike the previous version, does not limit its use to a single case study. It allows, by means of several Excel input files (presented in Appendix D), to study any socio-economic system, for which it is possible to measure its performance thanks to different indicators. But also to study a wider range of potentialities that can impact the system studied.

Figure 3.8 illustrates the virtual environment proposed to the user in this second prototype. As in the previous version, the white line represents both the timeline and the optimal performance trajectory. Around this white line gravitate different blue

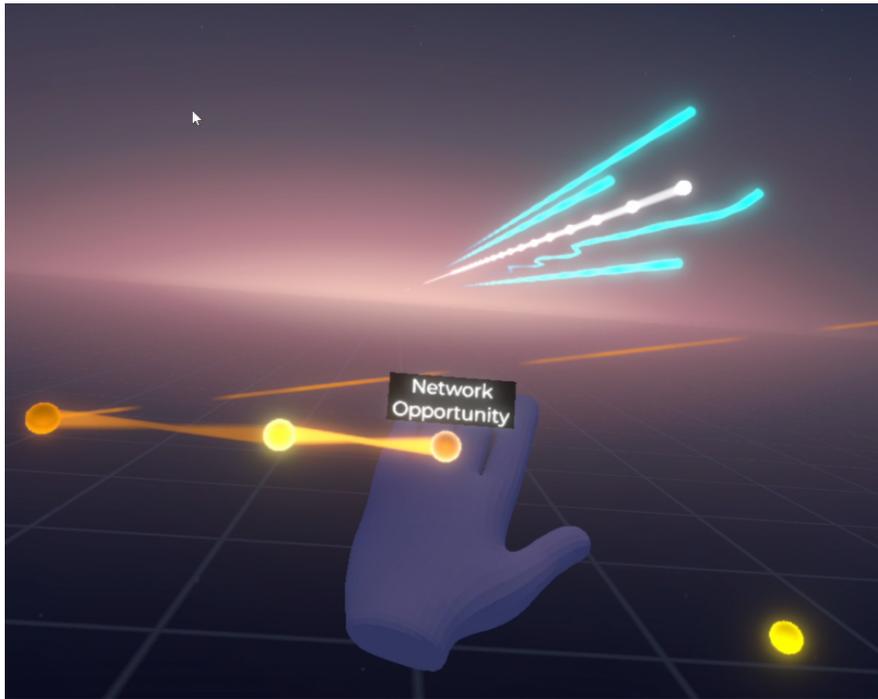


Figure 3.9 – Manipulation of potentialities in the proposed virtual environment

streams, representing the evolution over time of each measured KPI (which are no longer aggregated to form a single trajectory, as in the previous version). The yellow spheres gravitating around these flows represent the different potentialities studied (whatever their type, a single colour represents all the potentials, unlike the previous version, which represents a certain regression).

The operating principle remains broadly the same as in the previous version, considering the timeline as the direction to be followed by the user. The same type of reasoning (“what if”) is applied to observe the impact of the potentialities on the measured KPIs, in the form of deviations from the performance trajectories (the blue streams), as illustrated in Figure 3.9. These potentialities and the strategies implemented can then be compared through the deviations generated, which quantify the difference between a potentiality or set of potentialities and the ideal situation. The activation of potentialities is different from the previous version. In this virtual environment, the user no longer seeks to simply activate a potentiality, but to activate one of its activation conditions (materialised by an orange sphere), as illustrated in Figure 3.9.

The activation conditions will also make it possible to obtain the trajectories of the potentialities in the virtual environment. These trajectories are constructed from the probabilities of occurrence of the different activation conditions of each potentiality (P_{t_i, t_i}), in this case from the maximum value of each of these probabilities for each instant t_i considered (with i belonging to the interval $[0, n]$, n the total number of instants retained over the time range considered for the study of the system). The values of the probabilities of occurrence of the activation conditions are provided to the virtual environment via Excel input files, containing matrices identical to the one illustrated in Figure 3.10, square matrices of size (n, n) . In these matrices, each row and column corresponds to an instant t_i . For each instant t_i , selected via the *Timer console*

	t_0	t_i	t_{25}	...	t_n
t_0	P_{t_0,t_0}	P_{t_0,t_i}	P_{t_0,t_n}
\vdots	\vdots			\vdots			\vdots
\vdots	\vdots			\vdots			\vdots
t_i	P_{t_i,t_0}	P_{t_i,t_i}	P_{t_i,t_n}
t_{25}	P_{t_{25},t_0}	$P_{t_{25},t_{25}}$...	P_{t_{25},t_n}
\vdots	\vdots						\vdots
t_n	P_{t_n,t_n}	P_{t_n,t_n}

Figure 3.10 – Matrix of the origin of the potentiality trajectories

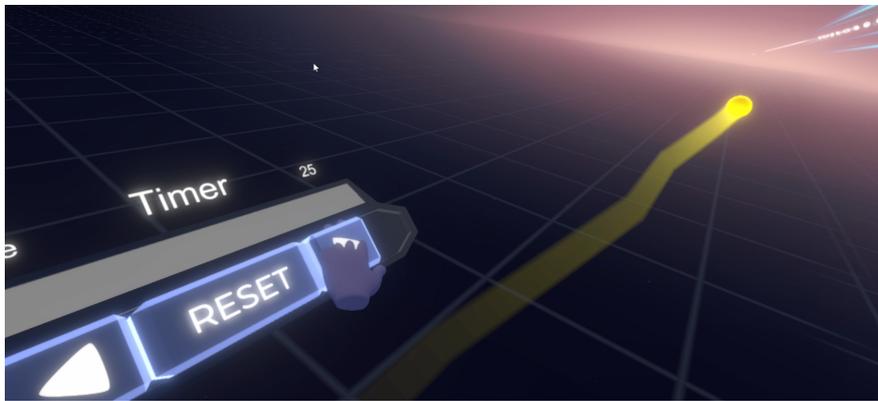


Figure 3.11 – In this virtual environment, the user is the master of time. Tracing the trajectory of a potentiality following the temporal advances made by the user

(available in the virtual environment and illustrated in Figure 3.11), the evolution of the trajectory of the potentialities is constructed from the reading of the different values of probabilities, at the level of the row t_i up to the column t_i , allowing the value of the probabilities to be updated and refined as the different predictions are made. The range of values read for each time t_i is shown by the purple boxes (as illustrated in Figure 3.10). The red box in Figure 3.10 shows the data read to materialise the yellow trajectory of the potentiality in Figure 3.11.

All of these elements allow us to highlight an important notion implemented in this virtual environment, the notion of *time*. Unlike the previous version, in which the user could not really control time (only three jumps in time are possible), in this version the user has absolute control over time, materialised by the *Timer console* (illustrated in Figure 3.11). This control over time greatly extends the range of use of this virtual environment (compared to the previous version). The user can thus feel the evolution of the situation and the potentialities as a function of time, thus adding a dynamic dimension to the virtual environment. This perception of time is reflected in the dynamic trajectories of the potentialities (illustrated in Figure 3.11), following the time advances made by the user and made possible by the previous matrices. As in the previous

	t_0	t_i	t_n
P_{t_0}	$KPI_{P_{t_0},t_0}$	$KPI_{P_{t_0},t_i}$	$KPI_{P_{t_0},t_n}$
\vdots	0			\vdots			\vdots
\vdots	\vdots			\vdots			\vdots
P_{t_i}	0	...	0	$KPI_{P_{t_i},t_i}$	$KPI_{P_{t_i},t_n}$
\vdots	\vdots						\vdots
\vdots	\vdots						\vdots
P_{t_n}	0	0	$KPI_{P_{t_n},t_n}$

Figure 3.12 – Matrix to formalise the difference in impact of potentialities over time

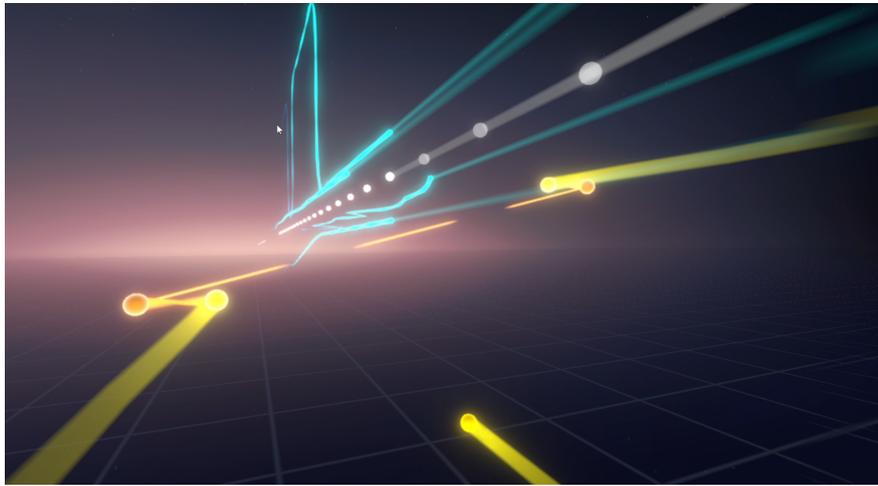


Figure 3.13 – User’s view following the activation of a potentiality (in this case a hurricane)

version, the distance between the white timeline and the yellow trajectories of the potentialities depends on the maximum value of the probability of occurrence of its activation conditions. Thus, the closer its trajectory is to the timeline, the greater its activation probability. The possible activation range of the potentialities is induced by the evolution of its trajectory.

In order to be able to provide the user with the real impact of each potentiality at any time t_i when they are activated (P_{t_i}). On the same principle as the probability of occurrence matrices of the potentiality activation conditions, matrices containing the impact of each potentiality at each time t_i on each measured KPI (obtained from simulation campaigns, for the version presented in this manuscript) are built (as illustrated in Figure 3.12). From these square matrices of size (n, n) , in which each row corresponds to the activation of the potentiality at time t_i and each column the value of the KPI at each time t_i , the virtual environment for building the future performance trajectory and observing the predicted deviations, comes to read the required information at the level of the row t_i from the column t_i . The range of values read for each row is materialised by the purple coloured boxes (as illustrated in Figure 3.12).

In this version of the prototype, the perceived meaning of each deviation is also improved, by observing each measured KPI as a single stream (blue streams in Figure 3.13). In the previous version, the perceived deviation had no real meaning in itself. In this version, despite the decomposition of the performance trajectory into several blue flows distributed around the timeline, the direction of the deviation does not have much more meaning than in the previous version. Following the activation of a potentiality, a blue flow that deviates from the white timeline means a degradation of the KPI it models. Conversely, the closer a blue stream is to the white timeline, the better the KPI it models. The further the performance trajectory deviates from the ideal trajectory, the more significant the quantitative deviation is indeed. However, the true quantitative interpretation of the deviations between the timeline and the set of blue flows will need to be improved, the information could be provided either by labels and read from the Excel input files containing the impact matrices, or by accessing other dashboards by touching a particular point on a trajectory.

A video illustrating the operation of this prototype is available [here](#) (last access on 7 March 2023).

The previous sections lay the foundations for our concept of an immersive dashboard for risk management. This technical contribution (in the form of two virtual reality prototypes) focuses essentially on the ability to offer decision-makers an immersive environment, in which they can grasp and manipulate some of the abstract elements relating to the PoD approach. This technical contribution highlights the important contributions offered by the performance space (introduced in Chapter 1) for decision making and supports the *choice* stage proposed by H. A. Simon (1955) in his bounded rationality model.

The question now arises as to how to evaluate the proposed technical contribution in terms of its maturity in terms of user integration and that of the virtual environment itself, but also its maturity in terms of a performance dashboard. These two evaluations presented in the next two subsections will also serve to highlight the limitations of this technical contribution.

3.3.3 Maturity assessment of the two prototypes using the Virtual Environment Integration Maturity (VEIM) framework

3.3.3.1 Presentation of the VEIM standard

The maturity of the two proposed virtual environment prototypes will be assessed by the VEIM framework, developed by Congès (2022). This framework is one of the few proposed to evaluate both user integration and virtual environment integration (Congès, 2022). The other systems are mostly limited to the evaluation of the immersion or interaction offered to the user (Congès, 2022). The VEIM repository has two objectives: (1) to provide a tool for assessing the integration maturity of virtual environments, and (2) to serve as a guide for the improvement or design of new virtual environments, focusing on the main criteria to be optimised to meet the objectives of the virtual environments developed (Congès, 2022).

This framework proposes to evaluate the maturity of a virtual environment according to four axes:

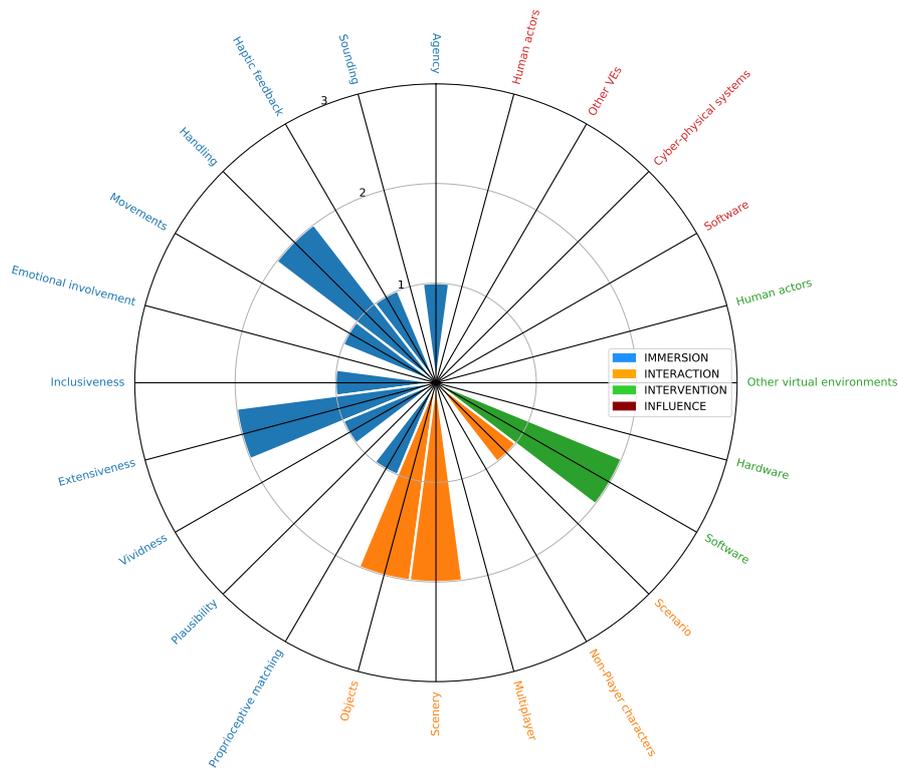
- *Immersion*: evaluates the integration capacity offered to the user, *i.e.* the capacity of the virtual environment studied to induce a feeling of presence for the user, thanks to its functionalities and its construction.
- *Interaction*: evaluates the interaction capacity offered to the user, *i.e.* the possibilities for the user to act on the virtual environment or its components.
- *Intervention*: assesses the ability of the virtual environment to communicate with external systems to receive data from external systems, resulting in the ability to process data, update or change the virtual environment.
- *Influence*: assesses the ability of the virtual environment to communicate with external systems, its ability to send data to external systems, resulting in changes to those systems.

Each of these four axes is divided into several criteria assessed at three levels (the lowest level corresponds to level 1, the highest to level 3), which serve as guidelines for assessing the maturity of the virtual environment. The VEIM framework is structured in a circular diagram divided into several sections. Once the assessment has been carried out, the more colourful the area of the diagram, the more mature the virtual environment.

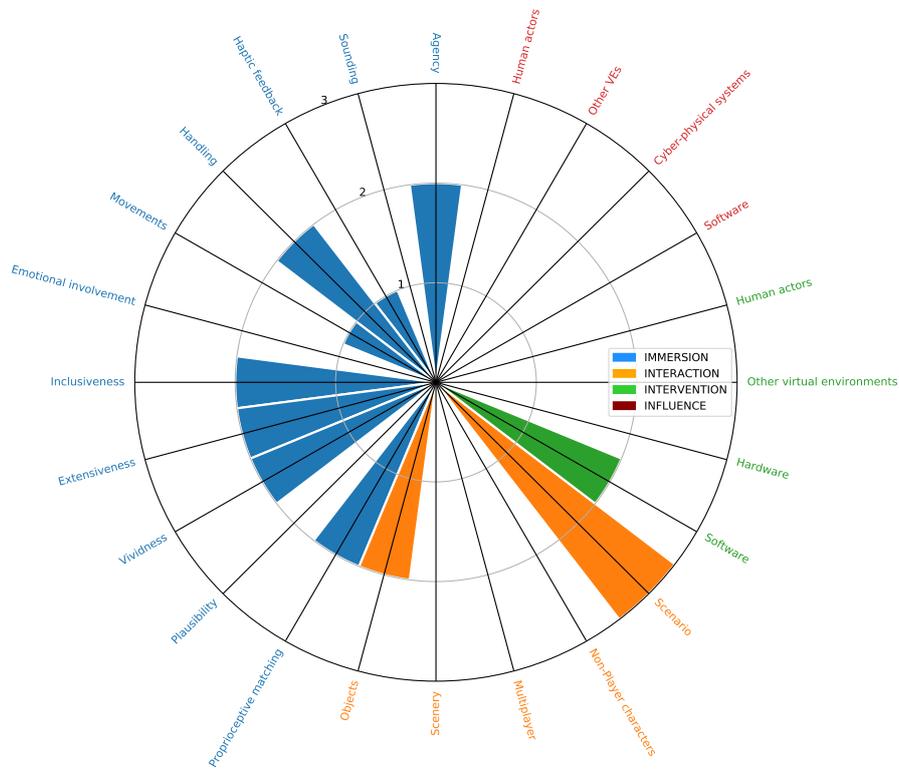
3.3.3.2 Application of the VEIM benchmark to assess the maturity of the two PoD prototypes

As developed in the previous sections, the virtual environments proposed in these two prototypes focus essentially on the ability to offer the user an immersive environment, in which he/she is able to take the full measure of abstract and uncertain elements (potentialities), to control them and to visualise their impacts on the multidimensional performance trajectory of a supply chain, according to its state (*i.e.* for a given situation and for a given moment). To do this, the user must be able to interact with the abstract objects developed, in particular by entering events to be moved to a timeline or activated by touch. The fidelity of the data, the consequences of the different events and the visualisation of the performance trajectories are critical and important elements for the two proposed virtual environments.

Figure 3.14 illustrates the results of the evaluation of these two prototypes using the VEIM framework. Tables E.1, E.2, E.3 and E.4 (in Appendix E) provide explanations for the scores given to each of the VEIM criteria (based on the evaluation of these two prototypes by Congès, 2022). If we consider the value of the different levels as scores, version 1 gets a score of 17/72 and version 2 a score of 21/72. While the scores may seem low, these two prototypes are not intended to immerse the user in virtual environments that replicate reality. These virtual environments are created to immerse the users in their own reality, the one that corresponds to our vision of instability management and decision making according to the paradigms of the PoD approach. Consequently, for the immersion and interaction axes, some criteria (such as emotional involvement and verisimilitude for the immersion axis, as well as the use of non-player characters for the interaction axis) are not intended to be covered by these two prototypes, so the scores on these two axes could be revised upwards. The progress on the scores obtained



(a) First version of the PoD prototype



(b) Second version of the PoD prototype

Figure 3.14 – Evaluation of the PoD prototype with the VEIM repository

between versions 1 and 2 of the prototypes underlines that the developments are going in the right direction and that the prototypes are becoming more and more complete.

However, the VEIM framework allows us to make an initial observation about these two prototypes. Despite the developments undertaken in the areas of immersion and interaction, the virtual environments obviously remain very abstract and require a very significant understanding of all the concepts presented. In order to help the user apprehend this abstract world and make him/her forget the “codes” of the real world, it will be necessary to find a way to solicit more of his/her senses (particularly touch and hearing). We must also be careful not to represent several abstract concepts by the same object. Indeed, the fact that the timeline is merged with the ideal performance trajectory is a source of confusion for some users. Moreover, from a purely visual point of view, the fact that this line is infinite masks its representation as a target, making it difficult for users to see this line as an “ideal” to be reached. The VEIM repository also highlights a lack of connectivity of virtual environments to the outside world, whether to provide information to them, but also to export information, such as an assessment and evaluation of the user’s various manipulations, in order to facilitate feedback and learning (which is one of the opportunities offered by these virtual environments).

3.3.4 Evaluation of the maturity of the two prototypes as a performance dashboard

Now that we have evaluated the two proposed prototypes in terms of the maturity of the virtual environments developed, it is interesting to tackle their evaluation in terms of performance dashboards. Unfortunately, there are no generic models in the literature for the design of performance dashboards, which would allow to define criteria that would guarantee their successful implementation in the industry (Bugwandeen et al., 2019). Bugwandeen et al. (2019) seek to fill this gap by proposing mandatory and optional criteria, bringing together theoretical guidelines and best practices for the design of performance dashboards. These theoretical criteria were obtained from the literature review and interviews with a manufacturing company.

Table 3.1 shows the criteria covered by the two versions of the proposed virtual reality prototypes. Of the 26 mandatory criteria, 16 are met by both prototypes. Of the 11 optional criteria, 7 for the first version and 6 for the second version are covered. Thus the first version of the prototype meets 23 of the 37 criteria (*i.e.* 62.2% of the criteria) and the second version 22 of the 37 criteria (*i.e.* 59.5% of the criteria).

In terms of content and form, the two versions of the virtual reality prototype cover most of the required criteria. They are well presented and condense the information into a single tool, viewable on a single screen. The concepts developed and represented, although abstract, are standard and simple to manipulate. The customisation of the two virtual environments proposed is limited. Access to “what if” analyses, combined with the use of virtual spaces, allows decision-makers to make their own decisions and learn from their mistakes. However, the lack of a final report on the manipulations carried out (the decisions made) is a hindrance to the learning process of the decision makers offered by these two prototypes. As highlighted by the VEIM framework, the fact that several decision-makers cannot use the prototypes at the same time hinders communication and collective decision making. The aggregation of information in the form of performance trajectories deviating from the system’s objectives as a result of the

realisation of potentialities, although condensing and reducing the volume of information and data to be manipulated and analysed by the decision-maker, may not be sufficient.

Work on access to other rooms for a more detailed analysis of the impact of a potentiality on the system's performance, via various graphs, will have to be carried out. For the second version of the prototype, the need for manual data, transcribed in the form of Excel files (which do not correspond in format and content to automated data extractions from a company's enterprise resource planning), could be an obstacle to its deployment. Work on a more automated integration of data will have to be carried out.

3.4 Towards a more complete version of the prototype: limitations and future developments

3.4.1 The limitations of current prototypes

These two prototype versions, although offering the basis for the visualisation and manipulation of abstract objects related to the concepts of the PoD approach, nevertheless have some limitations (highlighted in the maturity assessment presented in the two previous sub-sections, but also by the feedback from the various industrialists and academics who have tested or attended demonstrations of these prototypes). The following list of points outlines a set of initial limitations, which point the way to future developments:

- Making the flows representing the potentialities more comprehensible is one of the priorities. These flows should be improved in at least three aspects:
 1. the representation of the dangerousness and the range of action of the potentiality on the system (*e.g.* by playing on the thickness of the flow),
 2. the management of potentialities that can occur several times (in both prototypes, potentialities can only be activated once),
 3. the actors impacted (the case study used to illustrate the contributions of this technical paper focuses on a single company, but what about a study of the supply chain as a whole).
- The creation of other rooms, complementary to the decision space, is one of the major challenges for future developments, in particular to display dashboards detailing the nature of a deviation, its precise impact on a set of KPIs, a potentialities editor, etc.
- A great deal of work will have to be done to offer more freedom of manipulation to the user, who is currently confined to manipulating a list of potentialities and predefined scenarios, whose impact on the variation of the system's attributes has been preconfigured. This limitation justifies the creation of a second room, in which the potentials, activation conditions, etc. will be defined, *i.e.* a room in which the decision-maker will be able to create and configure the three chains (causal, propagating and decision, presented in Chapter 1).

Table 3.1 – Positioning of the two prototypes in relation to the list of criteria proposed by Bugwandeen et al. (2019), to be fulfilled for developing performance dashboards *Criteria in grey and italics are optional*

Category	Criteria	PODV1	PODV2
Content	KPIs	-	✓
	User consultation	✓	✓
	Accurate	✓	✓
	Actionable	✓	✓
	Relevant	✓	✓
	Day averages	-	-
	<i>Monetary impact</i>	-	-
Data analysis	Drill downs	-	-
	Predictive	✓	✓
	Historical trends	✓	✓
	Statistical analysis	-	-
	Intelligence and fault trees	-	-
	Synergetic	-	-
	<i>What if analysis</i>	✓	✓
Visual effects	Attractive	✓	✓
	Simplicity	✓	✓
	Single screen	✓	✓
	Unity	✓	✓
	Appropriate background colours	✓	✓
	Items positioned correctly	✓	✓
	Single line graphs	-	-
	Robot status	✓	-
Functionality	<i>Customisation</i>	✓	-
	<i>Interaction</i>	✓	✓
	<i>Tabs and filters</i>	-	-
	<i>Collaborative</i>	-	-
	<i>Trackability</i>	-	-
Platforms	Web-based	-	-
	Responsive and timely	-	-
	Intuitive, secured, scalable, industry compliant	✓	✓
	Largely automated	-	-
	Easy access	-	-
	Interactive	-	-
	<i>Single location for information</i>	✓	✓
	<i>Mobile device accessibility</i>	-	-
Performance and knowledge	<i>Process step in the value chain</i>	-	-
	<i>Overall factory performance</i>	✓	✓
	<i>Target and historical information</i>	✓	✓
	<i>Work instructions, videos, photos</i>	-	-
Business culture	Behavioural changes	✓	✓
	Software training	✓	✓
Maintenance	Technical maintenance	-	-
	IT maintenance	-	-

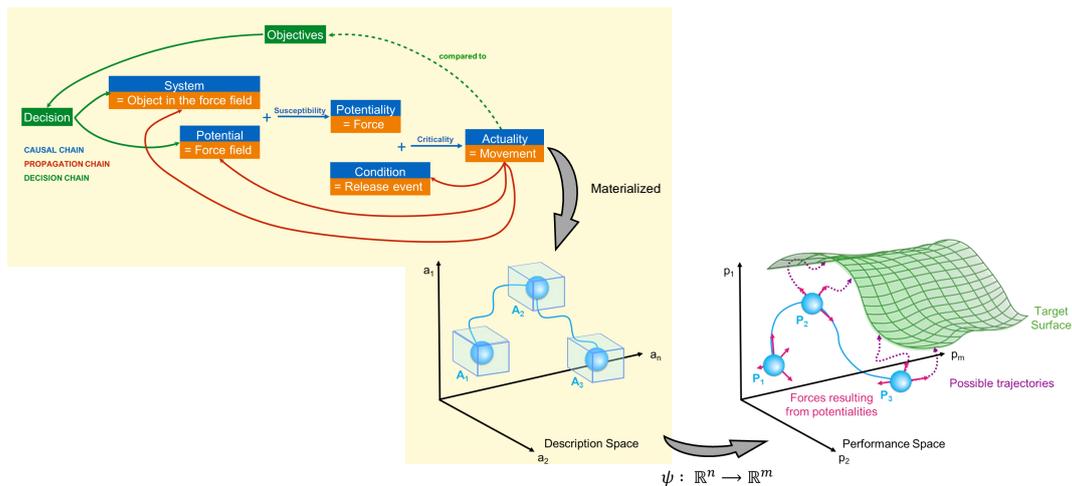


Figure 3.15 – Relationships between the different relative and basic elements of the PoD approach

3.4.2 Creation of a new viewing space: a space dedicated to the configuration of the three chains

The technical contribution proposed and illustrated by the two prototypes presented above, focuses essentially on the decision space. However, as presented in Chapter 1, the PoD approach is based on a vision of risk defined from three chains (causal, propagating and decision) and includes two spaces (description space and performance space). For the time being, in the proposed contribution, efforts have been concentrated on the visualisation and manipulation of the abstract elements of the performance space by decision-makers. Thus, the elements (in the yellow boxes in Figure 3.15) related to the description space and the three chains have been hidden. Currently, these elements are not accessible to the user and are included in the scenarios for each potentiality. Version 2 of the virtual reality prototype allows the visualisation of part of the propagation chain, illustrating the cascade effects between the activation conditions of the potentialities.

However, as our intention is to increase the complexity and improve the proposed contribution in an incremental way, one of the future developments will be to provide a virtual environment where the user can navigate in both a descriptive space (the description space) and a decision space (the performance space), in particular by offering the possibility for the user to switch from one space to the other. The visualisation space will be dedicated to the description and construction of the three chains. The visualisation space will thus present a structured view of the relationships between the observed system and its environment according to a set of predefined concepts (external factors, subsystem, potential, potentiality, trigger, actuality), linked by different relationships (generation, susceptibility, specialisation, sensitivity, implementation), illustrated in Figure 3.16.

The objective of this second space, the visualisation space, is not to limit itself to a visualisation of the different chains structuring the relations between the studied system and its environment, but to allow the user to be able to interact with the proposed chains and in adequacy with the studied system, in particular by modifying them with predefined elements, thus making it possible to create new chains or to modify

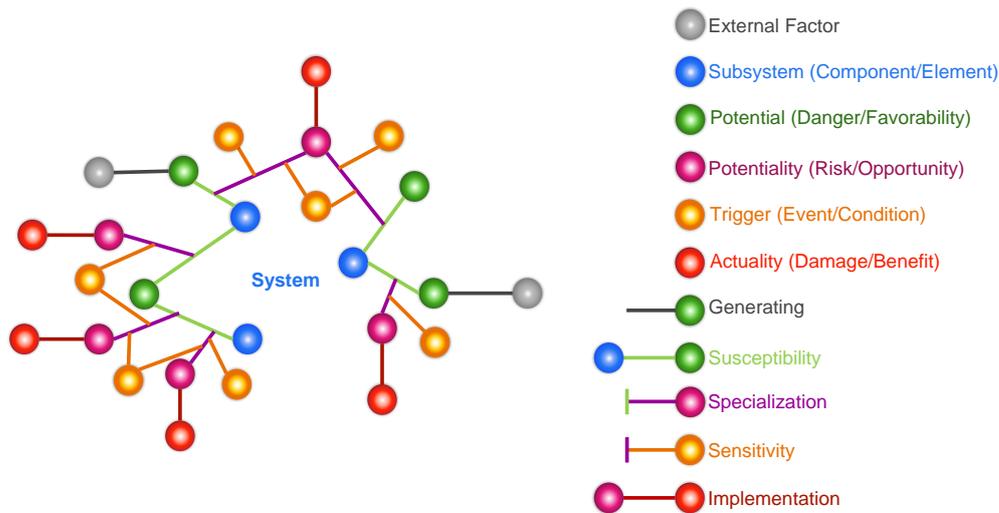


Figure 3.16 – A vision of the visualisation space

the values of the variations of the attributes following the realisation of the various potentialities. To do this, it is necessary to fully master the PoD approach, which serves as a link between the two proposed spaces, as illustrated in Figure 3.17, providing an overview of the next version of the prototype. Indeed, the PoD approach is used to define the concepts and support the computational part allowing to interpret in the decision space the modifications made by the user in the visualisation space. To achieve this, it is necessary either to be able to express mathematically the forces generated by the different potentialities and chains governing the system, or to find a tool capable of estimating them over a large field of study. In order to guarantee a certain comfort of use to the user, any modification in the visualisation space must be observable in a few seconds in the decision space. It is therefore essential to find a tool capable of replacing the simulation, it is not conceivable to make modifications in the visualisation space, export these modifications to the developed simulation models, wait for the runs to be made and the results exported to the VR prototype. To be fully exploitable, everything must be possible within the proposed prototype. Among the existing tools, neural networks could be a solution that meets all these expectations. However, in order to return reliable results, they need to be trained on a vast amount of data, which in our case will be obtained from vast simulation campaigns, thus allowing to cover a wide spectrum of the field of possibilities in the description and performance spaces.

3.5 Conclusion of the chapter

This chapter illustrates the solution chosen to represent, visualise and manage the performance of a supply chain seen as a multidimensional trajectory. Virtual reality is used to transform the performance space into a decision space, a decision support tool that can be used in a relevant and ergonomic way. Virtual reality was mainly used for its ability to transform the abstract concepts related to the PoD approach and the performance space into objects that can be represented by spatial metaphors and manipulated by the decision maker. This exploitation of virtual reality was illustrated through two prototype of virtual environments dedicated to decision making and

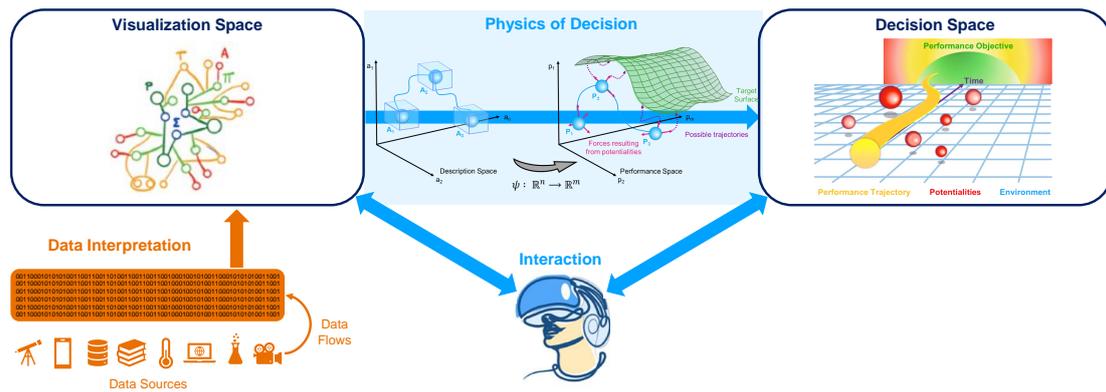


Figure 3.17 – Big picture of the next version of the prototype

representing our conception of the performance dashboards of tomorrow. In these virtual environments, the user is immersed in the decision space, in which the potentialities are modelled as coloured flows gravitating around a timeline, also representing the optimal performance of the supply chain. In these environments, the whole abstraction is based on the fact that a system is only managed by deviating its performance trajectory from its straight and infinite line of optimal performance, following the realisation of potentialities (activated by the decision maker according to a what if reasoning).

The work presented lays the foundations for future developments, in particular the creation of new rooms, in order to cover and group together in a single decision support tool all the concepts relating to the PoD approach and offer more freedom to decision-makers. In addition to the development of new rooms, before being the performance dashboard of tomorrow, these prototypes also need to be more adapted to the domain and the system studied. A great deal of work should be done to focus them more on the study of the potentialities of supply chains, in particular by grouping the potentialities according to the risk classifications put forward from the analysis of the literature proposed in Chapter 1, for example by creating rooms dedicated to the risks linked to the three main sources of variability in supply chains: *supply*, *manufacturing* and *demand*. This method could also reduce the number of flows related to the (potentially high) potentialities to be observed in the main room, thus proposing an “aggregation” of potentialities according to their typology. The observation and analysis of these three types of variability requires the ability to measure the performance of the specific processes impacted by these variabilities at different levels (strategic, tactical, operational, company-wide, network-wide, etc.). Thus, in order to make the decision space a complete performance measurement system, a significant amount of work on performance evaluation will have to be carried out, which implies creating a simulation model that can be reconfigured according to the different logistics network configurations studied and that is capable of generating the evolution of performance at different granularities.

Conclusion and Perspectives

The future depends on what you do today.

Mahatma Gandhi

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This chapter proposes in Section 4.1, a review of our contributions (made in each Chapter and Appendix), in relation to the problem posed, the different issues and research questions raised in the Introduction (p. 1) and Chapter 1. Section 4.2 introduces the many possible perspectives that could be the subject of future research, as well as the work still under development.

4.1 Summary of contributions

The work presented in this manuscript aims to test and evaluate the application of a new decision support methodology, the PoD approach, to study how supply chains can manage (anticipate and control) the potentialities (risks and opportunities) arising from instability, which in itself constitutes a first conceptual contribution. This approach, based in particular on the work carried out by the SCAN joint laboratory, aims to position itself at the top of the decision support tools in a context of instability, which is becoming the new norm (Benaben et al., 2021). To this end, this approach seeks to introduce the concepts of classical physics into the field of decision making and potentiality management, by proposing a decision support system based on analogies with the laws of motion physics, in order to anticipate and navigate between potentialities.

Inspired by physics in the definition of its concepts, the PoD approach models the impact of potentialities as physical forces, which push or pull the system, like an object in its performance space, in movements towards or away from its performance target zone, which managers seek to achieve. It is constructed from the objectives set for the

quantitative values of the KPIs, which serve as dimensions of the orthonormal framework that is the performance space. Thus, the objective for this approach is to characterise the forces that could impact the system, in order to discover the optimal combinations among the existing and activable forces to move the system towards the target area. The performance space is therefore a framework for decision making. However, decision making is not limited to activating different forces, it is also necessary to be able to offer decision makers the possibility to generate forces through their decisions, via the activation of attributes (system parameters), serving as decision levers. Thus the PoD approach requires a second orthonormal space, the description space, which deals with the attributes of the system and the characteristics of its environment. The two spaces therefore allow the performance of the system to be separated from its attributes and characteristics (parameters of its environment), in order to be able to decompose as far as possible the variations in the parameters of the system involved in a decision and the choices made by the decision-makers to achieve the performance objectives. Despite this decomposition, these two spaces are interconnected by equations linking the parameters of the system and the characteristics of its environment to its performance. Being able to define or estimate these relationships is a challenge in the application of the PoD approach. In this manuscript, the method proposed to link these two spaces is simulation. Two simulation models are proposed in this manuscript for this modelling phase: *Rich Kids*, presented in Chapter 2 and developed from discrete event simulation - the *McCamish Pavilion polling station* presented in Appendix A and developed from discrete event and agent-based simulation. These simulation models are in themselves a first contribution to the study of the applicability of the PoD approach.

Due to the unpredictable and unquantifiable nature of the potentialities emanating from the instability of the supply chain environment, supply chains need to withstand and recover from their impacts quickly, including by building resilience. In many areas, resilience is advocated as a remedy for dealing with dynamic and uncertain situations (Wieland et al., 2021). With the recurrent increase in disruptions impacting supply chains, it has become vital to estimate resilience in order to make decisions based on the study of risks (Pant et al., 2014). In this logic of applying the PoD approach to the management of potentialities impacting supply chains, it is therefore essential to study the contributions of the PoD approach to the management and measurement of resilience. This leads to the research question addressed in Chapter 2:

Research Question 1 (RQ1)

How can we develop supply chain resilience capabilities (its management and measurement) using a kinetic approach such as PoD?

Despite lengthy debates on how resilience should be conceptualised and measured (Chowdhury et al., 2017; B. H. Walker, 2020; Wieland et al., 2021), the literature review proposed in Chapter 2 highlights two visions of resilience for supply chains: engineering and ecological. These two views of resilience differ in their design and management objectives. Engineering resilience focuses on maintaining the effectiveness of the function (*i.e.* recovery time), whereas ecological resilience focuses on the ability to absorb shocks before they cause a change in the structure of an ecosystem (*i.e.* maintaining the existence of the function).

Ponomarov et al. (2009) see the search for measures of supply chain resilience as an important stream of research that can provide essential knowledge for its management. However, to our knowledge there is no approach that reconciles and measures both views of supply chain resilience.

Our contribution is to take advantage of the physics concepts on which the PoD approach is based, notably kinetics and the fundamental principle of dynamics, to quantify the resilience of supply chains. Thus, with this vision, a first contribution proposes to measure the engineering resilience from calculations of distances between different performance trajectories of the system (illustrated in Figure 2.10).

This contribution builds on the resilience triangle (illustrated in Figure 2.4), extending its concepts to consider the multidimensional property of resilience. The proposed distance-based resilience measure allows resilience to be assessed on more dimensions than the one-dimensional resilience triangle, in particular the performance space can be composed with as many dimensions as the number of KPIs to be measured. This allows us to assess the distance between the initial expected trajectory and the disrupted or corrected trajectories, regardless of the number of KPIs studied (even if it is not possible to visualise them beyond three dimensions).

A second contribution proposes to measure ecological resilience using the volume of a hyper-cone (illustrated in Figure 2.11), modelling the space defined by the set of *counter-forces* (corrective actions and decisions) that can be activated at each moment.

With this new measure of resilience, decision-makers will no longer need to wait for a disturbance to occur and the system to return to equilibrium before being able to assess resilience, unlike previous methods (the distance calculation and the resilience triangle). However, to be applicable and robust, this resilience measure requires: (1) a high level of knowledge of the system and its environment, in order to be able to identify all the corrective forces that are manageable at any given time; (2) the ability to estimate their impacts as accurately as possible (probably for most forces from previous or simulated data); and (3) the ability to define and measure the overall volume resulting from these forces (which in a space of more than three dimensions requires development). These needs, to make this measurement effective, also raise the question of the independence of the forces and their summability criteria, two points at the heart of this approach, which are not currently resolved.

In addition to its contribution to measuring resilience, being able to theoretically calculate the overall performance of the observed system in the form of performance trajectories impacted by various potentialities is a major contribution of the PoD approach. It is then necessary to find a way to make these results, these multidimensional performance trajectories, manipulable for decision-makers. From this observation follows the research question addressed in Chapter 3:

Research Question 2 (RQ2)

How to represent, visualise and manage the performance of a supply chain seen as a multidimensional trajectory (defined by numerous KPIs and impacted by numerous forces), in order to make it a relevant and ergonomic decision-making tool?

To meet this challenge, the technology chosen is virtual reality. Virtual reality is used for its ability to transform abstract concepts into objects that can be viewed and handled by the decision-maker, through the use of virtual environments that are sufficiently close to reality. The virtual environments developed allow the user to be immersed in a space in which the abstract concepts related to unstable situations (risks or opportunities) are represented in the form of coloured spheres, gravitating around a timeline, representing the optimal performance of the supply chain. In these environments, all the abstraction present is based on the fact that a system is managed only by combinations of deviations of its performance trajectory from its optimal line (an infinite straight line) following the activation of potentialities.

Based on these concepts, the proposed technical contribution is based on two versions of usable virtual reality prototypes, described in Chapter 3. These two prototypes define the basis of our vision of tomorrow's performance dashboard, to support supply chain managers in their decision making (reduced to visualising and piloting the multidimensional performance trajectory of the system following the activation of various potentialities) in a context of instability.

It is important to remember that the contribution of our work is limited to the second version of the prototype, the first version being realised during the first work on the PoD approach and serving essentially in this manuscript to highlight the development directions taken to develop the performance dashboard of tomorrow.

4.2 Future work and perspectives

As presented in the introductory chapter of this manuscript, the work on the PoD approach within the SCAN joint laboratory is not limited to the work presented in this manuscript and is positioned on several research axes (illustrated in Figure 4.1), in order to make this approach exploitable. The first part of this section, based on these research axes, will outline several general perspectives put forward by the work presented in this manuscript. In its second part, it will highlight the perspectives linked to the chosen vision for the future developments undertaken.

4.2.1 General perspectives

Building relationships between the description space and the performance space

In this manuscript, the mathematical relationships Ψ between the description space and the performance space were modelled and estimated using simulation models, which, like a *black box*, have made it possible to capture the internal dynamics of the system, with

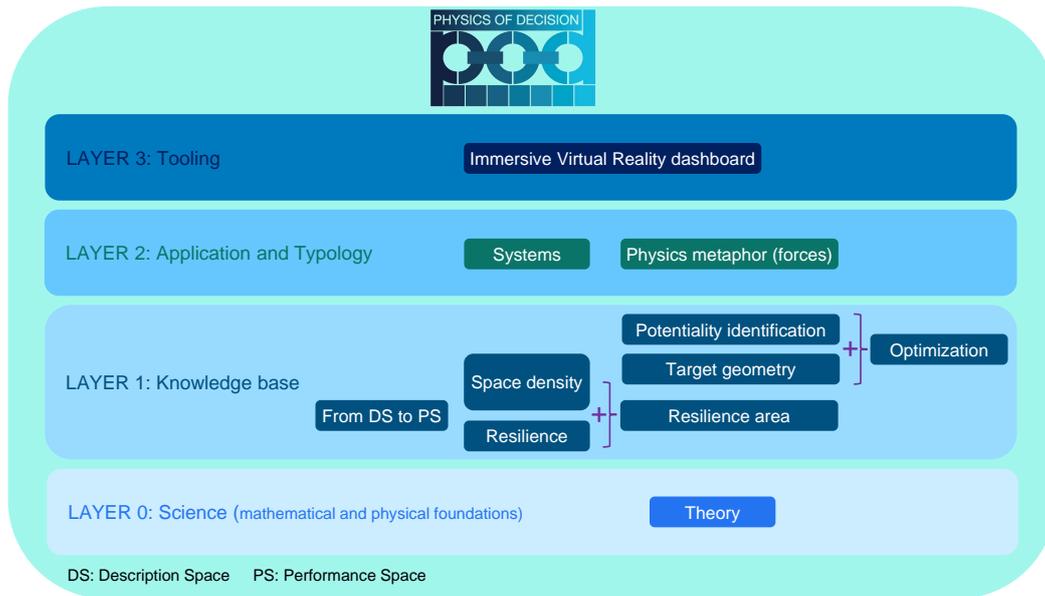


Figure 4.1 – Research areas within the PoD approach

a sufficient level of granularity to allow the observation of the impacts of a potentiality, by transforming its micro-impacts (variation of the attributes in the description space) into macro-impacts (variations of the KPIs in the performance space).

Of course, it is quite possible to use other more formal tools to create the link between these two spaces and model the dynamics of a system: mathematical modelling, machine learning, sparse identification of nonlinear dynamics, etc. The use of neural networks seems to be a promising solution. Recurrent neural networks (RNN), especially long-short-term-memory neural networks (LSTM), which allow the prediction of the future behaviour of a system (its performance trajectory) from time series of past data, could be a solution. The advantage of this solution over simulation is that, once trained properly on a large amount of training data (generated either by historical data or simulation campaigns), the neural network could: (1) avoid having to formalise and equate the forces generated by potentialities, (2) increase the study spectrum (*i.e.* have more flexibility in studying new potentialities) and (3) thus predict future performance trajectories for a wide range of potentialities. The development of such a solution is a priority, in order to participate in the developments of the future virtual reality prototype.

Study of the density of space

In addition to its use to estimate the relationships between the two spaces proposed by the PoD approach, the simulation, thanks to extensive campaigns (in particular by reusing those for the previous perspective) and sensitivity analyses, also opens the door to the study of the space of possibilities and the density of these two spaces. According to the concepts of the PoD approach, density is defined as the degree of ease or difficulty of access for the system (seen as a physical object) to a point or area in the performance space.

To be able to quantify the ease or otherwise of access to the different areas of the performance space, it is necessary to define a mathematical function (specific to each

system) to quantify the “cost” of moving to these areas. This function should at least link and take as constraints the time, costs and degrees of freedom of each attribute at each moment (focusing mainly on attributes that can be used as decision levers). In order to determine this function, analogies with the notion of force work can be studied.

Simulation, through sensitivity analyses, could provide a means to generate the different combinations and variations of attributes (model parameters) needed to study density and cover the range of possibilities in the performance space. For systems as large and complex as supply chains, the combinatory and volume of simulation runs to be processed could quickly become a hindrance to this study. Other tools, such as an unsupervised machine learning approach (*e.g.* clustering) could be considered.

Determining the resilience zones of a system

The study of the density of the performance space, combined with the proposal of the resilience cone (defined in Section 2.2.3), could also offer the possibility of identifying areas where a system is more or less resilient, thus offering the possibility of determining the best combination of forces (identified and activatable) to increase the volume of the hyper-cone and thus make the system more resilient.

Geometry of the target area

The geometry of the target area (defined and illustrated in Section 1.3.2) is yet to be defined. Different target shapes could be defined based on the specific values of the KPIs (one point for one KPI, one plane for two, one volume for more than two, etc.) and the constraints related to the definition interval of the associated KPIs, in which case the target could be constituted based on minimum, maximum or threshold values to be reached. The study of the density of the performance space could provide the necessary knowledge on this space to be able to define the geometry of the target area, but especially its evolution over time.

Defining the geometry of the target area requires an answer to this problem: assuming that we know the system and the forces (potentialities) impacting on it at each moment and for any position in its performance space, how can we study the best places to target in terms of the probability of occurrence of the potentialities (activation of the forces) and the costs?

Identification of risks and opportunities

In all of the proposed application cases, the PoD approach was used in each case on a list of predefined potentialities. However, being able to identify potentialities is an important task in risk management, which is more so when the approach developed seeks to support decision-makers in their decision-making by helping them to anticipate the potential impacts of potentialities on the performance of the managed system.

In the performance space, each deviation from the *inertia trajectory* (corresponding to the evolution of the system’s performance when subjected to only the expected load and contextual forces) is generated by a force, modelling the impact of a potentiality. Thus, the examination of performance trajectories constructed from historical data and inertia trajectories can provide insights into the behaviour and evolution of the system. The information obtained from the comparative study of these trajectories could be used to predict the future positions of the system in its performance space, thus providing a perspective for the identification of potentialities.

Optimisation of the performance trajectory

Assuming that we know the system, the set of forces impacting on it and that can be activated at each moment (in particular from the studies of the previous perspective) and that we perfectly define its performance target zone (as well as its evolution), the optimisation of the performance trajectory amounts to asking ourselves what is the set of potentialities to be activated at each moment to have the best chance of reaching the defined target zone at the lowest cost. Techniques such as reinforcement learning (based on reward mechanisms) or genetic algorithms could be used to find the optimal performance trajectory.

Pushing the analogies with physics even further

In all the studies proposed in this manuscript, the system is considered as a solid object moving in its performance space, whose axes are based on the quantitative values of the KPIs. Thus in this study, only analogies with point mechanics have been proposed. However, in addition to contributing to a means of understanding and evaluating the impacts of potentialities on the system, through the forces, trajectory and motion of the system in its performance space, other areas of physics could be investigated. In order to improve the resilience of a system, in particular its resistance and shock absorption capabilities, analogies with solid mechanics could be constructed, by studying the deformation and plasticity properties of the system. The study of the plasticity of the system could also be used to define its shape, *i.e.* its ability to be malleable by changing its attributes to maximise or minimise its susceptibility to a potentiality.

However, in order to realise all the perspectives (mentioned above), it will be necessary to carry out these studies for typologies of systems, impacted by typologies of potentialities and forces. Obtaining the necessary data to carry out these studies will require the creation of simulation models that are sufficiently exhaustive and comprehensive, but also reconfigurable and modular (capable of adapting quickly to different reconfigurations of the system), in order to be able to generically formulate the impact of a given disturbance on a given system, in the form of a function modelling the force impacting its performance trajectory.

4.2.2 Towards the development of an atomic vision of systems and performance

This need for modular and reconfigurable simulation models can also be found in industry, especially in a context where the need for simulation models has become indisputable, following the Covid-19 pandemic, forcing many companies to adapt very quickly the distribution of their offers to brutal variations in demand (Ivanov et al., 2021). Despite its ability to capture the dynamics of complex supply chains, simulation is not widely adopted by manufacturers (Ben Jbara, 2018). This low uptake is largely due to the complexity of developing a simulation model, the lack of modelling skills and/or the lack of time to develop a simulation model, especially from scratch (Cigolini et al., 2011). According to Ben Jbara (2018), the difficulties faced by industrialists in building simulation models are explained by the lack of commercial solutions with an easy-to-use interface, and by the mismatch between the proposed building blocks (regardless of the modelling method used: *system dynamics*, *agent-based* and *discrete event*) and the needs of industrialists for supply chain modelling. Development time is a major constraint, accounting for about 45% of the total effort of a simulation project

(Mackulak et al., 1998). The more complex the system, the more difficult it is to model, and the more expensive it is in terms of time, resources and energy (Cerabona et al., 2021b). Indeed, good simulation models can be costly, time-consuming to develop and especially to validate (Stefanovic et al., 2009). Typically, they require modelling and defining the relevant data set to produce valid results, which can be very difficult, especially for systems as complex as supply chains (Stefanovic et al., 2009). The lack of standardised methods for supply chain modelling and analysis does not favour its use by industry, despite the many supply chain modelling frameworks and methods developed (Long, 2014; Stefanovic et al., 2009). However, most of the models developed are situation or problem specific, they provide at best guidelines on how simulation models can be developed, but none offer a standard or widely accepted simulation model for supply chains (Macdonald et al., 2018).

In order to make simulation more attractive to industry, many researchers have asked the question of how to model supply chains in a standard way. To do so, they have relied on conceptual and reference models such as the SCOR model (described in Appendix B), a model that is widely recognised and accepted as an industry standard (Fayez et al., 2005). According to Stefanovic et al. (2009), the SCOR model provides a good starting point for creating a conceptual modelling framework.

Researchers have mainly sought to benefit from the advantages offered by the SCOR model, namely: a standard cross-functional framework offering a common vocabulary to all practitioners mastering it, a hierarchical model divided into four levels of processes with different granularities, a modelling of the three flows circulating in a supply chain (material, information and financial), understandable and standardised performance measures, as well as good practices (Long, 2014). Thus, based on the contributions of the SCOR model, particularly its standard processes, it has been possible to develop reusable modelling blocks and components in order to facilitate the construction of models and reduce their development costs. Its standard processes and the associated metrics for evaluating them should also enable simulation models to be created more quickly, especially for the conceptualisation and modelling phases (Persson, 2011).

The comparative study of three simulation tools, namely Witness (a commercial simulation software), iGrafx Process (a process modelling and evaluation tool) and e-SCOR (a tool developed by GenSym, dedicated to the simulation of supply chains based on the SCOR model), proposed by Albores et al. (2006) confirms the contributions of the SCOR framework for the construction of simulation models. Indeed, their experiments show that the tools based on the SCOR model allow to build models more quickly, whose comprehension is increased thanks to the use of standard processes and KPIs (particularly for people familiar with the SCOR model). On the other hand, they have some limitations, such as lack of flexibility and a risk of distorting reality by trying to fit certain strategies to the concepts of the SCOR model.

Many simulation models have been developed based on the SCOR framework. Hermann et al. (2003) develop a discrete event model along these lines. In the same vein, Persson et al. (2009), Persson (2011) and Persson et al. (2012) propose through these three articles, their work on the SCOR Template, a discrete event simulation model for supply chains, developed on the Arena® simulation software. The SCOR Template proposes to model and reconstruct the processes of a supply chain by assembling different simulation bricks based on *Level 2* or *3* of the SCOR model (depending on the versions presented). Long (2014) develops on the basis of the SCOR model, an agent-based simulation

model for the construction of logistics networks (in order to offer a solution for dealing with entities with agent characteristics and evolving in distributed environments, which the SCOR model cannot do). The use of the SCOR framework for simulation model building thus overcomes some of its limitations, in particular the fact that it is a static approach, not offering the possibility to perform dynamic analyses (Long, 2014; Persson et al., 2012).

Towards an atomic view of supply chains

Atomic Supply Chain Modelling for Risk Management based on SCOR

Abstract. At the time of instability becomes the norm (climate changes, natural disasters, epidemic, etc.) the management of collaborative networks, such as supply chains, is becoming more and more complex and critical. This instability only adds to the complexity of an already very complex system. Thus, supply chain managers have to adapt to multi-dimensional complex situations. Dealing with instability is a key expectation for these managers. One tool to help managers make decisions in this unstable environment is simulation. This article introduces some first results on an “atomic” reconfigurable supply chain simulation model based on Supply Chain Operations Reference (SCOR) model. This simulation tool will be used to apply an innovative physics-based approach of risk and opportunity management, that designs disturbances by forces moving the considered supply chain within its performance framework. This approach enables managers to monitor supply chain’s performance trajectory by viewing and merging the impact of risks and opportunities.

Keywords. SCOR, Supply Chain Management, Risk Management, Performance Measurement, Physics and System Modeling

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Publisher. Springer, Smart and Sustainable Collaborative Networks 4.0. PRO-VE 2021, IFIP Advances in Information and Communication Technology

Date of Publication. 25 November 2021

Reference. Cerabona et al., 2021b

Online Access. [Atomic Supply Chain Modelling for Risk Management based on SCOR](#)

As part of the PoD approach, the SCOR framework will be used to try to address its many challenges, including finding a way to formalise force typologies and seeking a way to estimate variations in the mass of a supply chain. To do this, our idea is to seek to reduce the domain of study, *i.e.* to fragment a supply chain into a network of standard elementary modules called “atoms”. This work in progress is the subject of a first publication, Cerabona et al. (2021b), which lays the foundations of our “atomistic” vision of the supply chain, the main idea of which proposes, in the same way as the work presented previously, to rely on and take advantage of the benefits offered by the SCOR framework to propose modular and reconfigurable simulation models for supply chains. Simulation models by brick, whose assembly and setup will allow the reconstruction of any logistics network. As the PoD approach is very recent and its application to

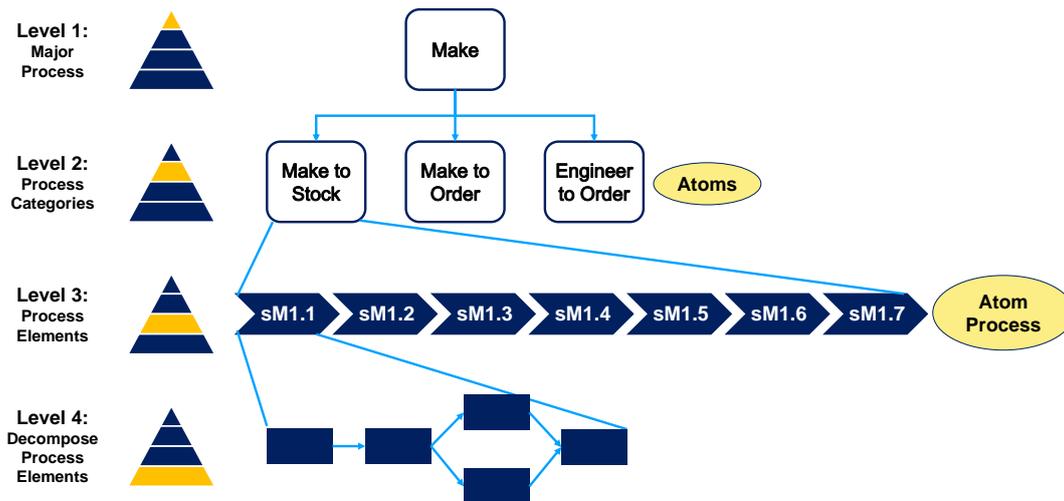


Figure 4.2 – Positioning of supply chain atoms in the SCOR framework (adapted from Cerabona et al., 2021b)

the management of potentialities impacting supply chains even more so, relying on the SCOR model to build and validate its future developments also allows to further legitimise its future results. Indeed, SCOR is a widely studied and recognised model in research and industry (Long, 2014).

The SCOR framework will thus serve as a basis for identifying the “atoms” of a supply chain. Cerabona et al. (2021b) propose to create them from the 32 processes of *Level 2* of the SCOR model (shown in Table B.2). In the first version currently under development, only the processes derived from the *Source*, *Make* and *Delivery* macro processes will be considered. Each atom must fulfil a main function of the supply chain, thus carrying out actions corresponding to the standard elements identified and defined by the *Level 3* processes of the SCOR framework (Cerabona et al., 2021b). Figure 4.2 positions our vision of the supply chain “atoms” in relation to the four-level hierarchical framework of the SCOR model.

Basically, its division into four hierarchical levels of processes tends to make discrete event simulation the preferred technique for modelling the SCOR framework and thus the atoms. Indeed, there are many works in the literature on *discrete event simulation* based on the SCOR model (Long 2014). However, this simulation technique (as discussed in Appendix C) has some limitations: the representation of a system at a global level, the difficulty in modelling large systems, the high data requirement and the difficulty in validating the developed models (Ben Jbara, 2018; Tako et al., 2012). Thus, in order to overcome these limitations and to offer a model with a high level of aggregation requiring little data and offering the possibility to evolve its behaviour during execution, our first developments turn to the creation of atoms based on a *system dynamics simulation* model. Furthermore, the use of *system dynamics simulation* as a black box to link the description and performance spaces will also allow us to study the contributions of modelling the relations between these two spaces in the form of differential equations.

In order to fully benefit from this atomic vision of supply chains, each atom must be as configurable as possible, *i.e.* its elementary attributes must be standard, covering and

adaptable to the supply chain under consideration, its potentialities and the decisions taken by its managers (Cerabona et al., 2021b). Each atom will then be associated with a description space (built from its elementary attributes) and a performance space (built from its elementary KPIs), which will be specific to it. Constructing such a performance space requires determining the elementary KPIs of an atom. SCOR, through its definition of standard metrics (for each of the defined hierarchical levels), seems to offer an excellent reference model for determining these KPIs. Indeed, thanks to its hierarchical decomposition of the metrics (see Appendix B for more details) and its proposal of a supply chain performance evaluation by root cause analysis (Cerabona et al., 2021b), SCOR is positioned as a very interesting method to measure the global performance of a supply chain built from the assembly of its different atoms (the proposed simulation bricks) according to its own arrangement.

However, when analysing in detail the SCOR model in its *Version 12* (APICS, 2017), there seems to be a gap between its desire to measure and analyse the performance of supply chains by root causes and the measures it proposes. Indeed, few mathematical aggregation formulas are proposed to link and express the KPIs of higher levels with those of lower levels. For example, in the case of the *performance attribute Reliability* only 22% of the *Level 3* metrics are considered for root cause analysis and to explain the deviations of the *Level 2* metrics. This raises the question of the usefulness of the 46 *Level 3* metrics that are not “used”. According to Beamon (1998), “an important component in supply chain design and analysis is the establishment of appropriate performance measures”. Thus the SCOR model is mainly used as “a performance process mapping tool, while the performance metrics were not highlighted about how much they affect the performance of a supply chain and the application of such decision support tool” (Yildiz et al., 2020). These last two points are fundamental for the applicability of the PoD approach and the definition of a decision space (the performance space transposed into virtual reality prototype environments). Indeed, “one of the major problems of the industries is to monitor their attributes and performance, to gather useful information in order to make a proper and prompt decision” (Yildiz et al., 2020). Thus, in order to make the decision space a comprehensive performance measurement system, a significant amount of work on the evaluation of supply chain performance will have to be carried out.

A first analysis of the literature (illustrated in Figure 4.3), through the following query (carried out on 15 December 2021): *((organisation* OR enterprise* OR organisation* OR enterprise* OR "logistics" OR "supply chain*" OR "cold chain*" OR process*) NEAR/2 performance*) AND ((indicator* OR (performance* NEAR/2 (assess* OR evaluate* OR measure* OR metric* OR expression* OR formula*)) NEAR/2 (aggregat* OR gather* OR typology OR typologies OR classification* OR taxonomy OR taxonomies OR metamodel* OR meta-model* OR ontology OR ontologies))*, confirms this observation. Out of the 98 papers analysed, 49% of them list the KPIs to be measured and only 9.2% propose formulas for calculating the selected indicators. This initial analysis of the literature highlights numerous methods for aggregating KPIs, but the majority of them focus only on the scale of a company, with only one article proposing aggregation methods based on the structure of a supply chain network.

This section thus lays the foundations for our current work aimed at creating a simulation model that can be reconfigured according to the different logistics network configurations

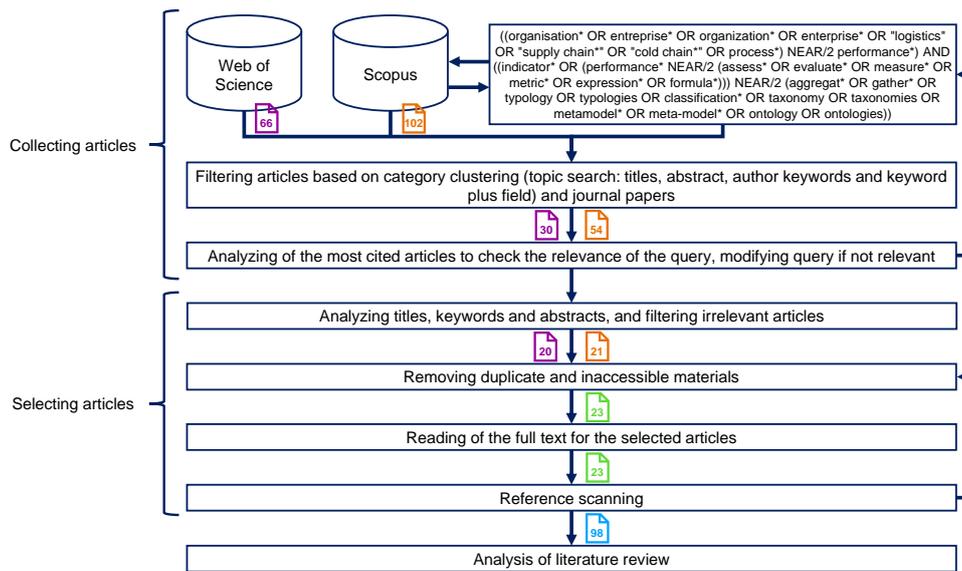


Figure 4.3 – Illustration of the literature review methodology followed in the case of the performance review

studied and that is capable of generating the evolution of performance according to different granularities and decision-making levels.

Application of the PoD approach to the management of US polling stations

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Physics of Decision: application to polling place risk managements

Abstract. Managing a system involves defining, assessing and trying to reach objectives. Objectives are often measured using Key Performance Indicators (KPIs). In the context of instability (crisis, global pandemic or just everyday uncertainty), managers have to adapt to multi-dimensional complex situations. This article introduces an innovative approach of risk and opportunity management to help managers in their decision-making processes. This approach enables managers to deal with the considered system's performance trajectory by viewing and assessing the impact of potentialities (risks and opportunities). Potentiality impacts are designed by forces, modifying the system's performance trajectory and its position within its multi-dimensional KPI framework. This approach is illustrated by an application to polling place risk management. This paper presents the results of simulations of a such place confronting pre-identified risks within a KPI framework.

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Publisher. IEEE, 2021 Winter Simulation Conference

Date of Publication. 23 February 2022

Reference. Cerabona et al., 2021a

Online Access. [Physics of Decision: application to polling place risk management](#)

In order to provide a first illustration of the PoD approach, this Appendix takes up and extends the work presented in the article (Cerabona et al., 2021a). This work was carried out as part of the Safe and Secure Election Project (initiated and led by professors at the University of Georgia Institute of Technology). The work presented is limited to the study of the McCamish Pavilion, the basketball arena of the Georgia Institute of Technology (Atlanta, USA), which was converted into a polling station for the November 2020 presidential elections. Polling stations play a crucial role in today's electoral systems. They are the guarantors of the smooth running of the various elections, whether in terms of efficiency, security or integrity. Their presence, for decades in electoral systems, tends to make us think that their management is mastered. However, certain elections, such as the June 2020 primary in the Georgia state, prove the contrary, with queues lasting several hours (Fowler, 2020). In this study, the contributions of the PoD approach are explored by applying it to the management of potentialities (risks and opportunities) of polling stations, in particular to measure their capacity to operate in a risky environment: such as equipment breakdowns, a health crisis context and cyber-attacks for example.

A.1 A first illustration of the three chains

Let us use this case study to illustrate, first, the causal, propagation and decision chains introduced in Chapter 1 and illustrated in Figure 1.3, in the case of a fraud risk using malware. Its effect is to change a certain percentage of ballots for candidate A into ballots for candidate B.

Causal chain. Consider the McCamish Pavilion polling station as a system, being located in Georgia, the equipment used to allow voters to seize their ballot is the BMD (Ballot Marking Device). This device does not record or tally the voters' choices, at the end of the computer entry through its touch screen, a paper ballot is printed. Some of these devices produce printouts with barcodes or QR codes in place of "traditional" paper ballots, making it impossible for voters to verify the ballots and thus giving hackers the opportunity to rewrite the ballots in an undetectable way (Cohn, 2018). The BMD, like any computer, is susceptible to being hacked by hackers (*potentiality*). This terrible observation is highlighted by the *2019 DEF CON Voting Machine Hacking Village report*, which notes that it is possible to "compromising every one of the devices in the room in ways that could alter stored vote tallies, change ballots displayed to voters, or alter the internal software that controls the machines" (Blaze et al., 2019). Since 2017, DEF CON (one of the leading information security conferences) has been organising a gathering of "ethical hackers" (*Voting Village* events), who study the vulnerabilities of electoral devices and propose solutions to strengthen them (Daily FEI, 2020).

During the election period, a lack of human resources (volunteers) to monitor voters inside the polling station (*condition*), combined with delays in the maintenance schedules of the BMDs (making these devices even more vulnerable to hacking), allowed hackers to infect several BMDs.

Propagation chain. In addition to changing the election results, this potential backlash will also change the system, adding corrupted equipment, which is likely to be reused for other elections, the virus may not be discovered and thus corrupt the next elections as well, or even corrupt other polling stations.

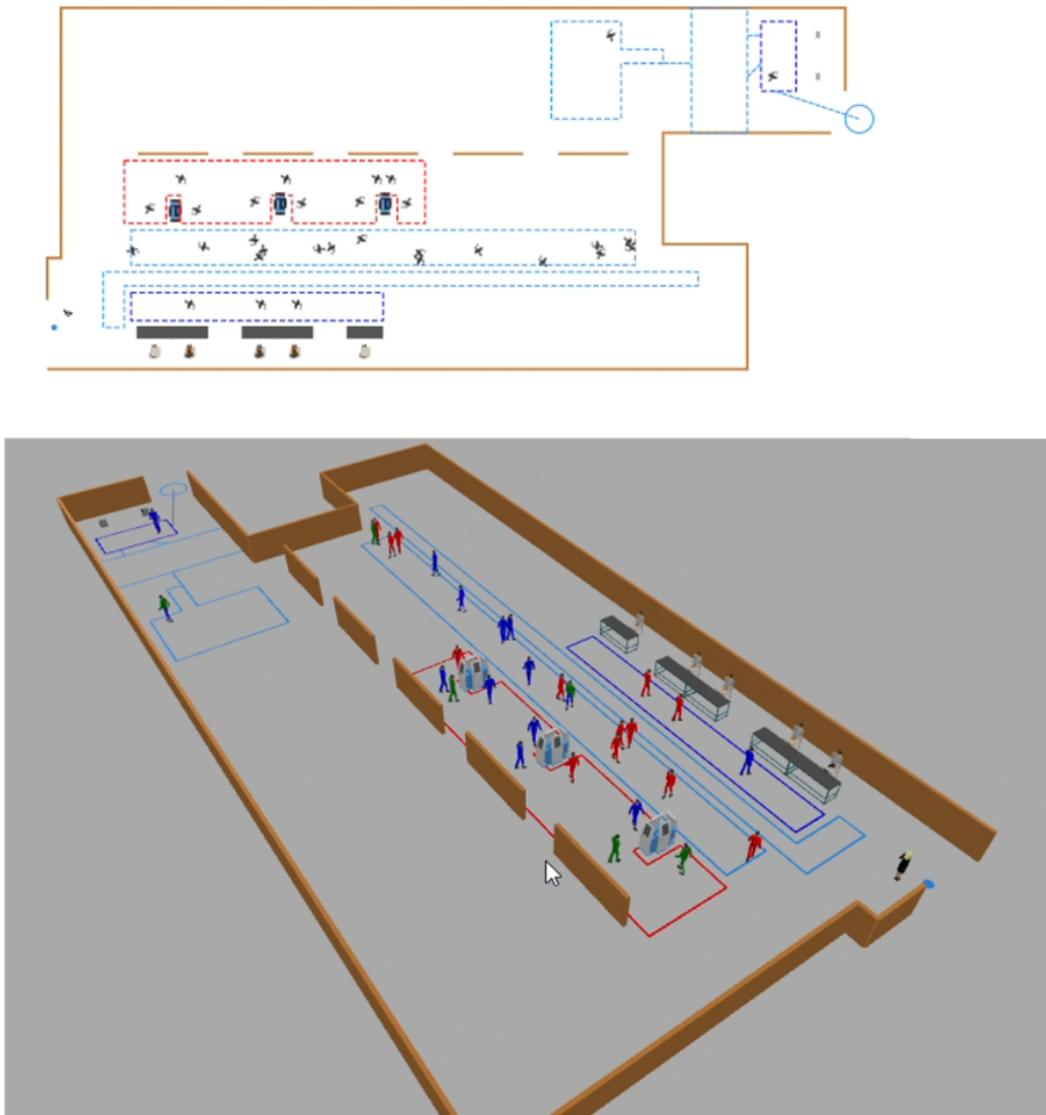


Figure A.1 – Dynamic layout for visual management of polling stations

Decision chain. Alerted to this danger, polling station officials could decide to implement measures to isolate BMDs with too many returns from voters who have identified errors on their ballots (as is currently done) or to implement a series of tests to be carried out at random times to check the integrity of the equipment used.

A.2 A simulation model to model the voting process

In this study, these three chains are represented as various events (called “disruptive scenarios” in the paper) and are modelled using a simulation model developed on the AnyLogic© simulation software, using discrete event and agent-based techniques (more information on these simulation techniques in Appendix C). This simulation model was mainly used to generate the data for the studied disruptive scenarios and the application of the PoD approach. The scenarios studied examine the impact of a massive influx

of voters into this polling station, failures of the main equipment used and attempted fraud. These scenarios will be used to stress the McCamish Pavilion polling station and the voting process (described in Cerabona et al., 2021a). The process of ballot review by voters is also modelled. Indeed, this is a process that should not be neglected (especially when studying risks related to fraud or cyber-attacks), as shown in the study by Bernhard et al. (2020): only 40% of voters check their ballots, of which only 6.6% report an error if they detect one.

In addition to its ability to generate data, the simulation model also offers the possibility of real-time monitoring of the functioning of the polling station (based on the dynamic layout generation, illustrated in Figure A.1), allowing in particular to follow its level of occupancy, which offers an interesting study opportunity in the framework of elections during a health crisis (the Covid-19).

A.3 Application of the Physics of Decision approach: first experiments and results

The description space is built from the *attributes* of the system under study, *i.e.* the parameters of the polling station (number of resources, capacity of the building in terms of capacity, etc.) and of the voters (speed, voting intentions, etc.), the different service times for each piece of equipment, as well as the different flows of voters are used as contextual elements (*characteristics*). The performance space is built from many KPIs, such as: voting time, number of voters waiting inside the voting area, number of votes cast, resource utilisation or so-called “omniscient” indicators offered by the simulation to assess the trust that can be placed in the voting process under study (thanks to the simulation, it is possible to have access to the “god’s” point of view and thus know everything about the voters’ votes, including their voting intentions and for which candidate they actually voted). In order to visualise the performance space (limiting it to three dimensions), the selected KPIs (*i.e.* the dimensions of the performance space) are: the average voting time, the number of voters waiting inside the voting area, and the “trust” indicator (which captures the gap between voting intentions and actual voting, by measuring the number of “actual” votes for a candidate against the number of “expected” votes).

The scenarios studied are used to generate the different forces, the *inflicted* forces are generated from scenarios modelling voter behaviour (the flow and behaviour of voters) or fraud (the type of equipment hacked), while the *managed* forces are generated from scenarios aiming at improving the capabilities of the polling station (the addition of new equipment). The PoD approach proposes to study three different types of performance trajectories. The first trajectory to be observed is the *inertia trajectory*, obtained by measuring the natural evolution of the system’s performance (when it is not subjected to any unanticipated potentiality). As mentioned in Chapter 1, this trajectory is considered as the reference trajectory for the study of potentialities (any deviation from this trajectory is considered as resulting from a potentiality and can be modelled by a force).

The *passive trajectory* represents the evolution of the system’s performance when subjected to a disturbance and without any measures put in place by the system’s managers. It combines both the force of inertia of the system and the force due to the

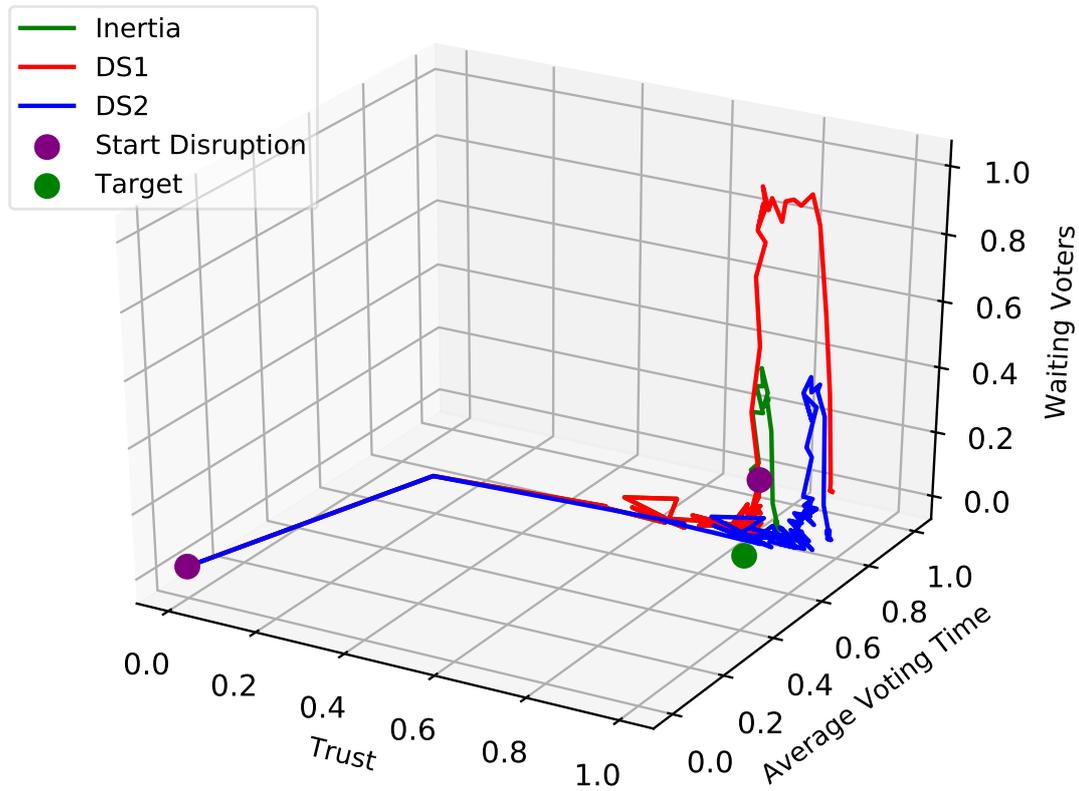


Figure A.2 – Performance trajectories

disturbance, which can be internal to the system or from its environment. In this study, the McCamish Pavilion voting centre is stressed by two disruptive scenarios (DS). The *DS1* scenario disrupts the system with the failure of three BMDs. *DS2* represents the hacking of all BMDs in the polling station. The installed malware turns 10% of the ballots for candidate A into ballots for candidate B. In this study, 50% of the voters intend to vote for candidate A, 45% for candidate B and the remaining 5% for the other candidates.

The *active trajectory* represents the evolution of the system's performance when it faces disturbances and when specific measures are put in place by the system's managers to reduce the consequences of the disturbances. It therefore combines both the changes in performance measured by the passive trajectory and the changes due to the forces resulting from these measures.

The study proposed in this appendix focuses mainly on the study of the first two types of performance trajectories proposed by the PoD approach (inertia and passive). Figure A.2 shows a representation of the inertia trajectory and the two passive trajectories considered in the performance framework composed of the three KPIs described above (the same type of visualisation and representation can be made for the active trajectories).

Table A.1 summarises all the information for the two scenarios studied. This study assumes that the forces occur instantaneously (at the times specified in Table A.1), no work on the occurrence of the two forces generated by these two disturbances will be carried out.

Table A.1 – Descriptions of the scenarios studied (adapted from Cerabona et al., 2021a)

Name	Short description	Force pattern	Force onset time and duration
DS1	Three BMDs down	Punching	From 5 pm to 9:30 pm (from t=600 to t=870)
DS2	Malware attack on all BMDs, changing 10% of Party A's votes to Party B's votes	Punching	From 7 am to 9:30 pm (from t=0 to t=870)

As the selected KPIs have different dimensions, to ensure that their deviations and variations can be compared, the values obtained for each of the scenarios carried out have been normalised (to have values between [0,1]) using the following formula: $KPI_{norm} = \frac{KPI - KPI_{min}}{KPI_{max} - KPI_{min}}$. Based on this normalisation formula and the definitions of the three measured KPIs, the target area (presented in section 1.3.2) is modelled as a point in the performance space of the McCamish Pavilion voting centre with coordinates (0.89, 0.62, 0), corresponding to a value of 1 for the trust indicator, an average voting time of 15 minutes and no people waiting in the voting centre.

The objective of the PoD approach is to be able to model the significant forces, namely: (1) the *perturbation force* (the forces generated by the disturbances) and (2) the *compensation force* (the force generated by the corrective action). To do this, the PoD approach relies on two strong assumptions: (1) neglecting the mass of the system and (2) the summability of the forces. These two assumptions are related to *Newton's second law*, which defines a simple relationship between the acceleration of an object of mass m and the resultant of the forces acting on this object: $\vec{F}_{net} = m\vec{a}$. Neglecting the mass of the system (considering it to be constant over time) allows the resultant of the forces applied to the system under study to be approximated by its overall acceleration with a constant proportionality factor, which will be neglected in this study. On the basis of these assumptions, the forces sought will be estimated from different local accelerations, measured by equation (2.2) of Chapter 2, for a measurement carried out every ten minutes from the beginning of the opening of the polling station (corresponding to t=0, i.e. 7am on 3 November 2020). Thus, in order to be able to estimate the disturbance and compensation forces, three accelerations have to be calculated. First, as for the different trajectories, the first acceleration to be obtained is the reference acceleration, corresponding to the *inertial acceleration* (the local acceleration of the inertia trajectory). The two other accelerations are none other than those associated with the significant forces: (1) the *perturbation acceleration* obtained by calculating the difference between the local acceleration of the passive trajectory and the inertial acceleration, and (2) the compensation acceleration obtained on the same principle, by calculating the difference between the local acceleration of the active trajectory and the perturbation acceleration.

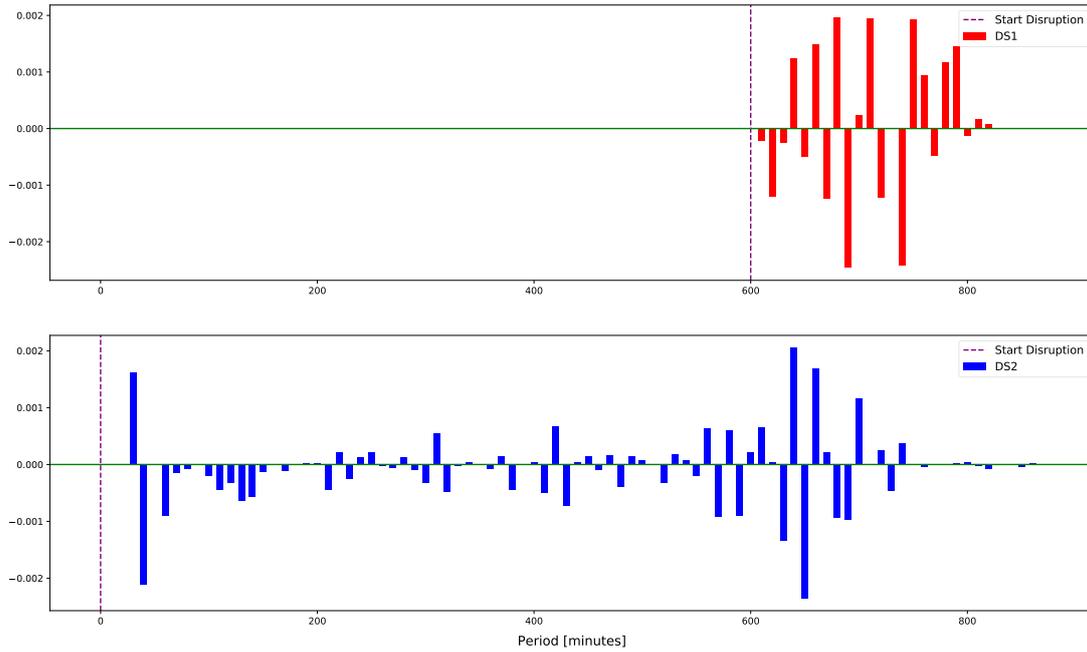


Figure A.3 – Approximation of the resulting forces

In this study, the *perturbation accelerations* were calculated by 3D vectors of the considered performance space (the same type of reasoning applies for the *compensation accelerations*). In order to evaluate the impact of each potentiality, it is important to consider these two elements: (1) the force intensity (approximated by the norm of the different acceleration vectors) and (2) the force contribution (its direction). The contribution of the force is equivalent to determining its direction, *i.e.* whether the force pushes or pulls the system away from its performance objectives. The contribution will be approximated by calculating the scalar product of the acceleration vector (perturbation or compensation acceleration) with the vector relating the position of the system at time t in its performance space and the position of the target zone (in this study the target point). The sign of the scalar product between these two vectors will determine whether the potentiality is a risk (negative sign) or an opportunity (positive sign). In addition to its sign, the scalar product will also provide a value for the cosine of the angle between these two vectors, the product of which with the intensity of the force gives the *resultant force* with respect to the target, *i.e.* the actual impact of the potentiality on the performance trajectory of the system. Figure A.3 illustrates this notion of *resultant force* for the two scenarios studied.

The analysis of the values obtained shows several aspects:

- No weights were used to privilege one KPI over the others, so at certain points *DS2* seems to be impacting and distancing the system as much as *DS1*. However, according to Figure A.3, *DS2* mainly disturbs the system on the trust indicator, while *DS1* impacts the average voting time and the number of voters helping in the voting centre.
- The impact of *DS1* is significant, as it occurs during the period of maximum voter turnout. The force generated by this disturbance tends to bring the system closer

to its target at certain times, which can be explained by the fact that at the end of the simulation the values of the trust indicator tend to be closer to its target value (the same observation applies to *DS2*). Thus two conclusions can be drawn: (1) the way in which the trust indicator is calculated should certainly be reviewed and (2) it is not appropriate for this type of disturbance and tends to bias the interpretations related to this disturbance. Finding (2) highlights the fact that the performance space is actually a rather subjective space. In order to be able to provide optimal decision support, work on the relevance and selection of the **KPIs** to be observed according to the type of potentialities studied should be carried out.

The results obtained on use cases illustrate the interest of the **PoD** contribution and of the study of the movement of the performance trajectories of a system as a support for decision making.

The Supply Chain Operations Reference (SCOR) model

In order to describe the SCOR framework, this appendix takes up and extends the literature review proposed in the article Cerabona et al. (2021b).

Atomic Supply Chain Modelling for Risk Management based on SCOR

Abstract. At the time of instability becomes the norm (climate changes, natural disasters, epidemic, etc.) the management of collaborative networks, such as supply chains, is becoming more and more complex and critical. This instability only adds to the complexity of an already very complex system. Thus, supply chain managers have to adapt to multi-dimensional complex situations. Dealing with instability is a key expectation for these managers. One tool to help managers make decisions in this unstable environment is simulation. This article introduces some first results on an “atomic” reconfigurable supply chain simulation model based on Supply Chain Operations Reference (SCOR) model. This simulation tool will be used to apply an innovative physics-based approach of risk and opportunity management, that designs disturbances by forces moving the considered supply chain within its performance framework. This approach enables managers to monitor supply chain’s performance trajectory by viewing and merging the impact of risks and opportunities.

Keywords. SCOR, Supply Chain Management, Risk Management, Performance Measurement, Physics and System Modeling

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Publisher. Springer, Smart and Sustainable Collaborative Networks 4.0. PRO-VE 2021, IFIP Advances in Information and Communication Technology

Date of Publication. 25 November 2021

Reference. Cerabona et al., 2021b

Online Access. [Atomic Supply Chain Modelling for Risk Management based on SCOR](#)

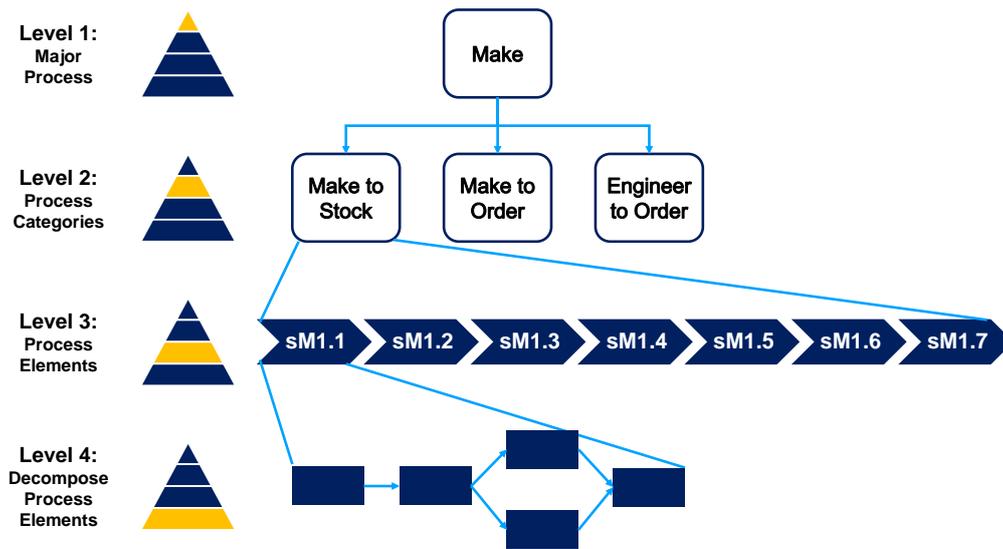


Figure B.1 – Hierarchical organisation of the SCOR model processes (adapted from Cerabona et al., 2021b)

The SCOR model is a reference model for improving supply chain processes and performance. It provides a methodology, standard process definitions, metrics, diagnostic tools, best practices and benchmarking tools to enable comparative assessments between different supply chains using this model (APICS, 2017). This model developed by APICS has been constantly reviewed and updated since its creation in 1996, in order to consider the evolution of practitioners’ needs, the evolution of research on supply chain management, but also changes in supply chain business practices (all the information in this appendix corresponds to the *SCOR model version 12*). SCOR consists mainly of three parts: a modelling tool that uses standardised processes as building blocks, a set of performance indicators (called *metrics*) and a benchmarking tool (Persson et al., 2009).

The first part of the SCOR model proposes a modelling tool that divides the supply chain processes into different standard blocks divided into four hierarchical levels, illustrated by Figure B.1 for the manufacturing macro process in the case of a *Make to Stock* business. The assembly of these blocks allows the modelling of all the processes (identified and defined by SCOR) of a supply chain.

Level 1 is the level of definition of the overall supply chain operations. It is broken down into six macro processes: *Source*, *Make*, *Deliver*, *Return*, *Plan* and *Enable* (APICS, 2017), defined in Table B.1. The macro processes *Source*, *Make*, *Deliver* and *Return* focus primarily on the flow of goods and information. The *Plan* process coordinates the previous four processes to meet the company’s objectives and customers’ expectations. To do this, this process supports the evaluation of suppliers, the aggregation and prioritisation of customer demand, and the planning of inventory, production and raw material requirements (Long, 2014). It thus seeks to plan the gross capacity of each product stream. The *Enable* process serves as a support process for the other five macro-processes, providing different supply chain management techniques (APICS, 2017). The *Source* process contains all the actions that enable the sourcing of components (raw materials) needed to make goods or services to meet customer demand, *i.e.* purchasing,

Table B.1 – Definition of the macro processes of the SCOR model (adapted from Cerabona et al., 2021b)

Macro Process	Definition
Plan	Seeks to balance demand with the supply of products and resources available in other processes (<i>Source, Make, Deliver, Return</i>), developing actions that are consistent with the company’s objectives and customers’ needs (Huang et al., 2005; Long, 2014).
Source	“Contains processes that procure goods and services to meet planned or actual demand” (Huang et al., 2005).
Make	Describes all the activities involved in transforming the various components exchanged in a supply chain into finished products.
Deliver	Consists of processes that distribute finished products or services that meet the expected or actual needs of customers (Persson et al., 2012).
Return	Handles activities related to the flow of defective products.
Enable	Describes all supporting processes dedicated to supply chain management (APICS, 2017).

receiving, inspection, storage, payment authorisation (Long, 2014). The *Make* process contains the activities to transform all the components circulating in the supply chains and necessary for the production of finished products, *i.e.* requesting and receiving materials, manufacturing, testing, quality control, packaging, storage (Long, 2014). The *Deliver* process contains all the activities related to the transport and distribution of products, to meet customer demand (Persson et al., 2012). The *Return* process manages actions related to the flow of defective products, both products returned to suppliers or by customers (Long, 2014).

Level 2 breaks down the macro processes of the level into process categories according to the management mode and strategies of the supply chain being modelled, *i.e.* make-to-stock (MTS), make-to-order (MTO) and engineer-to-order (ETO). For this level, the SCOR model proposes a toolbox of 32 process categories (described in Table B.2), to provide more detail, simplify and be able to model and configure any type of supply chain (Cerabona et al., 2021b).

Level 3 divides *Level 2* processes into generic and standard process elements, representing and describing a step or action in each of the *Level 2* process categories. Each of these elements has an identifier, a name, a standard definition, a list of input and output flows (the information exchanged with the other elements), performance indicators and good practices (Long, 2014). This inter-process breakdown by process brick allows, once assembled and executed according to a scheme predefined by SCOR, to carry out all the macro-processes defined previously, *i.e.* to plan the supply chain activities allowing to

Table B.2 – Level 2 processes of the SCOR model (adapted from APICS, 2017)

Macro Process	Rating	Level 2 processes
Plan	sP1	Supply Chain Plan
	sP2	Plan Source
	sP3	Plan Make
	sP4	Plan Deliver
	sP5	Plan Return
Source	sS1	Source Stocked Product
	sS2	Source Make-to-Order Product
	sS3	Source Engineer-to-Order Product
Make	sM1	Make-to-Stock
	sM2	Make-to-Order
	sM3	Engineer-to-Order
Deliver	sD1	Deliver Stocked Product
	sD2	Deliver Make-to-Order Product
	sD3	Deliver Engineer-to-Order Product
	sD4	Deliver Retail Product
Return	sSR1	Source Return Defective Product
	sDR1	Deliver Return Defective Product
	sSR2	Source Return MRO (Maintenance/Repair/Overhaul) Product
	sDR2	Deliver Return MRO Product
	sSR3	Source Return Excess Product
	sDR3	Deliver Return Excess Product
Enable	sE1	Manage Supply Chain Business Rules
	sE2	Manage Supply Chain Performance
	sE3	Manage Data and Information
	sE4	Manage Supply Chain Human Resources
	sE5	Manage Supply Chain Assets
	sE6	Manage Supply Chain Contracts
	sE7	Manage Supply Chain Network
	sE8	Manage Regulatory Compliance
	sE9	Manage Supply Chain Risk
	sE10	Manage Supply Chain Procurement
	sE11	Manage Supply Chain Technology

source materials, manufacture products, deliver goods or services and manage product returns (Cerabona et al., 2021b). *Level 4* is the implementation level, each process element of *Level 3* is detailed according to the tasks (activities and practices) specific to each organisation and therefore outside the boundaries of the framework proposed by the SCOR model (Ben Jbara, 2018; Long, 2014).

The second part of the SCOR model focuses on the evaluation of supply chain performance, defining different levels of performance indicators called *metrics* in this framework. The model proposes to assess the performance of a supply chain according to three elements: *performance attributes, key performance indicators and best practices* (APICS, 2017). The *performance attributes* are used to assess the strategic characteristics of supply chain performance, which must be aligned with the company's strategy in order to achieve its objectives. The SCOR model has five performance attributes (defined in Table B.3), which are divided into two categories: (1) customer-focused attributes (*reliability, responsiveness and agility*) and (2) attributes focused on the company's internal performance (*costs and assets*). Each performance attribute is associated with several KPIs (called *metrics*). The *metrics* follow the same decomposition into a hierarchical structure as the processes, *i.e.* at each level (*Level 1, 2 or 3*) a *metric* is associated to evaluate the process (Cerabona et al., 2021b). This hierarchical decomposition of the *metrics* allows an analysis of the supply chain performance according to the root causes (Cerabona et al., 2021b), *i.e.* the performance gaps observed in the metrics associated with the *Level 1* process can be explained by the analysis of the performance of the *metrics* associated with the *Level 2* processes that make up the processes of the higher level. Each process is associated with a list of best practices to improve the metrics and thus the performance of the supply chain (Persson et al., 2009).

The third part of the SCOR model proposes a benchmarking tool that allows companies and supply chains to compare themselves to each other, by comparing their KPIs and practices. This part, although of great interest, will not be developed further in this appendix, as it does not support the work presented in this manuscript.

The SCOR model links all the elements developed in these three parts (*i.e. standard processes, metrics and best practices*) in a single framework (APICS, 2017). This framework provides a balanced horizontal (*inter-process*) and vertical (*hierarchical*) view compared to traditional process decomposition models (Huang et al., 2005), dedicated to handling a specific configuration of process elements. It is designed to be (re)/configurable (Huang et al., 2005), thanks to the standard processes developed and their hierarchy. The objective of this process structuring is to improve and support the understanding of all supply chain processes, in particular by providing a common terminology and vocabulary (definitions, metrics and process elements), thus enabling all actors to speak the same language, thus greatly improving communication (Huang et al., 2005). It therefore provides a methodology where the documentation developed can be used as a guide to improve a company's supply chain (Persson et al., 2009), including its overall management and performance.

With the proposed inter-process and hierarchical view (Huang et al., 2005), SCOR describes, measures and evaluates the configurations of any supply chain. This decomposition into complementary modules, then, allows this model to be used to describe and model both simple and very complex supply chains.

Table B.3 – Definitions of the SCOR model performance attributes (adapted from APICS, 2017)

Performance Attribute	Definition
Reliability	Ability to achieve tasks as expected and focuses on predicting the result of a process.
Responsiveness	Speed of completion of a task.
Agility	Ability to respond to external disturbances, the capacity and speed of change.
Costs	Running costs of the supply chain process (it includes labour costs, material costs, and transportation costs).
Assets	Ability to use assets efficiently. In the supply chain, asset management strategies include inventory reduction and in-sourcing <i>vs.</i> outsourcing, for example.

Description of the three major simulation techniques

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C.2	Agent-based simulation	153
C.3	Discrete event simulation	154

The processes of a supply chain and its risk dynamics can be reproduced using three major simulation techniques: *system dynamics*, *agent-based* and *discrete event* (Kilubi, 2016), presented in this Appendix. These techniques have been well proven in several studies seeking to assess the impacts of risks and test different scenarios (J. B. Oliveira et al., 2019). Table C.1 summarises and provides a comparison of these three techniques according to the different properties highlighted in each of the descriptions provided below.

Table C.1 – Comparison of the three major simulation techniques (adapted from Ben Jbara, 2018)

Properties	System dynamics	Agent-based	Discrete event
Decision-making	Strategic	All levels	Tactical, operational
Aggregation	High	Medium	Low
Simulation	Continuous	Continuous, discrete	Discrete
Temporal mechanisms	Time step	Time step, next event	Next event
Data requirements	Low	Medium	High
Building behaviour change	Yes	Yes	No
Modelling approach	Top-down	Bottom-up	Bottom-up
Maturity	Mature	Needs development	Mature

C.1 System dynamics simulation

System dynamics is a modelling approach whose foundations were laid in the work of Jay Forrester (Forrester, 1961) on “industrial dynamics” (Heath et al., 2011). It was not until the 1990s that this modelling technique began to be widely used (Heath et al., 2011). System dynamics is a modelling approach that aims to analyse complex and dynamic systems, predicting their behaviour in order to support decision making (Lasch, 2018; C. Li et al., 2016). The system dynamics approach is considered an appropriate approach when used to support strategic decisions (Tako et al., 2012). System dynamics is based on a fundamental principle that implies that the structure of any real-world system determines its behaviour over time (Forrester, 1961; Heath et al., 2011; Lasch, 2018; Sterman, 2000). It therefore seeks to explain how the different components of a system (its structure, its state variables, and its action and decision times) are related and interact to influence its behaviour and performance (Ben Jbara, 2018; Heath et al., 2011). The evolution of a system’s behaviour can be surprising and counter-intuitive, and it is only by analysing the interactions between its components that this evolution can be understood and explained (Heath et al., 2011).

According to this approach, the components of a system interact with each other through delayed causal relationships and feedback (Lasch, 2018; Sterman, 2000). Models built from this simulation technique have multiple causal loops that can either balance or reinforce the variations and interactions between variables (Lasch, 2018). These relationships between variables are modelled as feedback loops, which are building blocks related to stocks and flows (Ben Jbara, 2018). Stocks model the accumulation of a “resource” (Law, 2013). Flows model a flow of a resource to or from a stock (Law, 2013). Stocks and flows serve as a basic representation of system structure, measuring the accumulation and dissipation of materials or information contained in a block stock over a period of time (Ben Jbara, 2018).

Mathematically, the relationships between the system dynamics modelling elements (stocks and flows) are described in the form of differential equations, representing the rates of change in the level of each stock (Heath et al., 2011; Lasch, 2018; Law, 2013). The use of differential equations to model the rates of change of state variables as a function of time makes system dynamics a so-called continuous simulation technique (Law, 2013), with changes in state being continuous and approximated over small time steps of equal length (Tako et al., 2012). Simulation models developed in this way typically consist of system-level state variables (usually representing aggregate information about the population(s) being modelled, making it a deterministic simulation model), their differential equations represent how the state variables depend on each other and change over time (Heath et al., 2011).

System dynamics has some advantages in the analysis and design of simulation models of supply chains with non-linear behaviour (Ben Jbara, 2018). Its advantages are due to the small amount of data that system dynamics requires to model a system, the ease of building a simulation model and the reduction in runtime (Tako et al., 2012).

System dynamics has been applied in many fields, such as supply chain management, biological and medical modelling, theory development in the natural and social sciences, etc. (Lasch, 2018). In the case of supply chain management, system dynamics has mainly been used to deal with inventory planning and management, bullwhip effect, evaluation of decisions at a strategic level and information sharing between actors in

a supply chain (C. Li et al., 2016; Tako et al., 2012). In the case of risk management, most approaches using this simulation technique apply a “what if” analysis, where the consequences of a specific risk and its impact on the behaviour of the modelled system are studied (Lasch, 2018). Thus, these simulation models focus mainly on the impact of the risk, but are of course able to correctly represent the interdependencies and the propagation of the impact of the studied risk (Lasch, 2018).

C.2 Agent-based simulation

Agent-based simulation is a powerful, relatively recent technique that gained attention in the 1990s with the work of Epstein et al. (1996) in their book *Growing Artificial Societies* (Ben Jbara, 2018). It is widely used to model complex systems (social, economic, ecological, etc.) from a set of agents and relationships (Ben Jbara, 2018; Heath et al., 2011; Lasch, 2018). By representing agents with their individual characteristics (attributes and state variables) and behaviours across an entire population, it is possible to consider and study how agent diversity affects the behaviour of a system as a whole and its evolution over time (Heath et al., 2011).

There is no consensus on the definition of an agent (Heath et al., 2011; Law, 2013), however, modelling an agent requires following some essential characteristics, especially to differentiate it from an ordinary object (Heath et al., 2011). An agent is a modular entity (*i.e.* it has boundaries, defined by its environment and the system being modelled), autonomous, uniquely identifiable, self-directed and able to sense its environment (Ben Jbara, 2018; Heath et al., 2011; Lasch, 2018; Law, 2013). An agent can operate independently in its interactions with other agents and its environment (Heath et al., 2011). Therefore, the behaviour of agents is described and governed by laws, algorithms of varying complexity and abstraction (Heath et al., 2011). Their behaviour can be modelled by simple deterministic “if-then-else” rules and decision trees, up to the use of complex artificial intelligence techniques (Heath et al., 2011; Lasch, 2018; Law, 2013). It is from these rules and its behaviour that the agent can act autonomously, as they constitute the link between the information captured by the agent and the way it processes it, *i.e.* the decisions it has to make on the basis of the information gathered (Heath et al., 2011). An agent also has an internal state, specified by the set of attributes (state variables) associated with it (Heath et al., 2011). The behaviour of an agent is based on and only on its state, making it a critical element for an agent-based simulation model (Heath et al., 2011). An agent can also learn (allowing it to gain a better understanding of its environment and the state of other agents) and thus adapt its behaviour over time, requiring the creation of a memory function in the agent (Law, 2013). In agent-based simulation, modelling follows a bottom-up approach, focusing on the description of the behaviour and interactions between agents (Law, 2013).

Agent-based simulation is particularly interesting for modelling systems that include entities that interact with each other and with their environment, when it is important that these entities are able to learn and adapt their behaviour (self-organise) to situations (in order to better understand their environment), and when the movement of entities depends on knowledge of the evolution of its environment (Lasch, 2018; Law, 2013). Thus, agent-based simulation has some advantages for modelling and analysing supply chains, due to its main features (Ben Jbara, 2018; Long, 2014; Swaminathan et al., 1998). It is one of the most effective simulation tools for modelling and analysing supply

chains (Long, 2014). Its advantages can be explained by the fact that supply chains consist of a complex and dynamic network of autonomous or semi-autonomous business entities (Fasli et al., 2011; Long, 2014), playing different roles in this network, having to coordinate and exchange information and flows with each other to achieve the desired level of competitiveness (Long, 2014). These entities are geographically dispersed in a heterogeneous environment and have similar characteristics to agents: interaction and perception of the environment, autonomy, responsiveness, and decision-making power (Long, 2014). Thus, the actors in a supply chain network can be represented by an agent or a group of agents, whose exchange of information and goods can be achieved through interactions between agents (Long, 2014). In this way, the process of modelling a supply chain network becomes intuitive, the concepts underlying agent-based simulation are similar to the real elements present in a supply chain (Ben Jbara, 2018; Long, 2014). Agent-based simulation has become an active research topic for supply chain network modelling (Amini et al., 2012; Long, 2014).

However, agent-based simulation has some limitations, notably the lack of tools adaptable to supply chain studies and simulation (Ben Jbara, 2018; Long, 2014), which makes it a time-consuming modelling task (Long, 2014). Furthermore, agent-based simulation requires high computational skills, mainly due to the heavy computations (updating the different agent behaviours at each point in time) that need to be performed for modelling large systems (Ben Jbara, 2018; Sumari et al., 2013). It is also not as powerful as approaches based on process modelling to manage and represent the different flows present in a supply chain (Long, 2014).

C.3 Discrete event simulation

Discrete event simulation is a simulation technique that aims to build models in which the value of state variables changes at discrete time steps (Ben Jbara, 2018; Heath et al., 2011; Law, 2013; Tako et al., 2012), which may be irregular. These time points correspond to the realisation of an event, which is defined as an instantaneous occurrence of the change of one or more variables leading to a change of state of the system (Ben Jbara, 2018; Law, 2013). It thus models the dynamic behaviour of the system as a discrete sequence of events over time (Lasch, 2018). Systems are modelled as a network of queues and activities where state changes occur at discrete times (Tako et al., 2012). Although conceptually, discrete event simulation calculations could be performed manually, the amount of data (manipulated and stored) required to model a real system using this type of simulation method dictates that they be performed digitally (Law, 2013).

Discrete event simulation can also have a process-oriented view (Heath et al., 2011). With this view, discrete event simulation typically consists of describing entities (objects or people) that move through various processes (Heath et al., 2011; Tako et al., 2012), which require different resources and (usually stochastic) execution time. Most commercial software offers this process-oriented view for discrete event simulation (Heath et al., 2011). With this view, entities are typically data containers and have no associated behaviours (Heath et al., 2011). Different attributes are associated with them to determine their treatments throughout the simulation (Tako et al., 2012), *i.e.* rules governing the flow of entities (Heath et al., 2011).

Discrete event simulation has been widely used in many supply chain analysis studies (Long, 2014), mainly to solve problems involving supply chain planning, inventory planning and management, production scheduling and supplier selection (Lasch, 2018; Tako et al., 2012). It has also been used in the context of supply chain risk analysis (Olivares-Aguila et al., 2021). The models built are generally aimed at understanding the functioning of supply chains over time, by comparing their performance under different conditions (Tako et al., 2012). Indeed, discrete event simulation has many advantages for assessing the performance of supply chains. Ben Jbara (2018) identifies three advantages of this simulation technique for this type of analysis. First, it allows the construction of models with a high level of detail if required (Ben Jbara, 2018). Secondly, it allows the representation and modelling of different flows, including the three main flows for a supply chain: financial flow, material flow and information flow. Thirdly, it allows for the analysis of the behaviour of the system in steady state and transient conditions (Ben Jbara, 2018). Discrete event simulation is also very useful for modelling systems in an unstable environment (Stefanovic et al., 2009). Discrete event simulation is therefore a natural approach to model complex supply chains, as the models developed are generally stochastic in nature, with randomness generated by the use of statistical distributions within the different modelling blocks (Tako et al., 2012), thus allowing for the consideration and evaluation of uncertainty in operation and transport times for example (Persson et al., 2012).

It is generally accepted that discrete event simulation is more suitable for modelling problems at tactical and operational decision levels (Tako et al., 2012), thus justifying its great interest in supply chain modelling (Ben Jbara, 2018). However, discrete event simulation has some limitations, with several papers suggesting that it is not suitable for modelling problems at strategic decision levels, as it has limitations in representing systems at a global level (Baines et al., 1999; Oyarbide et al., 2003; Tako et al., 2012). Discrete event simulation also has limitations in modelling large systems, as this simulation technique requires collecting a lot of data on the system being modelled (Ben Jbara, 2018). Moreover, the models developed are difficult to validate (Ben Jbara, 2018).

Description of the Excel input files for the second virtual reality prototype

D.1	Files of probabilities of occurrence of conditions of activation of potentialities	157
D.2	Impact files of potentials on KPIs	158
D.3	Potential description file	158
D.4	Cascading effect file between different activation conditions	159
D.5	Description files of the activation conditions	159

The second version of the virtual reality prototype presented in Chapter 3 takes as input five different types of Excel files:

- The files of the probabilities of occurrence of the conditions of activation of the potentialities,
- The impact files of the potentialities on the KPIs,
- The potentiality description file,
- The cascading effect file between the different activation conditions,
- The description files of the activation conditions.

D.1 Files of probabilities of occurrence of conditions of activation of potentialities

An Excel file for each activation condition of the potentialities, which contains the evolution of the predictions of its probability of occurrence (P_{i,t_i}), with i belonging to the interval $[0, n]$ (n the total number of instants retained over the time range considered for the study of the system). Each file thus contains a square matrix of size (n, n) , as illustrated in Figure 3.10. It is from these files that the virtual reality environment will be able to construct the trajectories of potentialities (materialised by yellow flows, the

layout of which evolves according to the jumps in time made by the user). The fact of having square matrices and not probabilities on a single line (*i.e.* a matrix of size $(1, n)$), makes it possible to refine the predictions made on the evolution of the probabilities of occurrence of the activation conditions, in particular when we approach its maximum range of realisation.

D.2 Impact files of potentials on KPIs

One Excel file per KPI measured and per potentiality studied, *e.g.* if the decision-maker wishes to observe the impact of five potentialities on four KPIs, then twenty such files will be needed. Following the same principle as the previous files, this type of Excel file also contains square matrices of size (n, n) , which provide the decision-maker with the actual impact of each potentiality at any time t_i when they are activated (as shown in Figure 3.12). In these files, the real impact is measured as the difference between the optimal value for each KPI (the performance objectives of the system studied in most cases) and the real values measured following the activation of a potentiality (at each time t_i), obtained for the studies proposed in this manuscript from simulation (in particular from the *Rich Kids* supply chain simulation model, presented in Chapter 2). The sign of the $KPI_{P_{t_i}, t_i}$ is important, if it is negative, then the potentiality moves the system away from its optimal performance trajectory (the white timeline). Conversely, if this value is positive, then the potentiality brings it closer to the white timeline. Thus, the way in which the impact is calculated will depend on whether the KPI is to be maximised or minimised.

From these square matrices of size (n, n) , in which each row corresponds to the activation of the potentiality at time t_i and each column the value of the KPI at each time t_i (as illustrated in Figure 3.12), the virtual environment for constructing the future performance trajectory comes to read the required information at the level of row t_i from column t_i .

D.3 Potential description file

A single Excel file (illustrated in Figure D.1), which is broken down into three blocks:

- The first line contains the absolute maximum impact for all impact files. This value will improve the visual rendering of the different deviations, which are plotted and smoothed by Bézier curves.
- The second row contains the names of the measured KPIs, which are used to label the blue streams.
- From the third line onwards, each line contains the information specific to each potentiality studied: its identifier, its name (for labelling), its short description and the identifiers of its different activation conditions (in order to link the right activation conditions, the orange spheres in this second virtual reality prototype, to the right potentialities).

A	B
	1
Profit,Delay,Quality,Backlogs	
1,Hurricane,Hurricane in the Gulf of Mexico,5	
2,New Customer,Potential skateboard seller from a ski domain ,1	
3,New Board Supplier,Potential wood board supplier,2,4	
4,New Wheel Supplier,Potential wheel supplier,3,5	
5,Strike,Strike at the board supplier,4	

Figure D.1 – Overview of the potentiality’s description file

D.4 Cascading effect file between different activation conditions

An Excel file containing a binary matrix of size (c, p) , where c is the number of activation conditions and p the number of potentialities studied. This matrix allows us to consider the cascading effects between the different potentialities (illustrated by the chain of propagation in Figure 1.3), a value of 1 means that there is a causal link between the potentialities (*i.e.* one potentiality leads to the activation of the condition of another potentiality), conversely a value of 0 implies the absence of a link.

D.5 Description files of the activation conditions

An Excel file per activation condition of the different potentialities studied, which contains the name of the activation condition, a short description and its identifier.

Summary tables of the maturity assessments of the two virtual reality prototypes

Tables E.1, E.2, E.3, and E.4 provide detailed explanations of the scores for each of the Virtual Environment Integration Maturity (VEIM) criteria, obtained from Congès (2022)'s assessment of these two prototypes (when illustrating the applicability of this assessment framework of the maturity of VEs).

Table E.1 – Explanations of the scores attributed to criteria *Immersion* and *Interaction* of the VEIM framework for the first version of the prototype

Criteria	Level	Explanations
Immersion		
Agency	1	It is easy for the user to understand that he/she is responsible for the movements of the objects he/she grabs and the resulting impact (modelled by the deviations of the performance trajectory). However, it is much more difficult for the user to make sense of these deviations, because of the aggregation of all the measured KPIs into a single trajectory.
Sounding	0	There are no sounds in this VE.
Haptic feedback	1	Very limited in this VE, limited to a few vibrations of the joystick.
Handling	2	There are not many objects available, but they can all be manipulated by the user.
Movements	1	This VE is designed to be used sitting or standing. The only movements possible are with the arms to pick up objects (faithfully reproduced) or to move closer to objects.
Emotional involvement	0	This VE is not intended to make the user feel emotions.
Inclusiveness	1	This VE plunges the user into an abstract environment, in which he/she has to make an effort to try to forget the real world, because few of his/her senses are called upon (only sight and a little touch).
Extensiveness	2	This VE is mainly a visual challenge for the user.
Vividness	1	This VE does not attempt to represent a real environment, so it does not have visual realism. However, the proposed trajectory concepts are perfectly faithful to the consequences or probabilities of the modelled events.
Plausibility	0	This VE does not attempt to represent a real environment.
Proprioceptive matching	1	The VE mimics the user's hands and head.
Interaction		
Objects	2	User interaction with objects in the virtual environment has an immediate impact on the performance trajectory of the system.
Scenery	2	In this VE, the user can change the setting and choose from a very limited selection of settings, but easily activated by the user.
Multiplayer	0	This VE is not designed for multiple users at the same time.
Non-player characters	0	This VE does not use non-player characters.
Scenarios	1	The user can only interact with available preset scenarios.

Table E.2 – Explanations of the scores attributed to criteria *Intervention* and *Influence* of the VEIM framework for the first version of the prototype

Criteria	Level	Explanations
Intervention		
Software	2	This VE uses data from simulation models to calculate deviations in performance trajectories following the activation of potentialities.
Hardware	0	This VE does not communicate with any hardware.
Other VEs	0	This VE does not receive information from other VEs.
Human actors	0	This VE does not receive information from outsiders.
Influence		
Software	0	This VE does not send information to third party software.
Cyber-physical systems	0	This VE does not communicate with cyber-physical systems.
Other VEs	0	This VE does not communicate with other VEs.
Human actors	0	This VE does not communicate with outsiders.

Table E.3 – Explanation of the scores attributed to criterion *Immersion* of the VEIM framework for the second version of the prototype

Criteria	Level	Explanations
Immersion		
Agency	2	It is easy for the user to understand that he/she is responsible for the movements of the objects they grasp and the resulting impact (modelled by the deviations in the performance trajectory). Unlike the previous version, it is easier for the user to make sense of the deviations of each of the performance trajectories for each KPI measured. Moreover, a new element is added in this version, the induced risks.
Sounding	0	There are no sounds in this VE.
Haptic feedback	1	Very limited in this VE, limited to a few vibrations of the joystick.
Handling	2	There are not many objects available, but they can all be manipulated by the user.
Movements	1	This VE is designed to be used sitting or standing. The only possible movements are with the arms to activate or to move closer to objects.
Emotional involvement	0	This VE is not intended to make the user feel emotions.
Inclusiveness	2	This VE plunges the user into an abstract environment, in which he/she has to make an effort to forget the real world, as few of his senses are used (only sight and a little touch). However, the control of time allows the user to remain more concentrated.
Extensiveness	2	This VE is mainly a visual challenge for the user.
Vividness	2	This VE does not attempt to represent a real environment, so it does not present visual realism. However, the proposed trajectory concepts are perfectly faithful to the consequences or probabilities of the modelled events.
Plausibility	0	This VE does not attempt to represent a real environment.
Proprioceptive matching	2	The VE mimics the user's hands, and triggers are activated by touch, as they would be in real life. Only the movements are different from reality, as they are done by teleporting.

Table E.4 – Explanation of the scores attributed to criteria *Interaction*, *Intervention* and *Influence* of the VEIM framework for the second version of the prototype

Criteria	Level	Explanations
Interaction		
Objects	2	The user’s interaction with objects in the VE has an immediate impact on the trajectories for each KPI measured.
Scenery	0	In this VE, the user can no longer change the setting.
Multiplayer	0	This VE is not designed for multiple users at the same time.
Non-player characters	0	This VE does not use non-player characters.
Scenarios	3	The user can only interact with the preset scenarios available. However, thanks to the Excel input files, it is possible to provide the user with a wide range of scenarios to manipulate. In addition, the data relating to each scenario and manipulation is more precise than in the previous version.
Intervention		
Software	2	This VE uses data from simulation models to calculate deviations in performance trajectories following the activation of potentialities.
Hardware	0	This VE does not communicate with any hardware.
Other VEs	0	This VE does not receive information from other VEs.
Human actors	0	This VE does not receive information from outsiders.
Influence		
Software	0	This VE does not send information to third party software.
Cyber-physical systems	0	This VE does not communicate with cyber-physical systems.
Other VEs	0	This VE does not communicate with other VEs.
Human actors	0	This VE does not communicate with outsiders.



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Acronyms

BMD Ballot Marking Devices.....	138, 140, 141
IMT Institut Mines-Télécom.....	5
KPI Key Performance Indicator.....	xii, xv–xvii, 4, 11, 25, 33–35, 37–40, 42, 47, 61, 68–70, 74–77, 86–88, 90, 92, 94, 97, 100, 101, 106, 108, 111, 112, 114, 119, 125, 127, 128, 130–132, 134, 135, 140, 141, 143, 149, 157, 158, 161, 168, 171
Lab Laboratory.....	5
PoD Physics of Decision.....	vii, ix, xi, xii, xv–xvii, xix, xx, 3–11, 14, 30, 35, 36, 38, 40, 41, 44, 46, 47, 50, 51, 72–74, 76, 79–81, 84, 87, 88, 91–94, 97, 100, 104, 107, 108, 111, 115, 116, 119, 121–123, 125–130, 133, 135, 137, 139–142, 144, 167–169, 202, 203
RQ Research Question.....	47
SC Supply Chain.....	53
SCAN Systèmes de Collaborations Agiles et Numériques (Agile and Digital Collaboration Systems).....	xii, 5, 125, 128
SCOR Supply Chain Operations Reference.....	xx, 70, 132–135, 145–147, 149, 169, 171, 172
SCRM Supply Chain Risk Management.....	21, 171
SIReN Sentient Immersive Response Networks.....	5
SME Small and Medium-sized Enterprises.....	41
VE Virtual Environment.....	161
VEIM Virtual Environment Integration Maturity.....	xix, 115, 116, 118, 161, 169, 172
VR Virtual Reality.....	121

Bibliography

- (Abdelfattah, 2013) M. Abdelfattah. “A Comparison of Several Performance Dashboards Architectures”. In: *Intelligent Information Management* 05.2 (2013), pp. 35–41 (cit. on p. 100).
- (Adobor, 2019) H. Adobor. “Supply chain resilience: a multi-level framework”. In: *International Journal of Logistics Research and Applications* 22.6 (Nov. 2, 2019), pp. 533–556 (cit. on pp. 3, 50).
- (Adobor et al., 2018) H. Adobor and R. S. McMullen. “Supply chain resilience: a dynamic and multidimensional approach”. In: *The International Journal of Logistics Management* 29.4 (Oct. 26, 2018), pp. 1451–1471 (cit. on pp. xi, 35, 52, 59, 60, 73–75, 104).
- (Akkermans et al., 2018) H. Akkermans and L. N. Van Wassenhove. “Supply Chain Tsunamis: Research on Low-Probability, High-Impact Disruptions”. In: *Journal of Supply Chain Management* 54.1 (Jan. 2018), pp. 64–76 (cit. on p. 35).
- (Albores et al., 2006) P. Albores, D. Love, M. Weaver, J. Stone, and H. Benton. “An evaluation of SCOR modelling techniques and tools”. In: (2006), p. 10 (cit. on pp. 82, 132).
- (Alejandro Huerta-Torruco et al., 2022) V. Alejandro Huerta-Torruco, Ó. Hernández-Uribe, L. Adriana Cárdenas-Robledo, and N. Amir Rodríguez-Olivares. “Effectiveness of virtual reality in discrete event simulation models for manufacturing systems”. In: *Computers & Industrial Engineering* 168 (June 2022), p. 108079 (cit. on pp. xix, 105).
- (Amini et al., 2012) M. Amini, T. Wakolbinger, M. Racer, and M. G. Nejad. “Alternative supply chain production–sales policies for new product diffusion: An agent-based modeling and simulation approach”. In: *European Journal of Operational Research* 216.2 (Jan. 2012), pp. 301–311 (cit. on p. 154).
- (Andersen et al., 2019) B. J. H. Andersen, A. T. A. Davis, G. Weber, and B. C. Wünsche. “Immersion or Diversion: Does Virtual Reality Make Data Visualisation More Effective?” In: *2019 International Conference on Electronics, Information, and Communication (ICEIC)*. 2019 International Conference on Electronics, Information, and Communication (ICEIC). Jan. 2019, pp. 1–7 (cit. on p. 103).
- (APICS, 2017) APICS. “Supply Chain Operations Reference Model SCOR, Version 12.0”. In: (2017) (cit. on pp. 70, 135, 146–150).

- (Aqlan et al., 2015) F. Aqlan and S. S. Lam. “A fuzzy-based integrated framework for supply chain risk assessment”. In: *International Journal of Production Economics* 161 (Mar. 2015), pp. 54–63 (cit. on p. 31).
- (Asbjørnslett, 2009) B. E. Asbjørnslett. “Assessing the vulnerability of supply chains”. In: *Supply chain risk: A handbook of assessment, management, and performance* (2009). Ed. by G. A. Zsidisin and B. Ritchie, pp. 15–33 (cit. on pp. 56, 57).
- (Baines et al., 1999) T. S. Baines and D. K. Harrison. “An opportunity for system dynamics in manufacturing system modelling”. In: *Production Planning & Control* 10.6 (Jan. 1999), pp. 542–552 (cit. on p. 155).
- (Bairagi et al., 2019) V. Bairagi and M. V. Munot. *Research Methodology: A Practical and Scientific Approach*. Google-Books-ID: wxaGDwAAQBAJ. CRC Press, Jan. 30, 2019. 321 pp. (cit. on pp. 6–8).
- (Ball, 1996) P. Ball. “Introduction to discrete event simulation”. In: *Proceedings of the 2nd DYCOMANS workshop on” Management and Control: Tools in Action*. 1996 (cit. on p. 82).
- (Barroso et al., 2011) A. P. Barroso, V. H. Machado, and V. Cruz Machado. “The resilience paradigm in the supply chain management: A case study”. In: *2011 IEEE International Conference on Industrial Engineering and Engineering Management*. 2011 IEEE International Conference on Industrial Engineering and Engineering Management. ISSN: 2157-362X. Dec. 2011, pp. 928–932 (cit. on pp. 3, 54, 58).
- (Baryannis et al., 2019) G. Baryannis, S. Validi, S. Dani, and G. Antoniou. “Supply chain risk management and artificial intelligence: state of the art and future research directions”. In: *International Journal of Production Research* 57.7 (Apr. 3, 2019), pp. 2179–2202 (cit. on pp. 16, 18, 20).
- (Batch et al., 2020) A. Batch, A. Cunningham, M. Cordeil, N. Elmqvist, T. Dwyer, B. H. Thomas, and K. Marriott. “There Is No Spoon: Evaluating Performance, Space Use, and Presence with Expert Domain Users in Immersive Analytics”. In: *IEEE Transactions on Visualization and Computer Graphics* 26.1 (Jan. 2020), pp. 536–546 (cit. on p. 103).
- (Beamon, 1998) B. M. Beamon. “Supply chain design and analysis: models and methods”. In: *International Journal of Production Economics* 55.3 (1998), pp. 281–294 (cit. on p. 135).
- (Behzadi et al., 2020) G. Behzadi, M. J. O’Sullivan, and T. L. Olsen. “On metrics for supply chain resilience”. In: *European Journal of Operational Research* 287.1 (Nov. 16, 2020), pp. 145–158 (cit. on pp. 57, 61, 63, 76).
- (Bekefi et al., 2008) T. Bekefi, M. J. Epstein, and K. Yuthas. “Managing Opportunities and Risks”. In: (2008), p. 39 (cit. on p. 33).
- (Ben Jbara, 2018) N. Ben Jbara. “Risk management in supply chains: A simulation and model-based approach”. Theses. Université Grenoble-Alpes, Jan. 2018 (cit. on pp. 16, 21, 24, 29–32, 82, 131, 134, 149, 151–155).
- (Benaben et al., 2021) F. Benaben, L. Faugere, B. Montreuil, M. Lauras, N. Moradkhani, T. Cerabona, J. Gou, and W. Mu. “Instability is the norm! A physics-based theory to navigate among risks and opportunities”. In: *Enterprise Information Systems* (Jan. 25, 2021), pp. 1–28 (cit. on pp. xi, 1, 3, 15, 32–36, 38, 101, 125).

-
- (Benaben et al., 2023) F. Benaben, A. Fertier, T. Cerabona, N. Moradkhani, M. Lauras, and B. Montreuil. “[Decision Support in uncertain contexts: Physics of Decision and Virtual Reality](#)”. In: *ISCRAM 2023 - 20th International Conference on Information Systems for Crisis Response and Management*. 2506. Omaha, United States: University of Nebraska Omaha University of Nebraska Omaha, May 2023, p. 54–66 (cit. on p. 108).
- (Benaben et al., 2019) F. Benaben, J. Li, I. Koura, B. Montreuil, M. Lauras, W. Mu, and J. Gou. “[A Tentative Framework for Risk and Opportunity Detection in A Collaborative Environment Based on Data Interpretation](#)”. In: Hawaii International Conference on System Sciences. 2019 (cit. on pp. 3, 15, 73, 94).
- (Benaben et al., 2020) F. Benaben, B. Montreuil, J. Gou, M. Lauras, L. Faugère, and W. Mu. “[A physics-based theory to navigate across risks and opportunities in the performance space: Application to crisis management](#)”. In: *HICSS 2020 - 53rd Hawaii International Conference on System Sciences*. Hawaii, United States, Jan. 2020, p. 2187–2196 (cit. on pp. 4, 30, 42).
- (Benaben et al., 2014) F. Benaben, W. Mu, N. Boissel-Dallier, A.-M. Barthe-Delanoé, S. Zribi, and H. Pingaud. “[Supporting interoperability of collaborative networks through engineering of a service-based Mediation Information System \(MISE 2.0\)](#)”. In: *Enterprise Information Systems* (Aug. 2014), pp. 1–27 (cit. on p. 57).
- (Bernhard et al., 2020) M. Bernhard, A. McDonald, H. Meng, J. Hwa, N. Bajaj, K. Chang, and J. A. Halderman. “[Can Voters Detect Malicious Manipulation of Ballot Marking Devices?](#)” In: *2020 IEEE Symposium on Security and Privacy (SP)*. 2020 IEEE Symposium on Security and Privacy (SP). San Francisco, CA, USA: IEEE, May 2020, pp. 679–694 (cit. on p. 140).
- (Bernstein, 1996) P. L. Bernstein. *Against the gods: the remarkable story of risk*. New York: John Wiley & Sons, 1996 (cit. on p. 12).
- (Beroggi et al., 1995) G. E. G. Beroggi, L. Waisel, and W. A. Wallace. “[Employing virtual reality to support decision making in emergency management](#)”. In: *Safety Science*. The International Emergency Management and Engineering Society 20.1 (July 1, 1995), pp. 79–88 (cit. on p. 102).
- (Bhamra et al., 2011) R. Bhamra, S. Dani, and K. Burnard. “[Resilience: the concept, a literature review and future directions](#)”. In: *International Journal of Production Research* 49.18 (Sept. 15, 2011), pp. 5375–5393 (cit. on pp. 59, 60).
- (Bititci et al., 2012) U. Bititci, P. Garengo, V. Dörfler, and S. Nudurupati. “[Performance Measurement: Challenges for Tomorrow*](#): Performance Measurement”. In: *International Journal of Management Reviews* 14.3 (Sept. 2012), pp. 305–327 (cit. on pp. 34, 101).
- (Blackhurst et al., 2005) J. Blackhurst, C. W. Craighead, D. Elkins, and R. B. Handfield. “[An empirically derived agenda of critical research issues for managing supply-chain disruptions](#)”. In: *International Journal of Production Research* 43.19 (Oct. 2005), pp. 4067–4081 (cit. on p. 32).
- (Blackhurst et al., 2011) J. Blackhurst, K. S. Dunn, and C. W. Craighead. “[An Empirically Derived Framework of Global Supply Resiliency: Framework of Global Supply Resiliency](#)”. In: *Journal of Business Logistics* 32.4 (Dec. 2011), pp. 374–391 (cit. on pp. 3, 56).

- (Blaze et al., 2019) M. Blaze, H. Hursti, M. Macalpine, M. Hanley, J. Moss, R. Wehr, K. Spencer, and C. Ferris. *DEF CON 27 Voting Machine Hacking Village*. 2019. URL: https://harris.uchicago.edu/files/def_con_27_voting_village_report.pdf (cit. on p. 138).
- (Bode et al., 2011) C. Bode, S. M. Wagner, K. J. Petersen, and L. M. Ellram. “Understanding Responses to Supply Chain Disruptions: Insights from Information Processing and Resource Dependence Perspectives”. In: *Academy of Management Journal* 54.4 (2011), pp. 833–856 (cit. on p. 56).
- (Bogataj et al., 2007) D. Bogataj and M. Bogataj. “Measuring the supply chain risk and vulnerability in frequency space”. In: *International Journal of Production Economics* 108.1 (July 2007), pp. 291–301 (cit. on pp. 24, 27, 41).
- (Bradley, 2010) J. R. Bradley. “The complexity of assessing supply chain risk”. In: *Supply chain security: International practices and innovations in moving goods safely and efficiently* (2010), p. 89 (cit. on p. 29).
- (Brand, 2009) F. Brand. “Critical natural capital revisited: Ecological resilience and sustainable development”. In: *Ecological Economics* 68.3 (Jan. 2009), pp. 605–612 (cit. on p. 59).
- (Brandon-Jones et al., 2014) E. Brandon-Jones, B. Squire, C. W. Autry, and K. J. Petersen. “A Contingent Resource-Based Perspective of Supply Chain Resilience and Robustness”. In: *Journal of Supply Chain Management* 50.3 (July 2014), pp. 55–73 (cit. on pp. 53, 55, 57).
- (Britannica, 2023) Britannica. *Mass | Definition, Units, & Facts | Britannica*. URL: <https://www.britannica.com/science/mass-physics> (cit. on p. 75).
- (Bruneau et al., 2003) M. Bruneau, S. E. Chang, R. T. Eguchi, G. C. Lee, T. D. O’Rourke, A. M. Reinhorn, M. Shinozuka, K. Tierney, W. A. Wallace, and D. von Winterfeldt. “A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities”. In: *Earthquake Spectra* 19.4 (Nov. 2003), pp. 733–752 (cit. on pp. xiv, 37, 53, 62–64, 66, 67, 72).
- (Brusset et al., 2017) X. Brusset and C. Teller. “Supply chain capabilities, risks, and resilience”. In: *International Journal of Production Economics* 184 (Feb. 2017), pp. 59–68 (cit. on pp. 3, 50).
- (Bryson, 1996) S. Bryson. “Virtual reality in scientific visualization”. In: *Communications of the ACM* 39.5 (May 1996), pp. 62–71 (cit. on p. 102).
- (Bugwandeen et al., 2019) K. Bugwandeen and M. Ungerer. “Exploring the design of performance dashboards in relation to achieving organisational strategic goals”. In: *South African Journal of Industrial Engineering* 30.2 (Aug. 2019) (cit. on pp. xix, 101, 102, 118, 120).
- (Caillaud et al., 2015) E. Caillaud, B. Rose et V. Goepp. « Comment valider les recherches en génie industriel et en ingénierie système? » In : (2015), p. 7 (cit. on p. 7).
- (Campuzano et al., 2011) F. Campuzano and J. Mula. *Supply Chain Simulation*. London: Springer London, 2011 (cit. on p. 83).
- (Cardoso et al., 2015) S. R. Cardoso, A. P. Barbosa-Povoa, S. Relvas, and A. Q. Novais. “Resilience metrics in the assessment of complex supply-chains performance operating under demand uncertainty”. In: *Omega* 56 (Oct. 2015), pp. 53–73 (cit. on p. 61).

-
- (Carpenter et al., 2001) S. Carpenter, B. Walker, J. M. Anderies, and N. Abel. “[From Metaphor to Measurement: Resilience of What to What?](#)” In: *Ecosystems* 4.8 (Dec. 2001), pp. 765–781 (cit. on pp. 60, 75, 79).
- (Carvalho et al., 2012) H. Carvalho, A. P. Barroso, V. H. Machado, S. Azevedo, and V. Cruz-Machado. “[Supply chain redesign for resilience using simulation](#)”. In: *Computers & Industrial Engineering* 62.1 (Feb. 2012), pp. 329–341 (cit. on pp. 2, 54, 58, 61, 68, 73, 83, 84, 88).
- (Carvalho et al., 2007) H. Carvalho and V. C. Machado. “[Designing principles to create resilient supply chains](#)”. In: *IIE annual conference. Proceedings*. Institute of Industrial and Systems Engineers (IISE). 2007, pp. 186–191 (cit. on p. 62).
- (Cavallo et al., 2019) M. Cavallo, M. Dholakia, M. Havlena, K. Ocheltree, and M. Podlaseck. “[Dataspace: A Reconfigurable Hybrid Reality Environment for Collaborative Information Analysis](#)”. In: *arXiv:1903.03700 [cs]* (Mar. 8, 2019). arXiv: 1903.03700 (cit. on pp. 102, 103).
- (Cavinato, 2004) J. L. Cavinato. “[Supply chain logistics risks: From the back room to the board room](#)”. In: *International Journal of Physical Distribution & Logistics Management* 34.5 (June 1, 2004), pp. 383–387 (cit. on pp. 24, 26).
- (Cerabona et al., 2021a) T. Cerabona, F. Benaben, B. Montreuil, A. V. Barenji, and D. Nazzal. “[Physics of Decision: Application to Polling Place Risk Management](#)”. In: *2021 Winter Simulation Conference (WSC)*. 2021 Winter Simulation Conference (WSC). Phoenix, AZ, USA: IEEE, Dec. 12, 2021, pp. 1–12 (cit. on pp. 6, 34, 36–38, 41, 42, 137, 138, 140, 142).
- (Cerabona et al., 2023) T. Cerabona, F. Benaben, B. Montreuil, M. Lauras, L. Faugère, M. R. Campos, and J. Jeany. “[The physics of decision approach: a physics-based vision to manage supply chain resilience](#)”. In: *International Journal of Production Research* (2023), pp. 1–20 (cit. on pp. 36, 38, 39, 51, 52, 70, 72, 75–81, 88).
- (Cerabona et al., 2020) T. Cerabona, M. Lauras, L. Faugère, J.-P. Gitto, B. Montreuil, and F. Benaben. “[A Physics-Based Approach for Managing Supply Chain Risks and Opportunities Within Its Performance Framework](#)”. In: *21st IFIP WG 5.5 Working Conference on Virtual Enterprises, (PRO-VE 2020)*. Ed. by L. M. Camarinha-Matos, H. Afsarmanesh, and A. Ortiz. Vol. 598. Boosting Collaborative Networks 4.0 21st IFIP WG 5.5 Working Conference on Virtual Enterprises, PRO-VE 2020, Valencia, Spain, November 23–25, 2020, Proceedings. Valence, Spain: Springer International Publishing, Nov. 2020, pp. 418–427 (cit. on pp. 6, 31, 38).
- (Cerabona et al., 2021b) T. Cerabona, M. Lauras, J.-P. Gitto, B. Montreuil, and F. Benaben. “[Atomic Supply Chain Modelling for Risk Management based on SCOR](#)”. In: *22nd Working Conference on Virtual Enterprises (PRO-VE 2021)*. Ed. by L. M. Camarinha-Matos, X. Boucher, and H. Afsarmanesh. Vol. AICT-629. Smart and Sustainable Collaborative Networks 4.0. Part 16: Sentient Immersive Response Network. Saint-Etienne, France: Springer International Publishing, Nov. 2021, pp. 601–610 (cit. on pp. 6, 36–38, 132–135, 145–147, 149).
- (Ceryno et al., 2013) P. S. Ceryno, L. F. Scavarda, K. Klingebiel, and G. Yüzgülec. “[Supply Chain Risk Management: A Content Analysis Approach](#)”. In: *International Journal of Industrial Engineering and Management* 4.3 (2013), pp. 141–150 (cit. on pp. 21, 22).
- (Chapman et al., 2011) C. Chapman, S. Ward, and J. Wiley. “[How to Manage Project Opportunity and Risk –](#)”. In: (2011), p. 7 (cit. on p. 34).

- (Cheng et al., 2022) Y. Cheng, E. A. Elsayed, and Z. Huang. “Systems resilience assessments: a review, framework and metrics”. In: *International Journal of Production Research* 60.2 (Jan. 17, 2022), pp. 595–622 (cit. on pp. 62, 63, 68).
- (Choi et al., 2002) T. Y. Choi and Y. Hong. “Unveiling the structure of supply networks: case studies in Honda, Acura, and DaimlerChrysler”. In: *Journal of Operations Management* 20.5 (Sept. 2002), pp. 469–493 (cit. on p. 1).
- (Chopra et al., 2007) S. Chopra, P. Meindl, and D. V. Kalra. *Supply Chain Management by Pearson*. Pearson Education India, 2007 (cit. on pp. 21, 24, 27).
- (Chopra et al., 2004) S. Chopra and M. S. Sodhi. “Managing Risk to Avoid Supply-Chain Breakdown”. In: *MIT Sloan Management Review* (Oct. 15, 2004) (cit. on pp. 24, 26, 31).
- (Chowdhury et al., 2017) M. M. H. Chowdhury and M. Quaddus. “Supply chain resilience: Conceptualization and scale development using dynamic capability theory”. In: *International Journal of Production Economics* 188 (June 2017), pp. 185–204 (cit. on pp. xiii, 45, 46, 53, 55, 56, 126).
- (Christopher et al., 2011) M. Christopher and M. Holweg. ““Supply Chain 2.0”: managing supply chains in the era of turbulence”. In: *International Journal of Physical Distribution & Logistics Management* 41.1 (Feb. 2011). Ed. by M. Crum, pp. 63–82 (cit. on pp. 35, 45).
- (Christopher et al., 2004a) M. Christopher and H. Lee. “Mitigating supply chain risk through improved confidence”. In: *International Journal of Physical Distribution & Logistics Management* 34.5 (June 2004), pp. 388–396 (cit. on p. 16).
- (Christopher et al., 2004b) M. Christopher and H. Peck. “Building the Resilient Supply Chain”. In: *The International Journal of Logistics Management* 15.2 (July 1, 2004), pp. 1–14 (cit. on pp. 3, 12, 24, 26, 32, 52, 54, 57–59, 73, 104).
- (Cigolini et al., 2011) R. Cigolini, M. Pero, and T. Rossi. “An object-oriented simulation meta-model to analyse supply chain performance”. In: *International Journal of Production Research* 49.19 (Oct. 2011), pp. 5917–5941 (cit. on p. 131).
- (Clapham, 1976) W. B. Clapham. “An Approach to Quantifying the Exploitability of Human Ecosystems”. In: *Human Ecology* 4.1 (1976). Publisher: Springer, pp. 1–30 (cit. on p. 73).
- (Clement et al., 2021) A. Clement, L. Wioland, V. Govaere, D. Gourc, J. Cegarra, F. Marmier, and D. Kamissoko. “Robustness, resilience: typology of definitions through a multidisciplinary structured analysis of the literature”. In: *European J. of Industrial Engineering* 15.4 (2021), p. 487 (cit. on pp. 58, 59).
- (Clément, 2019) A. Clément. « Proposition d’indicateurs de robustesse basés sur la prise en compte des risques afin d’évaluer les tournées de transport routier de marchandises ». Theses. École des Mines d’Albi-Carmaux, nov. 2019 (cit. on pp. 14, 21).
- (Closs et al., 2004) D. J. Closs and E. F. McGarrell. *Enhancing security throughout the supply chain*. IBM Center for the Business of Government Washington, DC, 2004 (cit. on p. 53).
- (Cohn, 2018) J. Cohn. *What is the latest threat to democracy?* Medium. May 5, 2018. URL: <https://jennycohn1.medium.com/what-is-the-latest-threat-to-democracy-ballot-marking-devices-a-k-a-electronic-pencils-16bb44917edd> (cit. on p. 138).

-
- (Colicchia et al., 2012) C. Colicchia and F. Strozzi. “Supply chain risk management: a new methodology for a systematic literature review”. In: *Supply Chain Management: An International Journal* 17.4 (June 15, 2012). Ed. by R. Wilding, pp. 403–418 (cit. on pp. xi, 19, 20, 34, 35).
- (Conges et al., 2021) A. Conges, P. Yang, F. Benaben, and C. J. Graham. “Using Virtual Reality to Facilitate Common Operational Pictures’ Representation”. In: *2021 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. 2021 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW). Lisbon, Portugal: IEEE, Mar. 2021, pp. 336–341 (cit. on p. 103).
- (Conges et al., 2020) A. Conges, A. Evain, O. Chabiron, C. J. Graham, and F. Benaben. “Virtual Reality to Train for Crisis Management”. In: *ISCRAM 2020-17th International conference on Information Systems for Crisis Response and Management*. Vol. 2020-May. Balcksburg, United States, May 2020, pp. 1100–1112 (cit. on pp. 101, 104).
- (Congès, 2022) A. Congès. “Conception and evaluation of virtual environments dedicated to crisis management”. Theses. Ecole des Mines d’Albi-Carmaux, 2022 (cit. on pp. xix, 103, 115, 116, 161).
- (Cope et al., 2007) D. Cope, M. S. Fayez, Mansooreh Mollaghasemi, and Assem Kaylani. “Supply chain simulation modeling made easy: An innovative approach”. In: *2007 Winter Simulation Conference*. 2007 Winter Simulation Conference. Washington, DC, USA: IEEE, 2007, pp. 1887–1896 (cit. on pp. 2, 82).
- (Cousins et al., 2004) P. D. Cousins, R. C. Lamming, and F. Bowen. “The role of risk in environment-related supplier initiatives”. In: *International Journal of Operations & Production Management* 24.6 (June 2004), pp. 554–565 (cit. on pp. 24, 26).
- (Craighead et al., 2007) C. W. Craighead, J. Blackhurst, M. J. Rungtusanatham, and R. B. Handfield. “The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities”. In: *Decision Sciences* 38.1 (Feb. 2007), pp. 131–156 (cit. on pp. 3, 67).
- (Crockford, 1986) N. Crockford. *An Introduction to Risk Management*. Tech. rep. ISBN 0-85941-332-2, 1986 (cit. on pp. 24, 26).
- (Daily FEI, 2020) Daily FEI. *Election Hacking: Facts Vs. Fears*. 2020. URL: <https://www.financialexecutives.org/FEI-Daily/October-2020/Election-Hacking-Facts-Vs-Fears.aspx> (cit. on p. 138).
- (Dalziell et al., 2004) E. P. Dalziell and S. T. McManus. “Resilience, Vulnerability, and Adaptive Capacity: Implications for System Performance”. In: (2004), p. 17 (cit. on pp. 34, 50).
- (Datta et al., 2011) P. P. Datta and M. G. Christopher. “Information sharing and coordination mechanisms for managing uncertainty in supply chains: a simulation study”. In: *International Journal of Production Research* 49.3 (Feb. 2011), pp. 765–803 (cit. on p. 1).
- (Davis et al., 2007) J. P. Davis, K. M. Eisenhardt, and C. B. Bingham. “Developing Theory Through Simulation Methods”. In: *Academy of Management Review* 32.2 (Apr. 2007), pp. 480–499 (cit. on pp. 7, 82).
- (Davoudi et al., 2013) S. Davoudi, E. Brooks, and A. Mehmood. “Evolutionary Resilience and Strategies for Climate Adaptation”. In: *Planning Practice and Research* 28.3 (June 2013), pp. 307–322 (cit. on p. 102).

- (Desroches, 2013) A. Desroches. « [Le management des risques par l'analyse globale des risques](#) ». In : *Transfusion Clinique et Biologique* 20.2 (mai 2013), p. 198-210 (cit. on p. 14).
- (Desroches et al., 2003) A. Desroches, A. Leroy, and F. Vallée. “La gestion des risques: principes et pratiques”. In: *Management et informatique* (2003) (cit. on p. 14).
- (Diabat et al., 2012) A. Diabat, K. Govindan, and V. V. Panicker. “[Supply chain risk management and its mitigation in a food industry](#)”. In: *International Journal of Production Research* 50.11 (June 2012), pp. 3039–3050 (cit. on p. 21).
- (Dolgui et al., 2018) A. Dolgui, D. Ivanov, and B. Sokolov. “[Ripple effect in the supply chain: an analysis and recent literature](#)”. In: *International Journal of Production Research* 56.1 (Jan. 17, 2018), pp. 414–430 (cit. on p. 53).
- (Donalek et al., 2014) C. Donalek, S. G. Djorgovski, A. Cioc, A. Wang, J. Zhang, E. Lawler, S. Yeh, A. Mahabal, M. Graham, A. Drake, S. Davidoff, J. S. Norris, and G. Longo. “[Immersive and collaborative data visualization using virtual reality platforms](#)”. In: *2014 IEEE International Conference on Big Data (Big Data)*. 2014 IEEE International Conference on Big Data (Big Data). Washington, DC, USA: IEEE, Oct. 2014, pp. 609–614 (cit. on p. 103).
- (Druzdzel et al., 1999) M. J. Druzdzel and R. R. Flynn. “Decision support systems. Encyclopedia of library and information science. A. Kent”. In: *Marcel Dekker, Inc. Last Login* 10.3 (1999), p. 2010 (cit. on p. 101).
- (Dugdale et al., 2004) J. Dugdale, B. Pavard, N. Pallamin, M. el Jed, and C. L. Maugan. “[Emergency fire incident training in a virtual world](#)”. In: *Proceedings ISCRAM* 167 (2004) (cit. on p. 103).
- (DuHadway et al., 2019) S. DuHadway, S. Carnovale, and B. Hazen. “[Understanding risk management for intentional supply chain disruptions: risk detection, risk mitigation, and risk recovery](#)”. In: *Annals of Operations Research* 283.1 (Dec. 2019), pp. 179–198 (cit. on pp. 25, 56).
- (Dwyer et al., 2018) T. Dwyer, K. Marriott, T. Isenberg, K. Klein, N. Riche, F. Schreiber, W. Stuerzlinger, and B. H. Thomas. “[Immersive Analytics: An Introduction](#)”. In: *Immersive Analytics*. Ed. by K. Marriott, F. Schreiber, T. Dwyer, K. Klein, N. H. Riche, T. Itoh, W. Stuerzlinger, and B. H. Thomas. Vol. 11190. Series Title: Lecture Notes in Computer Science. Cham: Springer International Publishing, 2018, pp. 1–23 (cit. on p. 103).
- (Ebrahimi et al., 2012) D. S. Ebrahimi, P. David, and G. Alpan. “[A model based specification for a decision support tool for supply chain risk management](#)”. In: *CIE42 proceedings, Cape Town, South Africa* (2012), p. 15 (cit. on pp. xi, 13, 18, 20, 33).
- (Eckerson, 2010) W. W. Eckerson. *Performance Dashboards: Measuring, Monitoring, and Managing Your Business*. Google-Books-ID: 5nuYDwAAQBAJ. John Wiley & Sons, Nov. 9, 2010. 336 pp. (cit. on p. 102).
- (El Baz et al., 2021) J. El Baz and S. Ruel. “[Can supply chain risk management practices mitigate the disruption impacts on supply chains' resilience and robustness? Evidence from an empirical survey in a COVID-19 outbreak era](#)”. In: *International Journal of Production Economics* 233 (Mar. 2021), p. 107972 (cit. on p. 56).
- (El Beheiry et al., 2019) M. El Beheiry, S. Doutreligne, C. Caporal, C. Ostertag, M. Dahan, and J.-B. Masson. “[Virtual Reality: Beyond Visualization](#)”. In: *Journal of Molecular Biology* 431.7 (Mar. 2019), pp. 1315–1321 (cit. on p. 103).

-
- (Epstein et al., 1996) J. M. Epstein and R. Axtell. *Growing artificial societies: social science from the bottom up*. Brookings Institution Press, 1996 (cit. on p. 153).
- (Estampe et al., 2013) D. Estampe, S. Lamouri, J.-L. Paris, and S. Brahim-Djelloul. “A framework for analysing supply chain performance evaluation models”. In: *International Journal of Production Economics* 142.2 (Apr. 2013), pp. 247–258 (cit. on p. 62).
- (Evrard Samuel, 2013) K. Evrard Samuel. « *Concevoir des supply chains résilientes : simple évolution du management des risques ou mutation stratégique majeure ?* » In : *Logistique & Management* 21.2 (jan. 2013), p. 33-45 (cit. on p. 2).
- (Falasca et al., 2008) M. Falasca, C. W. Zobel, and D. Cook. “A decision support framework to assess supply chain resilience”. In: *Proceedings of the 5th International ISCRAM Conference*. Washington, DC. 2008, pp. 596–605 (cit. on pp. 53, 54, 58, 67, 68, 84).
- (Fang et al., 2012) C. Fang and F. Marle. “A simulation-based risk network model for decision support in project risk management”. In: *Decision Support Systems* 52.3 (Feb. 2012), pp. 635–644 (cit. on pp. 33, 101).
- (Fasli et al., 2011) M. Fasli and Y. Kovalchuk. “Learning approaches for developing successful seller strategies in dynamic supply chain management”. In: *Information Sciences* 181.16 (Aug. 2011), pp. 3411–3426 (cit. on p. 154).
- (Fattahi et al., 2020) M. Fattahi, K. Govindan, and R. Maihami. “Stochastic optimization of disruption-driven supply chain network design with a new resilience metric”. In: *International Journal of Production Economics* 230 (Dec. 2020), p. 107755 (cit. on p. 63).
- (Fayez et al., 2005) M. Fayez, L. Rabelo, and M. Mollaghasemi. “Ontologies for Supply Chain Simulation Modeling”. In: *Proceedings of the Winter Simulation Conference, 2005*. Winter Simulation Conference, 2005. Orlando, FL. USA: IEEE, 2005, pp. 2364–2370 (cit. on p. 132).
- (Ferreira et al., 2009) A. Ferreira and D. Otley. “The design and use of performance management systems: An extended framework for analysis”. In: *Management Accounting Research* 20.4 (Dec. 2009), pp. 263–282 (cit. on p. 73).
- (Fertier, 2018) A. Fertier. “Interprétation automatique de données hétérogènes pour la modélisation de situations collaboratives : application à la gestion de crise”. Theses. Ecole des Mines d’Albi-Carmaux, Nov. 2018 (cit. on p. 14).
- (Fiksel, 2006) J. Fiksel. “Sustainability and resilience: toward a systems approach”. In: *Sustainability: Science, Practice and Policy* 2.2 (Oct. 2006), pp. 14–21 (cit. on pp. xiii, 45).
- (Fiksel, 2015) J. Fiksel. “From Risk to Resilience”. In: *Resilient by Design: Creating Businesses That Adapt and Flourish in a Changing World*. Ed. by J. Fiksel. Washington, DC: Island Press/Center for Resource Economics, 2015, pp. 19–34 (cit. on p. 3).
- (Fiksel et al., 2015) J. Fiksel, M. Polyviou, K. L. Croxton, and T. J. Pettit. “From risk to resilience: learning to deal with disruption”. In: (2015), p. 12 (cit. on p. 45).
- (Folke, 2006) C. Folke. “Resilience: The emergence of a perspective for social–ecological systems analyses”. In: *Global Environmental Change* 16.3 (Aug. 2006), pp. 253–267 (cit. on p. 60).

- (Forrester, 1961) J. Forrester. “Industrial Dynamics MIT Press Cambridge”. In: (1961) (cit. on p. 152).
- (Fowler, 2020) S. Fowler. “Why Do Nonwhite Georgia Voters Have To Wait In Line For Hours? Too Few Polling Places”. In: *NPR* (Oct. 17, 2020) (cit. on p. 138).
- (Franceschini et al., 2006) F. Franceschini, M. Galetto, D. Maisano, and L. Viticchiè. “The condition of uniqueness in manufacturing process representation by performance/quality indicators”. In: *Quality and Reliability Engineering International* 22.5 (2006), pp. 567–580 (cit. on p. 61).
- (Gao et al., 2016) J. Gao, B. Barzel, and A.-L. Barabási. “Universal resilience patterns in complex networks”. In: *Nature* 530.7590 (Feb. 2016). Number: 7590 Publisher: Nature Publishing Group, pp. 307–312 (cit. on p. 45).
- (Ghadge et al., 2012) A. Ghadge, S. Dani, and R. Kalawsky. “Supply chain risk management: present and future scope”. In: *The International Journal of Logistics Management* 23.3 (Nov. 2, 2012), pp. 313–339 (cit. on pp. 16, 19, 20, 83).
- (Giannakis et al., 2011) M. Giannakis and M. Louis. “A multi-agent based framework for supply chain risk management”. In: *Journal of Purchasing and Supply Management* 17.1 (Mar. 2011), pp. 23–31 (cit. on pp. 25, 29).
- (Golan et al., 2020) M. S. Golan, L. H. Jernegan, and I. Linkov. “Trends and applications of resilience analytics in supply chain modeling: systematic literature review in the context of the COVID-19 pandemic”. In: *Environment Systems and Decisions* 40.2 (June 2020), pp. 222–243 (cit. on pp. 53, 56, 60).
- (Gourc, 2006) D. Gourc. “Vers un modèle général du risque pour le pilotage et la conduite des activités de biens et de services : Propositions pour une conduite des projets et une gestion des risques intégrées”. Habilitation à diriger des recherches. Institut National Polytechnique de Toulouse - INPT, Apr. 2006 (cit. on p. 13).
- (Graça et al., 2017) P. Graça and L. M. Camarinha-Matos. “Performance indicators for collaborative business ecosystems — Literature review and trends”. In: *Technological Forecasting and Social Change* 116 (Mar. 2017), pp. 237–255 (cit. on p. 37).
- (Grest et al., 2021) M. Grest, M. Metin Inan, Y. M. Cohen, A. V. Barenji, M. Dahan, M. Lauras, and B. Montreuil. “Design of a Simulation-Based Experiment for Assessing the Relevance of the Physical Internet Concept for Humanitarian Supply Chains”. In: (June 2021), 10 p. (Cit. on p. 86).
- (Groff, 2007) E. R. Groff. “Simulation for Theory Testing and Experimentation: An Example Using Routine Activity Theory and Street Robbery”. In: *Journal of Quantitative Criminology* 23.2 (Mar. 27, 2007), pp. 75–103 (cit. on p. 82).
- (Grose, 1992) V. L. Grose. “Risk Management from a Technological Perspective”. In: *The Geneva Papers on Risk and Insurance - Issues and Practice* 17.3 (1992), pp. 335–342 (cit. on p. 12).
- (Gunderson, 2000) L. H. Gunderson. “Ecological Resilience—In Theory and Application”. In: *Annual Review of Ecology and Systematics* 31.1 (Nov. 2000), pp. 425–439 (cit. on pp. 59, 60).
- (Gurtu et al., 2021) A. Gurtu and J. Johny. “Supply Chain Risk Management: Literature Review”. In: *Risks* 9.1 (Jan. 6, 2021), p. 16 (cit. on p. 2).
- (Hallikas et al., 2004) J. Hallikas, I. Karvonen, U. Pulkkinen, V.-M. Virolainen, and M. Tuominen. “Risk management processes in supplier networks”. In: *International Journal of Production Economics* 90.1 (July 2004), pp. 47–58 (cit. on pp. 21, 23).

-
- (Han et al., 2020) Y. Han, W. K. Chong, and D. Li. “A systematic literature review of the capabilities and performance metrics of supply chain resilience”. In: *International Journal of Production Research* 58.15 (Aug. 2, 2020), pp. 4541–4566 (cit. on pp. xiv, 57, 61, 68, 69, 72).
- (Harland et al., 2003) C. Harland, R. Brenchley, and H. Walker. “Risk in supply networks”. In: *Journal of Purchasing and Supply Management* 9.2 (Mar. 2003), pp. 51–62 (cit. on p. 2).
- (Harrison et al., 2007) J. R. Harrison, Z. Lin, G. R. Carroll, and K. M. Carley. “Simulation modeling in organizational and management research”. In: *Academy of Management Review* 32.4 (Oct. 2007), pp. 1229–1245 (cit. on pp. 7, 82).
- (Hassan, 2006) M. M. D. Hassan. “Engineering supply chains as systems”. In: *Systems Engineering* 9.1 (2006), pp. 73–89 (cit. on p. 1).
- (Hearnshaw et al., 2013) E. J. S. Hearnshaw and M. M. J. Wilson. “A complex network approach to supply chain network theory”. In: *International Journal of Operations & Production Management* 33.4 (Mar. 15, 2013), pp. 442–469 (cit. on p. 2).
- (Heath et al., 2011) S. K. Heath, S. C. Brailsford, A. Buss, and C. M. Macal. “Cross-paradigm simulation modeling: Challenges and successes”. In: *Proceedings of the 2011 Winter Simulation Conference (WSC)*. 2011 Winter Simulation Conference - (WSC 2011). Phoenix, AZ, USA: IEEE, Dec. 2011, pp. 2783–2797 (cit. on pp. 152–154).
- (Heckmann et al., 2015) I. Heckmann, T. Comes, and S. Nickel. “A critical review on supply chain risk – Definition, measure and modeling”. In: *Omega* 52 (Apr. 2015), pp. 119–132 (cit. on pp. 12, 16, 17, 19, 29, 38, 44, 47, 102).
- (Helbing et al., 2006) D. Helbing, H. Ammoser, and C. Kühnert. “Disasters as Extreme Events and the Importance of Network Interactions for Disaster Response Management”. In: *Extreme Events in Nature and Society*. Ed. by S. Albeverio, V. Jentsch, and H. Kantz. Red. by D. Dragoman, M. Dragoman, A. C. Elitzur, M. P. Silverman, J. Tuszynski, and H. D. Zeh. Series Title: The Frontiers Collection. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 319–348 (cit. on p. 2).
- (Hendricks et al., 2005) K. B. Hendricks and V. R. Singhal. “Association Between Supply Chain Glitches and Operating Performance”. In: *Management Science* 51.5 (May 2005), pp. 695–711 (cit. on p. 3).
- (Hermann et al., 2003) J. W. Hermann, E. Lin, and G. Pundoor. “Supply Chain Simulation Modeling Using the Supply Chain Operations Reference Model”. In: *Volume 1: 23rd Computers and Information in Engineering Conference, Parts A and B*. ASME 2003 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. Chicago, Illinois, USA: ASMEDC, Jan. 1, 2003, pp. 461–469 (cit. on pp. 83, 132).
- (Hevner et al., 2008) A. Hevner, S. March, J. Park, and S. Ram. “Design Science in Information Systems Research”. In: *Management Information Systems Quarterly* 28.1 (Dec. 12, 2008), p. 6 (cit. on pp. 6, 7).
- (Hillson, 2002) D. Hillson. “Extending the risk process to manage opportunities”. In: *International Journal of Project Management* 20.3 (Apr. 2002), pp. 235–240 (cit. on pp. 13, 14, 21, 25, 29, 31, 32).
- (Ho et al., 2015) W. Ho, T. Zheng, H. Yildiz, and S. Talluri. “Supply chain risk management: a literature review”. In: *International Journal of Production Research* 53.16 (Aug. 18, 2015), pp. 5031–5069 (cit. on pp. 16, 17, 19–25, 28, 32, 43, 84).

- (Hohenstein et al., 2015) N.-O. Hohenstein, E. Feisel, E. Hartmann, and L. Giunipero. “Research on the phenomenon of supply chain resilience: A systematic review and paths for further investigation”. In: *International Journal of Physical Distribution & Logistics Management* 45.1 (Jan. 1, 2015). Ed. by P. Maria Jesus Saenz and D. Xenophon Koufteros. Publisher: Emerald Group Publishing Limited, pp. 90–117 (cit. on pp. 55, 57, 58, 68).
- (Holling, 1973) C. S. Holling. “RESILIENCE AND STABILITY OF ECOLOGICAL SYSTEMS”. In: *Annual review of ecology and systematics* 4.1 (1973), pp. 1–23 (cit. on pp. xiii, 52, 59, 72, 73, 79).
- (Holling, 1996) C. S. Holling. “Engineering resilience versus ecological resilience”. In: *Engineering within ecological constraints* 31.1996 (1996), p. 32 (cit. on pp. 59, 60, 72).
- (Hornby et al., 2005) A. Hornby, S. Wehmeier, C. McIntosh, and J. Turnbull. *Oxford Advanced Learner’s Dictionary*. 2005 (cit. on p. 20).
- (Hosseini et al., 2016a) S. Hosseini and K. Barker. “Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports”. In: *Computers & Industrial Engineering* 93 (Mar. 2016), pp. 252–266 (cit. on pp. 50, 53).
- (Hosseini et al., 2016b) S. Hosseini, K. Barker, and J. E. Ramirez-Marquez. “A review of definitions and measures of system resilience”. In: *Reliability Engineering & System Safety* 145 (Jan. 2016), pp. 47–61 (cit. on pp. 50, 52, 61, 63, 64, 66).
- (Hosseini et al., 2019a) S. Hosseini, D. Ivanov, and A. Dolgui. “Review of quantitative methods for supply chain resilience analysis”. In: *Transportation Research Part E: Logistics and Transportation Review* 125 (May 2019), pp. 285–307 (cit. on pp. 8, 53, 56).
- (Hosseini et al., 2019b) S. Hosseini, N. Morshedlou, D. Ivanov, M. Sarder, K. Barker, and A. Al Khaled. “Resilient supplier selection and optimal order allocation under disruption risks”. In: *International Journal of Production Economics* 213 (2019), pp. 124–137 (cit. on p. 52).
- (Huang et al., 2005) S. H. Huang, S. K. Sheoran, and H. Keskar. “Computer-assisted supply chain configuration based on supply chain operations reference (SCOR) model”. In: *Computers & Industrial Engineering* 48.2 (Mar. 2005), pp. 377–394 (cit. on pp. 147, 149).
- (Hubbard, 2014) D. W. Hubbard. *How to Measure Anything: Finding the Value of Intangibles in Business*. Google-Books-ID: EAPXAgAAQBAJ. John Wiley & Sons, Mar. 17, 2014. 432 pp. (cit. on p. 20).
- (Hult et al., 2010) G. T. M. Hult, C. W. Craighead, and D. J. Ketchen Jr. “Risk uncertainty and supply chain decisions: a real options perspective”. In: *Decision Sciences* 41.3 (2010), pp. 435–458 (cit. on p. 2).
- (ISO31000, 2018) ISO31000. *ISO 31000:2018(fr), Management du risque — Lignes directrices*. 2018. URL: <https://www.iso.org/obp/ui/#iso:std:iso:31000:ed-2:v1:fr> (cit. on pp. 13, 21).
- (Ivanov et al., 2020) D. Ivanov and A. Dolgui. “Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak”. In: *International Journal of Production Research* 58.10 (May 18, 2020), pp. 2904–2915 (cit. on pp. 53, 56, 57).
- (Ivanov et al., 2021) D. Ivanov and A. Dolgui. “A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0”. In: *Production Planning & Control* 32.9 (July 4, 2021), pp. 775–788 (cit. on pp. 33, 83, 84, 101, 131).

-
- (Ivanov et al., 2017) D. Ivanov, A. Dolgui, B. Sokolov, and M. Ivanova. “Literature review on disruption recovery in the supply chain”. In: *International Journal of Production Research* 55.20 (Oct. 18, 2017), pp. 6158–6174 (cit. on pp. 24, 28, 83).
- (Ivanov et al., 2013) D. Ivanov and B. Sokolov. “Control and system-theoretic identification of the supply chain dynamics domain for planning, analysis and adaptation of performance under uncertainty”. In: *European Journal of Operational Research* 224.2 (Jan. 2013), pp. 313–323 (cit. on pp. 54, 56–58).
- (Jain et al., 2006) H. Jain, K. Ramamurthy, and S. Sundaram. “Effectiveness of visual interactive modeling in the context of multiple-criteria Group decisions”. In: *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans* 36.2 (Mar. 2006), pp. 298–318 (cit. on p. 103).
- (Johnson, 2001) M. E. Johnson. “Learning from Toys: Lessons in Managing Supply Chain Risk from the Toy Industry”. In: *California Management Review* 43.3 (Apr. 1, 2001). Publisher: SAGE Publications Inc, pp. 106–124 (cit. on pp. 24, 26).
- (Jüttner et al., 2011) U. Jüttner and S. Maklan. “Supply chain resilience in the global financial crisis: an empirical study”. In: *Supply Chain Management: An International Journal* 16.4 (Jan. 1, 2011). Publisher: Emerald Group Publishing Limited, pp. 246–259 (cit. on pp. 45, 46, 53, 57).
- (Jüttner et al., 2003) U. Jüttner, H. Peck, and M. Christopher. “Supply chain risk management: outlining an agenda for future research”. In: *International Journal of Logistics Research and Applications* 6.4 (Dec. 2003), pp. 197–210 (cit. on pp. 17–20, 22, 23, 26, 29).
- (Kamalahmadi et al., 2016) M. Kamalahmadi and M. M. Parast. “A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research”. In: *International Journal of Production Economics* 171 (Jan. 2016), pp. 116–133 (cit. on pp. xiv, 52, 53, 55, 56, 58, 61).
- (R. S. Kaplan et al., 1992) R. S. Kaplan and D. P. Norton. *The balanced scorecard: measures that drive performance*. Harvard business review US, 1992, pp. 71–79 (cit. on p. 62).
- (S. Kaplan et al., 1981) S. Kaplan and B. J. Garrick. “On The Quantitative Definition of Risk”. In: *Risk Analysis* 1.1 (Mar. 1981), pp. 11–27 (cit. on p. 12).
- (Karl et al., 2018) A. A. Karl, J. Micheluzzi, L. R. Leite, and C. R. Pereira. “Supply chain resilience and key performance indicators: a systematic literature review”. In: *Production* 28 (2018), p. 16 (cit. on pp. 68, 69).
- (Katsaliaki et al., 2021) K. Katsaliaki, P. Galetsi, and S. Kumar. “Supply chain disruptions and resilience: a major review and future research agenda”. In: *Annals of Operations Research* (Jan. 8, 2021) (cit. on pp. 2, 24, 45, 83).
- (Kersten et al., 2007) W. Kersten, P. Hohrath, and M. Böger. “An Empirical Approach to Supply Chain Risk Management: Development of a Strategic Framework”. In: *Proceeding POMS2007 Conference*. 2007, pp. 1–20 (cit. on p. 20).
- (Khan et al., 2007) O. Khan and B. Burnes. “Risk and supply chain management: creating a research agenda”. In: *The International Journal of Logistics Management* 18.2 (Aug. 21, 2007), pp. 197–216 (cit. on p. 12).
- (Kilubi, 2016) I. Kilubi. “The strategies of supply chain risk management – a synthesis and classification”. In: *International Journal of Logistics Research and Applications* 19.6 (Nov. 2016), pp. 604–629 (cit. on pp. 16, 151).

- (Kleindorfer et al., 2005) P. R. Kleindorfer and G. H. Saad. “[Managing Disruption Risks in Supply Chains](#)”. In: *Production and Operations Management* 14.1 (2005), pp. 53–68 (cit. on p. 23).
- (Knemeyer et al., 2009) A. M. Knemeyer, W. Zinn, and C. Eroglu. “[Proactive planning for catastrophic events in supply chains](#)”. In: *Journal of Operations Management* 27.2 (Apr. 2009), pp. 141–153 (cit. on pp. 2, 16).
- (Knight, 1921) F. H. Knight. *Risk, uncertainty and profit*. Vol. 31. Houghton Mifflin, 1921 (cit. on p. 19).
- (Kumar et al., 2008) R. L. Kumar, S. Park, and C. Subramaniam. “[Understanding the Value of Countermeasure Portfolios in Information Systems Security](#)”. In: *Journal of Management Information Systems* 25.2 (Sept. 1, 2008). Publisher: Routledge _eprint: <https://doi.org/10.2753/MIS0742-1222250210>, pp. 241–280 (cit. on p. 64).
- (Lasch, 2018) R. Lasch. *Supply Chain Disruption Models: A Critical Review*. 5th ed. DE: Bundesvereinigung Logistik (BVL) e.V, 2018 (cit. on pp. 18–20, 152–155).
- (Law, 2013) A. M. Law. *Simulation modeling and analysis*. Fifth edition. McGraw-Hill series in industrial engineering and management science. Dubuque: McGraw-Hill Education, 2013 (cit. on pp. 7, 86, 152–154).
- (Le Duff et al., 2022) C. Le Duff, J.-P. Gitto, J. Jeany, R. Falco, M. Lauras, and F. Benaben. “[A physics-based approach to evaluate crisis impacts on project management](#)”. In: *ISCRAM 2022 - 19th International Conference on Information Systems for Crisis Response and Management*. Tarbes, France: ENIT, May 2022, p. 134–143 (cit. on p. 6).
- (Lederer et al., 1990) A. L. Lederer and R. Nath. “[Making Strategic Information Systems Happen](#)”. In: *Academy of Management Perspectives* 4.3 (Mar. 1990). Publisher: Academy of Management, pp. 76–83 (cit. on p. 102).
- (Lee, 1993) H. L. Lee. “Design for supply chain management: concepts and examples”. In: *Perspectives in operations management: Essays in honor of Elwood S. Buffa* (1993), pp. 45–65 (cit. on p. 1).
- (Lempinen, 2013) H. Lempinen. *Design Framework for Performance Management Systems: An Ensemble Approach*. Aalto University, 2013, p. 198 (cit. on p. 106).
- (C. Li et al., 2016) C. Li, J. Ren, and H. Wang. “[A system dynamics simulation model of chemical supply chain transportation risk management systems](#)”. In: *Computers & Chemical Engineering* 89 (June 2016), pp. 71–83 (cit. on pp. 152, 153).
- (R. Li et al., 2017) R. Li, Q. Dong, C. Jin, and R. Kang. “[A New Resilience Measure for Supply Chain Networks](#)”. In: *Sustainability* 9.1 (Jan. 19, 2017), p. 144 (cit. on pp. xvi, 65–67, 76, 77, 91).
- (Y. Li et al., 2020) Y. Li, C. W. Zobel, O. Seref, and D. Chatfield. “[Network characteristics and supply chain resilience under conditions of risk propagation](#)”. In: *International Journal of Production Economics* 223 (May 2020), p. 107529 (cit. on p. 56).
- (Lima-Junior et al., 2019) F. R. Lima-Junior and L. C. R. Carpinetti. “[Predicting supply chain performance based on SCOR® metrics and multilayer perceptron neural networks](#)”. In: *International Journal of Production Economics* 212 (June 2019), pp. 19–38 (cit. on p. 62).

-
- (Linkov et al., 2014) I. Linkov, T. Bridges, F. Creutzig, J. Decker, C. Fox-Lent, W. Kröger, J. H. Lambert, A. Levermann, B. Montreuil, J. Nathwani, R. Nyer, O. Renn, B. Scharte, A. Scheffler, M. Schreurs, and T. Thiel-Clemen. “[Changing the resilience paradigm](#)”. In: *Nature Climate Change* 4.6 (June 2014), pp. 407–409 (cit. on pp. xi, 35, 45, 46, 50, 53, 73, 97).
- (Long, 2014) Q. Long. “[Distributed supply chain network modelling and simulation: integration of agent-based distributed simulation and improved SCOR model](#)”. In: *International journal of production research* 52.23 (2014), pp. 6899–6917 (cit. on pp. 132–134, 146, 147, 149, 153–155).
- (Louka et al., 2001) M. N. Louka and C. Balducelli. “[Virtual Reality Tools for Emergency Operation Support and Training](#)”. In: *Proceedings of TIEMS (The International Emergency Management Society), Oslo* (2001), p. 10 (cit. on p. 103).
- (Lowrance, 1980) W. Lowrance. *The Nature of Risk'in Schwing, RC and Albers, WA (eds.) How Safe is Safe Enough*. 1980 (cit. on p. 12).
- (Lücker et al., 2019) F. Lücker, R. W. Seifert, and I. Biçer. “[Roles of inventory and reserve capacity in mitigating supply chain disruption risk](#)”. In: *International Journal of Production Research* 57.4 (Feb. 16, 2019), pp. 1238–1249 (cit. on p. 84).
- (MacCready et al., 2010) P. MacCready and W. R. Geyer. “[Advances in Estuarine Physics](#)”. In: *Annual Review of Marine Science* 2.1 (Jan. 1, 2010), pp. 35–58 (cit. on p. 96).
- (Macdonald et al., 2018) J. R. Macdonald, C. W. Zobel, S. A. Melnyk, and S. E. Griffis. “[Supply chain risk and resilience: theory building through structured experiments and simulation](#)”. In: *International Journal of Production Research* 56.12 (June 18, 2018), pp. 4337–4355 (cit. on pp. 44, 64, 87, 132).
- (Mackulak et al., 1998) G. T. Mackulak, F. P. Lawrence, and T. Colvin. “[Effective simulation model reuse: a case study for AMHS modeling](#)”. In: *1998 Winter Simulation Conference. Proceedings (Cat. No. 98CH36274)*. Vol. 2. IEEE. 1998, pp. 979–984 (cit. on p. 132).
- (Maestrini et al., 2017) V. Maestrini, D. Luzzini, P. Maccarrone, and F. Caniato. “[Supply chain performance measurement systems: A systematic review and research agenda](#)”. In: *International Journal of Production Economics* 183 (Jan. 2017), pp. 299–315 (cit. on p. 47).
- (Mani et al., 2014) M. Mani, J. Madan, J. H. Lee, K. W. Lyons, and S. K. Gupta. “[Sustainability characterisation for manufacturing processes](#)”. In: *International Journal of Production Research* 52.20 (2014), pp. 5895–5912 (cit. on p. 62).
- (Manuj et al., 2008) I. Manuj and J. T. Mentzer. “[Global supply chain risk management strategies](#)”. In: *International Journal of Physical Distribution & Logistics Management* 38.3 (Apr. 11, 2008), pp. 192–223 (cit. on pp. 1, 14, 18, 20, 22, 24, 27, 57).
- (March et al., 1987) J. G. March and Z. Shapira. “[Managerial Perspectives on Risk and Risk Taking](#)”. In: *Management Science* 33.11 (Nov. 1987), pp. 1404–1418 (cit. on p. 13).
- (Martinsons et al., 2007) M. G. Martinsons and R. M. Davison. “[Strategic decision making and support systems: Comparing American, Japanese and Chinese management](#)”. In: *Decision Support Systems* 43.1 (Feb. 2007), pp. 284–300 (cit. on p. 101).

- (McCormack et al., 2018) J. McCormack, J. C. Roberts, B. Bach, C. D. S. Freitas, T. Itoh, C. Hurter, and K. Marriott. “[Multisensory Immersive Analytics](#)”. In: *Immersive Analytics*. Ed. by K. Marriott, F. Schreiber, T. Dwyer, K. Klein, N. H. Riche, T. Itoh, W. Stuerzlinger, and B. H. Thomas. Vol. 11190. Series Title: Lecture Notes in Computer Science. Cham: Springer International Publishing, 2018, pp. 57–94 (cit. on p. 103).
- (Mele et al., 2007) F. D. Mele, G. Guillén, A. Espuña, and L. Puigjaner. “[An agent-based approach for supply chain retrofitting under uncertainty](#)”. In: *Computers & Chemical Engineering* 31.5 (May 2007), pp. 722–735 (cit. on p. 1).
- (Melnik et al., 2014) S. A. Melnyk, R. Narasimhan, and H. A. DeCampos. “[Supply chain design: issues, challenges, frameworks and solutions](#)”. In: *International Journal of Production Research* 52.7 (Apr. 3, 2014), pp. 1887–1896 (cit. on p. 3).
- (Mena et al., 2020) C. Mena, S. A. Melnyk, M. Baghersad, and C. W. Zobel. “[Sourcing Decisions under Conditions of Risk and Resilience: A Behavioral Study](#)”. In: *Decision Sciences* 51.4 (Aug. 2020), pp. 985–1014 (cit. on p. 3).
- (Millais et al., 2018) P. Millais, S. L. Jones, and R. Kelly. “[Exploring Data in Virtual Reality: Comparisons with 2D Data Visualizations](#)”. In: *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems*. CHI EA '18. New York, NY, USA: Association for Computing Machinery, Apr. 20, 2018, pp. 1–6 (cit. on p. 103).
- (Miller, 1992) K. D. Miller. “[A Framework for Integrated Risk Management in International Business](#)”. In: *Journal of International Business Studies* 23.2 (June 1992), pp. 311–331 (cit. on p. 13).
- (Min et al., 2002) H. Min and G. Zhou. “[Supply chain modeling: past, present and future](#)”. In: *Computers & Industrial Engineering* 43.1 (July 2002), pp. 231–249 (cit. on pp. 24, 26).
- (Mitchell, 1995) V.-W. Mitchell. “[Organizational Risk Perception and Reduction: A Literature Review](#)”. In: *British Journal of Management* 6.2 (June 1995), pp. 115–133 (cit. on p. 12).
- (Moen et al., 2009) R. Moen and C. Norman. “[Evolution of the PDCA Cycle](#)”. In: *Proceedings of the 7th ANQ Congress*. Tokyo, Japan: Asian Network for Quality, Sept. 2009, p. 11 (cit. on pp. 7, 8).
- (Moore, 2017) J. Moore. “[Data Visualization in Support of Executive Decision Making](#)”. In: *Interdisciplinary Journal of Information, Knowledge, and Management* 12 (2017), pp. 125–138 (cit. on pp. 47, 102).
- (Moradkhani et al., 2021) N. Moradkhani, F. Benaben, B. Montreuil, A. V. Barenji, and D. Nazzal. “[Physics of Decision for Polling Place Management: A Case Study from the 2020 USA Presidential Election](#)”. In: *ICMS 2021-15th International Conference on Modeling and Simulation*. Vol. 15. World Academy of Science, Engineering and Technology [Industrial and Manufacturing Engineering] 9. Toronto (Online), Canada, June 2021, pp. 440–448 (cit. on pp. 6, 40, 96).
- (Moradkhani et al., 2022a) N. Moradkhani, F. Benaben, B. Montreuil, M. Lauras, J. Jeany, and L. Faugere. “[Multi-criteria performance analysis based on Physics of Decision — Application to COVID-19 and future pandemics](#)”. In: *IEEE Transactions on Services Computing* (2022), pp. 1–12 (cit. on pp. 4, 6, 35).

-
- (Moradkhani et al., 2022b) N. Moradkhani, H. Dolidon, and F. Benaben. “Persistent physics-based crisis management framework: A case study of traffic in the Nantes city due to flood exposure”. In: Hawaii International Conference on System Sciences. 2022 (cit. on p. 6).
- (Morgan et al., 1990) M. G. Morgan, M. Henrion, and M. Small. *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. Google-Books-ID: ajd1V305PgQC. Cambridge University Press, 1990. 354 pp. (cit. on p. 12).
- (Mosler et al., 2001) H.-J. Mosler, K. Schwarz, F. Ammann, and H. Gutscher. “Computer Simulation as a Method of Further Developing a Theory: Simulating the Elaboration Likelihood Model”. In: *Personality and Social Psychology Review* 5.3 (Aug. 2001), pp. 201–215 (cit. on pp. 7, 82).
- (Mouloudi et al., 2022) L. Mouloudi and K. Evrard Samuel. “Critical Materials Assessment: A Key Factor for Supply Chain Risk Management”. In: *Supply Chain Forum: An International Journal* 23.1 (Jan. 2, 2022), pp. 53–67 (cit. on pp. 1, 2).
- (Müller et al., 2008) M. Müller and D. Pfahl. “Simulation methods”. In: *Guide to advanced empirical software engineering* (2008), pp. 117–152 (cit. on p. 84).
- (Munoz et al., 2015) A. Munoz and M. Dunbar. “On the quantification of operational supply chain resilience”. In: *International Journal of Production Research* 53.22 (Nov. 17, 2015), pp. 6736–6751 (cit. on p. 77).
- (Myerson et al., 2001) J. Myerson, L. Green, and M. Warusawitharana. “AREA UNDER THE CURVE AS A MEASURE OF DISCOUNTING”. In: *Journal of the Experimental Analysis of Behavior* 76.2 (Sept. 2001), pp. 235–243 (cit. on p. 64).
- (Nair et al., 2009) A. Nair, R. Narasimhan, and T. Y. Choi. “Supply Networks as a Complex Adaptive System: Toward Simulation-Based Theory Building on Evolutionary Decision Making”. In: *Decision Sciences* 40.4 (Nov. 2009), pp. 783–815 (cit. on pp. 7, 82).
- (Nair et al., 2011) A. Nair and J. M. Vidal. “Supply network topology and robustness against disruptions – an investigation using multi-agent model”. In: *International Journal of Production Research* 49.5 (Mar. 2011), pp. 1391–1404 (cit. on p. 53).
- (Nakano et al., 2020) M. Nakano and A. K. W. Lau. “A systematic review on supply chain risk management: using the strategy-structure-process-performance framework”. In: *International Journal of Logistics Research and Applications* 23.5 (Sept. 2, 2020), pp. 443–473 (cit. on pp. xi, 1, 47).
- (Natarajarathinam et al., 2009) M. Natarajarathinam, I. Capar, and A. Narayanan. “Managing supply chains in times of crisis: a review of literature and insights”. In: *International Journal of Physical Distribution & Logistics Management* 39.7 (Aug. 7, 2009). Ed. by R. Glenn Richey, pp. 535–573 (cit. on p. 20).
- (Neely et al., 1995) A. Neely, M. Gregory, and K. Platts. “Performance measurement system design: A literature review and research agenda”. In: *International Journal of Operations & Production Management* 15.4 (Apr. 1995), pp. 80–116 (cit. on pp. 4, 62).
- (Neu et al., 2002) H. Neu, T. Hanne, J. Münch, S. Nickel, and A. Wirsén. “Simulation-Based Risk Reduction for Planning Inspections”. In: *Product Focused Software Process Improvement*. Ed. by M. Oivo and S. Komi-Sirviö. Red. by G. Goos, J. Hartmanis, and J. van Leeuwen. Vol. 2559. Series Title: Lecture Notes in Computer Science. Berlin, Heidelberg: Springer Berlin Heidelberg, 2002, pp. 78–93 (cit. on p. 83).

- (Neufeld et al., 2010) R. W. Neufeld, K. Boksman, D. Vollick, L. George, and J. R. Carter. “Stochastic dynamics of stimulus encoding in schizophrenia: Theory, testing, and application”. In: *Journal of Mathematical Psychology* 54.1 (Feb. 2010), pp. 90–108 (cit. on pp. 7, 82).
- (Nudurupati et al., 2022) S. S. Nudurupati, S. Tebboune, P. Garengo, R. Daley, and J. Hardman. “Performance measurement in data intensive organisations: resources and capabilities for decision-making process”. In: *Production Planning & Control* (June 15, 2022), pp. 1–21 (cit. on p. 37).
- (Nyoman Pujawan et al., 2009) I. Nyoman Pujawan and L. H. Geraldin. “House of risk: a model for proactive supply chain risk management”. In: *Business Process Management Journal* 15.6 (Nov. 6, 2009), pp. 953–967 (cit. on p. 21).
- (Oger, 2019) R. Oger. “A decision support system for long-term supply chain capacity planning : a model-driven engineering approach”. Theses. Ecole des Mines d’Albi-Carmaux, Nov. 2019 (cit. on p. 7).
- (Olivares-Aguila et al., 2021) J. Olivares-Aguila and W. ElMaraghy. “System dynamics modelling for supply chain disruptions”. In: *International Journal of Production Research* 59.6 (Mar. 19, 2021), pp. 1757–1775 (cit. on p. 155).
- (J. B. Oliveira et al., 2019) J. B. Oliveira, M. Jin, R. S. Lima, J. E. Kobza, and J. A. B. Montevechi. “The role of simulation and optimization methods in supply chain risk management: Performance and review standpoints”. In: *Simulation Modelling Practice and Theory* 92 (Apr. 2019), pp. 17–44 (cit. on pp. 46, 83, 151).
- (U. R. d. Oliveira et al., 2017) U. R. de Oliveira, F. A. S. Marins, H. M. Rocha, and V. A. P. Salomon. “The ISO 31000 standard in supply chain risk management”. In: *Journal of Cleaner Production* 151 (May 2017), pp. 616–633 (cit. on p. 16).
- (Olson et al., 2010) D. L. Olson and D. Dash Wu. “A review of enterprise risk management in supply chain”. In: *Kybernetes* 39.5 (June 15, 2010). Ed. by D. Dash Wu, pp. 694–706 (cit. on pp. 24, 27).
- (Olsson, 2007) R. Olsson. “In search of opportunity management: Is the risk management process enough?” In: *International Journal of Project Management* 25.8 (Nov. 2007), pp. 745–752 (cit. on p. 14).
- (Orians, 1975) G. H. Orians. “Diversity, stability and maturity in natural ecosystems”. In: *Unifying Concepts in Ecology: Report of the plenary sessions of the First international congress of ecology, The Hague, the Netherlands, September 8–14, 1974*. Ed. by W. H. van Dobben. Springer. Springer Netherlands, 1975, pp. 139–150 (cit. on p. 73).
- (Oyarbide et al., 2003) A. Oyarbide, T. S. Baines, J. M. Kay, and J. Ladbroke. “Manufacturing systems modelling using system dynamics: forming a dedicated modelling tool”. In: *Journal of Advanced Manufacturing Systems* 2.1 (June 2003), pp. 71–87 (cit. on p. 155).
- (Pant et al., 2014) R. Pant, K. Barker, and C. W. Zobel. “Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors”. In: *Reliability Engineering & System Safety* 125 (May 2014), pp. 92–102 (cit. on pp. 45, 68, 126).
- (Park et al., 2013) J. Park, T. P. Seager, P. S. C. Rao, M. Convertino, and I. Linkov. “Integrating Risk and Resilience Approaches to Catastrophe Management in Engineering Systems: Perspective”. In: *Risk Analysis* 33.3 (Mar. 2013), pp. 356–367 (cit. on pp. xiii, 44, 45, 52, 72, 73).

-
- (Paulsson, 2004) U. Paulsson. *Supply chain risk management*. Ashgate Aldershot, 2004, pp. 79–96 (cit. on p. 19).
- (Pauwels et al., 2009) K. Pauwels, T. Ambler, B. H. Clark, P. LaPointe, D. Reibstein, B. Skiera, B. Wierenga, and T. Wiesel. “Dashboards as a Service: Why, What, How, and What Research Is Needed?” In: *Journal of Service Research* 12.2 (Nov. 2009), pp. 175–189 (cit. on pp. 100, 106).
- (Persson, 2011) F. Persson. “SCOR template—A simulation based dynamic supply chain analysis tool”. In: *International Journal of Production Economics* 131.1 (2011), pp. 288–294 (cit. on pp. 2, 132).
- (Persson et al., 2009) F. Persson and M. Araldi. “The development of a dynamic supply chain analysis tool—Integration of SCOR and discrete event simulation”. In: *International Journal of Production Economics* 121.2 (Oct. 2009), pp. 574–583 (cit. on pp. 132, 146, 149).
- (Persson et al., 2012) F. Persson, C. Bartoll, A. Ganovic, M. Lidberg, M. Nilsson, J. Wibaeus, and F. Winge. “Supply chain dynamics in the SCOR model — A simulation modeling approach”. In: *Proceedings Title: Proceedings of the 2012 Winter Simulation Conference (WSC)*. 2012 Winter Simulation Conference - (WSC 2012). Berlin, Germany: IEEE, Dec. 2012, pp. 1–12 (cit. on pp. 132, 133, 147, 155).
- (Petitdemange, 2020) É. Petitdemange. “SAMUFLUX : une démarche outillée de diagnostic et d’amélioration à base de doubles numériques : application aux centres d’appels d’urgence de trois SAMU”. Theses. Ecole des Mines d’Albi-Carmaux, Nov. 2020 (cit. on p. 6).
- (Pettit et al., 2013) T. J. Pettit, K. L. Croxton, and J. Fiksel. “Ensuring Supply Chain Resilience: Development and Implementation of an Assessment Tool”. In: *Journal of Business Logistics* 34.1 (Mar. 2013), pp. 46–76 (cit. on pp. 3, 50, 53, 54, 58).
- (Pettit et al., 2010) T. J. Pettit, J. Fiksel, and K. L. Croxton. “Ensuring supply chain resilience: development of a conceptual framework”. In: *Journal of Business Logistics* 31.1 (Mar. 2010), pp. 1–21 (cit. on pp. 3, 50, 60).
- (Pfohl et al., 2010) H.-C. Pfohl, H. Köhler, and D. Thomas. “State of the art in supply chain risk management research: empirical and conceptual findings and a roadmap for the implementation in practice”. In: *Logistics Research* 2.1 (June 2010), pp. 33–44 (cit. on pp. 14, 17–21).
- (Pires Ribeiro et al., 2018) J. Pires Ribeiro and A. Barbosa-Povoa. “Supply Chain Resilience: Definitions and quantitative modelling approaches – A literature review”. In: *Computers & Industrial Engineering* 115 (Jan. 2018), pp. 109–122 (cit. on pp. 46, 50, 53).
- (Ponis et al., 2012) S. T. Ponis and E. Koronis. “Supply Chain Resilience: Definition Of Concept And Its Formative Elements”. In: *Journal of Applied Business Research (JABR)* 28.5 (Aug. 21, 2012), p. 921 (cit. on pp. 52–54, 59).
- (Ponis et al., 2016) S. T. Ponis and A. C. Ntalla. “Supply Chain Risk Management Frameworks and Models: A Review”. In: *International Journal of Supply Chain Management* 5.4 (2016), pp. 1–11 (cit. on pp. 16, 19, 20).
- (Ponomarov et al., 2009) S. Y. Ponomarov and M. C. Holcomb. “Understanding the concept of supply chain resilience”. In: *The International Journal of Logistics Management* 20.1 (May 22, 2009), pp. 124–143 (cit. on pp. 2, 3, 50, 52–54, 59, 61, 69, 73, 127).

- (Prakash et al., 2017) S. Prakash, G. Soni, and A. P. S. Rathore. “A critical analysis of supply chain risk management content: a structured literature review”. In: *Journal of Advances in Management Research* 14.1 (Feb. 6, 2017), pp. 69–90 (cit. on p. 1).
- (Prater et al., 2001) E. Prater, M. Biehl, and M. A. Smith. “International supply chain agility - Tradeoffs between flexibility and uncertainty”. In: *International Journal of Operations & Production Management* 21.5 (May 1, 2001), pp. 823–839 (cit. on p. 57).
- (Priya Datta et al., 2007) P. Priya Datta, M. Christopher, and P. Allen. “Agent-based modelling of complex production/distribution systems to improve resilience”. In: *International Journal of Logistics Research and Applications* 10.3 (Sept. 2007), pp. 187–203 (cit. on pp. 1, 54, 68).
- (Pruessner et al., 2003) J. C. Pruessner, C. Kirschbaum, G. Meinlschmid, and D. H. Hellhammer. “Two formulas for computation of the area under the curve represent measures of total hormone concentration versus time-dependent change”. In: *Psychoneuroendocrinology* 28.7 (Oct. 2003), pp. 916–931 (cit. on p. 64).
- (Ptak et al., 2019) C. Ptak and C. Smith. *The Demand Driven Adaptive Enterprise: Surviving, Adapting, and Thriving in a VUCA World*. Industrial Press, Incorporated, 2019 (cit. on pp. 24, 28).
- (Rajaratnam et al., 2021) D. Rajaratnam and F. Sunmola. “Adaptations in SCOR based performance metrics of airline catering supply chain during COVID-19 pandemic”. In: *Journal of Industrial Engineering and Management* 14.4 (Oct. 14, 2021), p. 808 (cit. on p. 70).
- (Rajesh, 2016) R. Rajesh. “Forecasting supply chain resilience performance using grey prediction”. In: *Electronic Commerce Research and Applications* 20 (Nov. 2016), pp. 42–58 (cit. on pp. 70, 71).
- (Rangel et al., 2015) D. A. Rangel, T. K. de Oliveira, and M. S. A. Leite. “Supply chain risk classification: discussion and proposal”. In: *International Journal of Production Research* 53.22 (Nov. 17, 2015), pp. 6868–6887 (cit. on p. 24).
- (Rice et al., 2003) J. B. Rice and F. Caniato. “Building a secure and resilient supply network”. In: *Supply Chain Management Review* 7.5 (2003) (cit. on pp. 52, 54, 58).
- (Ritchie et al., 2007a) B. Ritchie and C. Brindley. “An emergent framework for supply chain risk management and performance measurement”. In: *Journal of the Operational Research Society* 58.11 (Nov. 2007), pp. 1398–1411 (cit. on p. 34).
- (Ritchie et al., 2007b) B. Ritchie and C. Brindley. “Supply chain risk management and performance: A guiding framework for future development”. In: *International Journal of Operations & Production Management* 27.3 (Mar. 6, 2007), pp. 303–322 (cit. on p. 20).
- (Roberta Pereira et al., 2014) C. Roberta Pereira, M. Christopher, and A. Lago Da Silva. “Achieving supply chain resilience: the role of procurement”. In: *Supply Chain Management: An International Journal* 19.5 (Sept. 2, 2014), pp. 626–642 (cit. on pp. 53, 55).
- (Rowe, 1980) W. D. Rowe. *Risk Assessment Approaches and Methods in “Society, Technology and Risk Assessment”* J. Conrad, ed. 1980 (cit. on p. 14).
- (Ruhl, 2010) J. B. Ruhl. “General Design Principles for Resilience and Adaptive Capacity in Legal Systems - With Applications to Climate Change Adaptation”. In: *North Carolina Law Review* 89 (2010), p. 33 (cit. on p. 60).

-
- (Sabahi et al., 2020) S. Sabahi and M. M. Parast. “Firm innovation and supply chain resilience: a dynamic capability perspective”. In: *International Journal of Logistics Research and Applications* 23.3 (May 3, 2020), pp. 254–269 (cit. on pp. xi, 2, 3).
- (Saghafian et al., 2016) S. Saghafian and M. P. Van Oyen. “Compensating for Dynamic Supply Disruptions: Backup Flexibility Design”. In: *Operations Research* 64.2 (Apr. 2016), pp. 390–405 (cit. on p. 63).
- (Samvedi et al., 2013) A. Samvedi, V. Jain, and F. T. S. Chan. “Quantifying risks in a supply chain through integration of fuzzy AHP and fuzzy TOPSIS”. In: *International Journal of Production Research* 51.8 (Apr. 2013), pp. 2433–2442 (cit. on pp. 25, 28, 43).
- (Saunders et al., 2019) J. Saunders, S. Davey, P. S. Bayerl, and P. Lohrmann. “Validating Virtual Reality as an Effective Training Medium in the Security Domain”. In: *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*. 2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR). Osaka, Japan: IEEE, Mar. 2019, pp. 1908–1911 (cit. on p. 104).
- (Senna et al., 2020) P. Senna, A. da Cunha Reis, A. Castro, and A. C. Dias. “Promising research fields in supply chain risk management and supply chain resilience and the gaps concerning human factors: A literature review”. In: *Work* 67.2 (Nov. 9, 2020), pp. 487–498 (cit. on p. 3).
- (Serdarasan, 2013) S. Serdarasan. “A review of supply chain complexity drivers”. In: *Computers & Industrial Engineering* 66.3 (Nov. 2013), pp. 533–540 (cit. on p. 2).
- (Serrano et al., 2005) A. Serrano and M. den Hengst. “Modelling the integration of BP and IT using business process simulation”. In: *Journal of Enterprise Information Management* 18.6 (Dec. 1, 2005), pp. 740–759 (cit. on pp. 7, 82).
- (Sheffi et al., 2005) Y. Sheffi and J. B. Rice Jr. “A Supply Chain View of the Resilient Enterprise”. In: *MIT Sloan Management Review* (Oct. 15, 2005) (cit. on pp. 52–54, 56).
- (Shekarian et al., 2021) M. Shekarian and M. Mellat Parast. “An Integrative approach to supply chain disruption risk and resilience management: a literature review”. In: *International Journal of Logistics Research and Applications* 24.5 (Sept. 3, 2021), pp. 427–455 (cit. on p. 16).
- (Sillanpää, 2015) I. Sillanpää. “Empirical study of measuring supply chain performance”. In: *Benchmarking: An International Journal* 22.2 (Mar. 2, 2015). Ed. by Kohtamäki and M. Petri Helo, pp. 290–308 (cit. on p. 68).
- (Simchi-Levi, 2010) D. Simchi-Levi. “The 6 forces driving supply chain design”. In: *MIT Sloan Management Review* 51.2 (2010), pp. 17–24 (cit. on p. 35).
- (Simchi-Levi et al., 2018) D. Simchi-Levi, H. Wang, and Y. Wei. “Increasing Supply Chain Robustness through Process Flexibility and Inventory”. In: *Production and Operations Management* 27.8 (Aug. 2018), pp. 1476–1491 (cit. on p. 68).
- (H. A. Simon, 1955) H. A. Simon. “A behavioral model of rational choice”. In: *The quarterly journal of economics* 69.1 (1955), pp. 99–118 (cit. on pp. 2, 34, 35, 40, 41, 46, 48, 100, 104, 115).
- (P. Simon et al., 1997) P. Simon et al. “PRAM Project Risk Analysis and Management Guide-Association for Project Management”. In: *High Wycombe, UK* (1997) (cit. on p. 12).

- (Singhal et al., 2011) P. Singhal, G. Agarwal, and M. L. Mittal. “Supply chain risk management: Review, classification and future research directions”. In: *International Journal of Business Science & Applied Management (IJBSAM)* 6.3 (2011). Place: s.l. Publisher: International Journal of Business Science & Applied Management, pp. 15–42 (cit. on pp. 16, 19, 83).
- (Snider, 1991) H. W. Snider. “Risk management: a retrospective view”. In: *Risk Management* 38.4 (Apr. 1, 1991). Publisher: Sabinet Online, pp. 47–54 (cit. on p. 12).
- (Sodhi et al., 2012a) M. S. Sodhi, B.-G. Son, and C. S. Tang. “Researchers’ Perspectives on Supply Chain Risk Management: Perspectives on Supply Chain Risk Management”. In: *Production and Operations Management* 21.1 (Jan. 2012), pp. 1–13 (cit. on p. 28).
- (Sodhi et al., 2012b) M. S. Sodhi and C. S. Tang. *Managing Supply Chain Risk*. Springer Science & Business Media, Feb. 25, 2012. 333 pp. (cit. on pp. 2, 24, 29).
- (Soni et al., 2014) U. Soni, V. Jain, and S. Kumar. “Measuring supply chain resilience using a deterministic modeling approach”. In: *Computers & Industrial Engineering* 74 (Aug. 2014), pp. 11–25 (cit. on pp. 2, 61).
- (Souza et al., 2015) R. de Souza and R. Zhou. “Improve Robustness and Resilience of Networked Supply Chains”. In: *Proceedings of the 18th Asia Pacific Symposium on Intelligent and Evolutionary Systems - Volume 2*. Ed. by H. Handa, H. Ishibuchi, Y.-S. Ong, and K.-C. Tan. Vol. 2. Series Title: Proceedings in Adaptation, Learning and Optimization. Cham: Springer International Publishing, 2015, pp. 589–597 (cit. on p. 32).
- (Spiegler et al., 2012) V. L. M. Spiegler, M. M. Naim, and J. Wikner. “A control engineering approach to the assessment of supply chain resilience”. In: *International Journal of Production Research* 50.21 (Nov. 2012), pp. 6162–6187 (cit. on pp. xiv, 56, 61, 62, 69).
- (Stefanovic et al., 2009) D. Stefanovic, N. Stefanovic, and B. Radenkovic. “Supply network modelling and simulation methodology”. In: *Simulation Modelling Practice and Theory* 17.4 (Apr. 2009), pp. 743–766 (cit. on pp. 82, 83, 132, 155).
- (Sterman, 2000) J. D. Sterman. *Business Dynamics: Modeling and Simulation for a Complex World*. 2000 (cit. on p. 152).
- (Sumari et al., 2013) S. Sumari, R. Ibrahim, N. H. Zakaria, and A. H. Ab Hamid. “Comparing Three Simulation Model Using Taxonomy: System Dynamic Simulation, Discrete Event Simulation and Agent Based Simulation”. In: *International Journal of Management Excellence* 1.3 (Aug. 30, 2013), p. 54 (cit. on p. 154).
- (Svensson, 2000) G. Svensson. “A conceptual framework for the analysis of vulnerability in supply chains”. In: *International Journal of Physical Distribution & Logistics Management* 30.9 (Nov. 1, 2000), pp. 731–750 (cit. on p. 20).
- (Swaminathan et al., 1998) J. M. Swaminathan, S. F. Smith, and N. M. Sadeh. “Modeling Supply Chain Dynamics: A Multiagent Approach”. In: *Decision Sciences* 29.3 (July 1998), pp. 607–632 (cit. on p. 153).
- (Tako et al., 2012) A. A. Tako and S. Robinson. “The application of discrete event simulation and system dynamics in the logistics and supply chain context”. In: *Decision Support Systems* 52.4 (Mar. 2012), pp. 802–815 (cit. on pp. 134, 152–155).
- (Taleb, 2007) N. N. Taleb. *The Black Swan. The Impact of the Highly Improbable*. New York: Random House, 2007. Reviewed by James Iain Gow Université de Montréal, Canada. 2007 (cit. on pp. xi, 1, 58).

-
- (Taleb, 2014) N. N. Taleb. *Antifragile: Things that gain from disorder*. Vol. 3. Random House Trade Paperbacks, 2014 (cit. on pp. xi, 1, 58).
- (Tan et al., 2020) W. J. Tan, W. Cai, and A. N. Zhang. “[Structural-aware simulation analysis of supply chain resilience](#)”. In: *International Journal of Production Research* 58.17 (Sept. 1, 2020), pp. 5175–5195 (cit. on p. 50).
- (C. S. Tang, 2006a) C. S. Tang. “[Perspectives in supply chain risk management](#)”. In: *International Journal of Production Economics* 103.2 (Oct. 2006), pp. 451–488 (cit. on pp. 3, 20–22, 24, 27, 52).
- (C. S. Tang, 2006b) C. S. Tang. “[Robust strategies for mitigating supply chain disruptions](#)”. In: *International Journal of Logistics Research and Applications* 9.1 (Mar. 2006), pp. 33–45 (cit. on p. 56).
- (O. Tang et al., 2011) O. Tang and S. Nurmayana. “[Identifying risk issues and research advancements in supply chain risk management](#)”. In: *International Journal of Production Economics* 133.1 (Sept. 2011), pp. 25–34 (cit. on pp. 24, 27).
- (Taticchi et al., 2015) P. Taticchi, P. Garengo, S. S. Nudurupati, F. Tonelli, and R. Pasqualino. “[A review of decision-support tools and performance measurement and sustainable supply chain management](#)”. In: *International Journal of Production Research* 53.21 (Nov. 2, 2015), pp. 6473–6494 (cit. on p. 37).
- (Tazelaar et al., 2013) F. Tazelaar and C. Snijders. “[Operational risk assessments by supply chain professionals: Process and performance](#)”. In: *Journal of Operations Management* 31.1 (Jan. 2013), pp. 37–51 (cit. on p. 29).
- (Thierry et al., 2008) C. Thierry, G. Bel, and A. Thomas. “[Simulation for supply Chain management: an Overview](#)”. In: *Control Systems, robotics and manufacturing series* (2008). Ed. by C. Thierry, A. Thomas, and G. Bel. Synthesis of Vendome team research works (team belonging to GDR MACS - CNRS), pp. 1–36 (cit. on p. 83).
- (Thomas, 1985) J. Thomas. “[Force field analysis: A new way to evaluate your strategy](#)”. In: *Long Range Planning* 18.6 (Dec. 1985), pp. 54–59 (cit. on pp. 13, 14).
- (Thun et al., 2011) J.-H. Thun and D. Hoenig. “[An empirical analysis of supply chain risk management in the German automotive industry](#)”. In: *International Journal of Production Economics* 131.1 (May 2011), pp. 242–249 (cit. on pp. 20–22).
- (Tran et al., 2018) T. H. Tran, M. Dobrovnik, and S. Kummer. “[Supply chain risk assessment: a content analysis-based literature review](#)”. In: *International Journal of Logistics Systems and Management* 31.4 (2018), p. 562 (cit. on pp. 16, 21, 24, 29–31).
- (Trkman et al., 2009) P. Trkman and K. McCormack. “[Supply chain risk in turbulent environments—A conceptual model for managing supply chain network risk](#)”. In: *International Journal of Production Economics* 119.2 (June 2009), pp. 247–258 (cit. on pp. 2, 23, 24, 27, 43).
- (Tukamuhabwa et al., 2015) B. R. Tukamuhabwa, M. Stevenson, J. Busby, and M. Zorzini. “[Supply chain resilience: definition, review and theoretical foundations for further study](#)”. In: *International Journal of Production Research* 53.18 (Sept. 17, 2015), pp. 5592–5623 (cit. on pp. 50, 53, 57, 59, 63, 72).
- (Tummala et al., 2011) R. Tummala and T. Schoenherr. “[Assessing and managing risks using the Supply Chain Risk Management Process \(SCRMP\)](#)”. In: *Supply Chain Management: An International Journal* 16.6 (Sept. 27, 2011). Ed. by C. Xie, pp. 474–483 (cit. on pp. 21, 27).

- (Tuncel et al., 2010) G. Tuncel and G. Alpan. “[Risk assessment and management for supply chain networks: A case study](#)”. In: *Computers in Industry* 61.3 (Apr. 2010), pp. 250–259 (cit. on pp. 21, 23, 29, 32).
- (Vorst et al., 2002) J. G. A. J. van der Vorst and A. J. M. Beulens. “[Identifying sources of uncertainty to generate supply chain redesign strategies](#)”. In: *International Journal of Physical Distribution & Logistics Management* 32.6 (Aug. 1, 2002), pp. 409–430 (cit. on p. 19).
- (Wagner et al., 2006) S. M. Wagner and C. Bode. “[An empirical investigation into supply chain vulnerability](#)”. In: *Journal of Purchasing and Supply Management* 12.6 (Nov. 2006), pp. 301–312 (cit. on pp. 13, 17–19).
- (Wagner et al., 2008) S. M. Wagner and C. Bode. “[An empirical examination of supply chain performance along several dimensions of risk](#)”. In: *Journal of Business Logistics* 29.1 (Mar. 2008), pp. 307–325 (cit. on p. 2).
- (Wagner et al., 2010) S. M. Wagner and N. Neshat. “[Assessing the vulnerability of supply chains using graph theory](#)”. In: *International Journal of Production Economics* 126.1 (2010), pp. 121–129 (cit. on pp. xi, 1).
- (B. Walker et al., 2004) B. Walker, C. S. Holling, S. R. Carpenter, and A. P. Kinzig. “[Resilience, Adaptability and Transformability in Social-ecological Systems](#)”. In: *Ecology and Society* 9.2 (2004), art5 (cit. on p. 73).
- (B. H. Walker, 2020) B. H. Walker. “[Resilience: what it is and is not](#)”. In: *Ecology and Society* 25.2 (2020), art11 (cit. on pp. 46, 126).
- (Wang et al., 2016) Y. Wang and R. Xiao. “[An ant colony based resilience approach to cascading failures in cluster supply network](#)”. In: *Physica A: Statistical Mechanics and its Applications* 462 (Nov. 2016), pp. 150–166 (cit. on pp. 53, 55).
- (Westman, 1978) W. E. Westman. “[Measuring the Inertia and Resilience of Ecosystems](#)”. In: *BioScience* 28.11 (Nov. 1978), pp. 705–710 (cit. on pp. 73, 75).
- (A. White et al., 2005) A. White, E. M. Daniel, and M. Mohdzain. “[The role of emergent information technologies and systems in enabling supply chain agility](#)”. In: *International Journal of Information Management* 25.5 (2005), pp. 396–410 (cit. on p. 2).
- (D. White, 1995) D. White. “[Application of systems thinking to risk management: a review of the literature](#)”. In: *Management Decision* 33.10 (Dec. 1995), pp. 35–45 (cit. on pp. 23, 31).
- (Whitin, 1955) T. M. Whitin. “[Inventory Control and Price Theory](#)”. In: *Management Science* 2.1 (Oct. 1955), pp. 61–68 (cit. on p. 64).
- (Wicaksana et al., 2022) A. Wicaksana, W. Ho, S. Talluri, and A. Dolgui. “[A decade of progress in supply chain risk management: risk typology, emerging topics, and research collaborators](#)”. In: *International Journal of Production Research* (May 23, 2022), pp. 1–23 (cit. on pp. 2, 17, 19, 21, 24, 25, 28).
- (Wieland, 2021) A. Wieland. “[Dancing the Supply Chain: Toward Transformative Supply Chain Management](#)”. In: *Journal of Supply Chain Management* 57.1 (Jan. 2021), pp. 58–73 (cit. on pp. xv, 72, 102).
- (Wieland et al., 2021) A. Wieland and C. F. Durach. “[Two perspectives on supply chain resilience](#)”. In: *Journal of Business Logistics* 42.3 (July 2021), pp. 315–322 (cit. on pp. xi, xv, 35, 45, 46, 72, 96, 126).

-
- (Wieland et al., 2012) A. Wieland and C. M. Wallenburg. “Dealing with supply chain risks: Linking risk management practices and strategies to performance”. In: *International Journal of Physical Distribution & Logistics Management* 42.10 (Nov. 2, 2012), pp. 887–905 (cit. on pp. 34, 57).
- (Wieland et al., 2013) A. Wieland and C. M. Wallenburg. “The influence of relational competencies on supply chain resilience: a relational view”. In: *International Journal of Physical Distribution & Logistics Management* 43.4 (May 17, 2013). Ed. by H. L. Töyli and J. Lauri Ojala, pp. 300–320 (cit. on pp. 55–58).
- (Wildgoose et al., 2012) N. Wildgoose, P. Brennan, and S. Thompson. “Understanding your supply chain to reduce the risk of supply chain disruption”. In: *Journal of Business Continuity & Emergency Planning* 6.1 (May 1, 2012), pp. 55–67 (cit. on p. 16).
- (Wilkinson et al., 1998) I. Wilkinson, L. C. Young, D. Welch, and L. Welch. “Dancing to success: export groups as dance parties and the implications for network development”. In: *Journal of Business & Industrial Marketing* 13.6 (Jan. 1, 1998). Publisher: MCB UP Ltd, pp. 492–510 (cit. on p. 102).
- (D. Wu et al., 2015) D. Wu, D. L. Olson, and A. Dolgui. “Decision making in enterprise risk management: A review and introduction to special issue”. In: *Omega* 57 (Dec. 2015), pp. 1–4 (cit. on p. 82).
- (T. Wu et al., 2009) T. Wu and J. Blackhurst, eds. *Managing Supply Chain Risk and Vulnerability: Tools and Methods for Supply Chain Decision Makers*. London: Springer London, 2009 (cit. on pp. 14, 23, 31, 47, 102, 104).
- (T. Wu et al., 2006) T. Wu, J. Blackhurst, and V. Chidambaram. “A model for inbound supply risk analysis”. In: *Computers in Industry* 57.4 (May 2006), pp. 350–365 (cit. on pp. 23, 24, 27).
- (Yao et al., 2018) Y. Yao and N. Fabbe-Costes. “Can you measure resilience if you are unable to define it? The analysis of Supply Network Resilience (SNRES)”. In: *Supply Chain Forum: An International Journal* 19.4 (Oct. 2, 2018), pp. 255–265 (cit. on pp. 55, 56, 60).
- (Yazdani et al., 2017) M. Yazdani, P. Zarate, A. Coulibaly, and E. K. Zavadskas. “A group decision making support system in logistics and supply chain management”. In: *Expert Systems with Applications* 88 (Dec. 2017), pp. 376–392 (cit. on p. 33).
- (Yeoh et al., 2014) W. Yeoh, G. Richards, and S. Wang. “Benefits and Barriers to Corporate Performance Management Systems”. In: *Journal of Computer Information Systems* 55.1 (Sept. 2014), pp. 105–116 (cit. on p. 102).
- (Yigitbasioglu et al., 2012) O. M. Yigitbasioglu and O. Velcu. “A review of dashboards in performance management: Implications for design and research”. In: *International Journal of Accounting Information Systems* 13.1 (Mar. 2012), pp. 41–59 (cit. on pp. 100, 106).
- (Yildiz et al., 2020) K. Yildiz and M. T. Ahi. “Innovative decision support model for construction supply chain performance management”. In: *Production Planning & Control* (Nov. 16, 2020), pp. 1–13 (cit. on p. 135).
- (Yin, 2009) R. K. Yin. *Case Study Research: Design and Methods*. Sage, 2009. 241 pp. (cit. on p. 7).

- (Zeng et al., 2017) B. Zeng and B. P.-C. Yen. “Rethinking the role of partnerships in global supply chains: A risk-based perspective”. In: *International Journal of Production Economics* 185 (Mar. 2017), pp. 52–62 (cit. on pp. 14, 15).
- (Zhengping et al., 2013) L. Zhengping, T. P. Siew, Y. Q. M. Gabriel, N. Q. Chinh, O. Y. Soon, and C. Xianshun. “A Review of Complex Systems Technologies for Supply Chain Risk Management”. In: *2013 IEEE International Conference on Systems, Man, and Cybernetics*. 2013 IEEE International Conference on Systems, Man and Cybernetics (SMC 2013). Manchester: IEEE, Oct. 2013, pp. 2783–2789 (cit. on pp. xi, 35).
- (Zobel, 2010) C. W. Zobel. “Comparative Visualization of Predicted Disaster Resilience”. In: *ISCRAM*. 2010, p. 7 (cit. on pp. xvi, 64–66, 76).
- (Zobel, 2011) C. W. Zobel. “Representing perceived tradeoffs in defining disaster resilience”. In: *Decision Support Systems* 50.2 (Jan. 2011), pp. 394–403 (cit. on pp. 63, 66).
- (Zobel et al., 2014) C. W. Zobel and L. Khansa. “Characterizing multi-event disaster resilience”. In: *Computers & Operations Research* 42 (Feb. 2014), pp. 83–94 (cit. on pp. 66, 67).
- (Zobel et al., 2021) C. W. Zobel, C. A. MacKenzie, M. Baghersad, and Y. Li. “Establishing a frame of reference for measuring disaster resilience”. In: *Decision Support Systems* 140 (Jan. 2021), p. 113406 (cit. on pp. xiv, 62–64, 68).
- (Zsidisin et al., 2019) G. A. Zsidisin and M. Henke. *Revisiting supply chain risk*. Springer, 2019 (cit. on p. 25).
- (Zsidisin, 2003) G. A. Zsidisin. “A grounded definition of supply risk”. In: *Journal of Purchasing and Supply Management* 9.5 (Sept. 2003), pp. 217–224 (cit. on pp. 17, 18).
- (Zsidisin et al., 2005) G. A. Zsidisin and M. E. Smith. “Managing Supply Risk with Early Supplier Involvement: A Case Study and Research Propositions”. In: *The Journal of Supply Chain Management* 41.4 (Nov. 2005), pp. 44–57 (cit. on p. 52).

Résumé

Étude de l'application d'une approche d'aide à la décision basée sur les principes de la physique classique pour la gestion des risques et des opportunités des supply chains dans leur cockpit immersif de pilotage de la performance

En raison de leur nature complexe en réseau de divers acteurs interconnectés et interdépendants, les supply chains n'ont jamais été aussi sujettes et fragiles à l'instabilité, générée par une augmentation massive des catastrophes naturelles et anthropiques au cours de ces dernières décennies et devient la norme. Il est devenu impossible d'ignorer et d'éliminer l'instabilité qui y règne. Être en mesure de faire face à cette instabilité devient alors un défi incontournable et une attente forte des managers. Pour répondre à ce besoin, nos travaux étudient l'applicabilité de l'approche de la Physique de la Décision (de l'anglais *Physics of Decision*, PoD), une approche innovante d'aide à la décision basée sur les lois du mouvement de la physique classique. Dans cette approche l'accent est mis sur le développement d'un cadre théorique et mathématique pour modéliser l'impact des risques et des opportunités perturbant une supply chain comme des forces physiques, la déviant telle un objet de ses objectifs de performance dans son référentiel de performance multidimensionnel, construit à partir de ses indicateurs quantitatifs clés de performance. Cette connexion forte entre l'atteinte des objectifs de performance d'une supply chain et son exposition aux risques et aux opportunités à travers l'utilisation de lois physiques est une contribution forte de l'approche PoD. Elle permet (1) d'examiner l'évolution de la supply chain dans son référentiel de performance grâce à une analyse cinématique de sa trajectoire de performance multidimensionnelle et (2) de proposer une analyse réactive et prédictive sur la base des forces physiques identifiées. Ainsi, être capable d'évaluer et de formaliser ces forces de déviation est l'un des défis majeurs pour l'application de l'approche PoD. En raison de la nature imprévisible et non quantifiable des perturbations, la gestion des risques et des opportunités des supply chains ne peut se contenter de dresser une liste des forces l'impactant. Dans ce contexte de forte instabilité, les supply chains se doivent de renforcer leur résilience (leur capacité à résister, à s'adapter et à répondre aux perturbations). Dans la littérature, deux définitions de sa résilience se distinguent : la résilience technique (la rapidité de retour à l'équilibre) et la résilience écologique (la quantité de forces extrinsèques qu'elle est capable de supporter). Nos travaux de recherche cherchent à étudier les apports de l'approche PoD pour mesurer en une seule approche ces deux visions fondamentales de la résilience des supply chains, ce qui à notre connaissance n'a jamais été proposé. Les apports de l'approche PoD réside également dans la maîtrise du référentiel de performance (un espace au cœur du processus de décision) et le calcul théorique de la performance globale d'une supply chain observée comme une trajectoire multidimensionnelle. Cependant pour les supply chains, il est rare que les managers se limitent à observer trois indicateurs. Il est donc impératif de trouver un moyen de rendre ces résultats manipulables et visualisables dans un référentiel à plus de trois dimensions. La réalité virtuelle est la solution explorée pour immerger les décideurs dans une version virtuelle du référentiel de performance, dans laquelle ils peuvent visualiser et interagir avec les trajectoires et les forces, ouvrant la porte à une nouvelle génération de tableau de bord de performance.

MOTS-CLÉS : Physique de la décision, Gestion des supply chains, Risque et opportunité, Mesure de la résilience, Réalité virtuelle, Gestion de la performance

Abstract

Study of the application of a decision support approach based on classical physics principles for managing supply chain risks and opportunities within its immersive performance management cockpit

Due to their complex networked nature of diverse interconnected and interdependent actors, supply chains have never been more prone and fragile to instability, which has been generated by a massive increase in natural and man-made disasters over the past decades and is becoming the norm. It has become impossible to ignore and eliminate the instability that exists. Being able to cope with this instability becomes an inescapable challenge and a strong expectation of managers. To meet this need, our works study the applicability of the Physics of Decision (PoD) approach, an innovative approach to decision support based on the laws of motion of classical physics. In this approach the focus is on developing a theoretical and mathematical framework to model the impact of risks and opportunities disrupting a supply chain as physical forces, deviating it like an object from its performance objectives in its multidimensional performance framework, built from its quantitative key performance indicators. This strong connection between the achievement of the performance objectives of a supply chain and its exposure to risks and opportunities through the use of physical laws is a strong contribution of the PoD approach. It allows (1) to examine the evolution of the supply chain in its performance framework through a kinematic analysis of its multidimensional performance trajectory and (2) to propose a reactive and predictive analysis based on the identified physical forces. Thus, being able to assess and formalize these deviation forces is one of the major challenges for the application of the PoD approach. Due to the unpredictable and unquantifiable nature of disruptions, supply chain risk and opportunity management cannot simply list the forces impacting it. In this highly volatile environment, supply chains need to build resilience (their ability to resist, adapt and respond to disruptions). In the literature, two definitions of supply chain resilience can be distinguished: engineering resilience (the speed of return to equilibrium) and ecological resilience (the amount of extrinsic forces it is able to withstand). Our research seeks to investigate the contributions of the PoD approach to measure in a single approach these two fundamental views of resilience, which to our knowledge has never been proposed. The contributions of the PoD approach also lie in the mastery of the performance framework (seen as a space at the heart of the decision process) and the theoretical calculation of the overall performance of a supply chain observed as a multidimensional trajectory. However, for systems such as supply chains, it is rare for managers to limit themselves to the observation of three indicators. It is therefore imperative to find a way to make these results easy to handle and visualizable in a more than three-dimensional framework. Virtual reality is the solution being explored to immerse decision-makers in a virtual version of the performance framework, in which they can visualize and interact with trajectories and forces, opening the door to a new generation of performance dashboards.

KEYWORDS: Physics of decision, Supply chain management, Risk and opportunity, Resilience measurement, Virtual Reality, Performance management