Supporting decision-making for solving design issues in the development phase of automotive vehicles

Timothé Sissoko

université PARIS-SACLAY

NNT : 2019SACLC103

CentraleSupélec

Supporting decision-making for solving design issues in the development phase of automotive vehicles

Thèse de doctorat de l'Université Paris-Saclay
préparée à CentraleSupélec

École doctorale n°573 Approches interdisciplinaires, fondements, applications et innovation (Interfaces)
Spécialité de doctorat: Génie Industriel

Thèse présentée et soutenue à Gif-sur-Yvette, le 19 décembre 2019, par

Timothé M. Sissoko

Composition du Jury :

Eric Bonjour Professeur, Université de Lorraine Equipe de Recherche sur les Processus Innovatifs	Rapporteur
Benoit Eynard Professeur, Université de Technologie de Compiègne Département Génie des Systèmes Mécaniques	Rapporteur
Michael Kokkolaras Professeur, McGill University Department of Mechanical Engineering	Président
Eric Landel Expert Leader, Renault Direction Ingénierie des Prestations clients, de la Simulation numérique et des Tests, CAE intégré & PLM	Examinateur
Bernard Yannou Professeur, CentraleSupélec Laboratoire Génie Industriel	Examinateur
Marija Jankovic Professeur, CentraleSupélec Laboratoire Génie Industriel	Directrice de thèse
Christiaan J. J. Paredis Professeur, Clemson University Department of Automotive Engineering	Co-Directeur de thèse

Thèse de doctorat

université PARIS-SACLAY
ÉCOLE DOCTORALE
INTERFACES
Approches Interdisciplinaires : Fondements, Applications et Innovation

Titre : Aide à la décision pour la résolution de problèmes de conception dans la phase de développement des véhicules automobiles

Mots clés : analyse de la décision, modélisation et simulation, résolution de problème, industrie automobile

Résumé : L'objectif de nos travaux est d'aider la prise de décision liée à la résolution de problèmes de conception dans la phase de développement de systèmes complexes dans un contexte de simulation numérique. Nous avons conduit nos travaux au sein d'une entreprise automobile multinationale.
La première partie de notre recherche s'est concentrée sur l'identification des difficultés rencontrées dans le processus de résolution de problème, en s'intéressant particulièrement à la prise de décision, et aux méthodes et outils. Une étude qualitative menée auprès de 11 experts et portant sur 40 problèmes de décision a mis en lumière le fait que les décideurs choisissent parmi un ensemble d'alternatives relatives au processus plutôt que des alternatives liées à l'artefact (i.e. uniquement liées au produit). Les conséquences de ces alternatives relatives au processus telles que le recalcul, l'intégration de nouvelles informations, l'attente de l'évolution de la définition technique du véhicule, etc. ne sont pas explicites. Nous avons constaté que l'absence d'un cadre rigoureux était une perspective d'amélioration.
La deuxième partie consista donc à proposer un cadre pour aider la prise de décision en matière de conception. Les questions relatives à l'ingénierie concourante et aux contraintes de ressources liées à la gestion de projet en analyse de la décision n'ont été que rarement approfondies dans la littérature Decision Based Design.
Pour tenter de combler cette lacune, nous avons conçu le framework IRDS. Par le biais de IRDS, nous proposons de rendre explicites les alternatives liées au processus, et de rassembler des données économiques et des prévisions d'experts dans un modèle décisionnel fondé sur la théorie prescriptive de la décision, incluant la maximisation de l'utilité espérée et la valeur économique de l'information imparfaite.
La troisième partie de nos travaux s'est intéressée à l'impact de l'incertitude sur le processus de collecte des données et sur la décision. Pour ce faire, nous avons proposé de réaliser des analyses de sensibilité à partir des données brutes disponibles, en amont de l'approfondissement par élicitation d'expert. Les impacts sur le processus décisionnel et les échanges d'informations entre les parties prenantes, ainsi que les ressources consommées par les nouvelles pratiques que nous proposons ont également été étudiés à un niveau plus superficiel. Nous présentons le déploiement et le test de ces méthodes sur 5 études de cas. La validation de cette approche exige de recueillir davantage de données empiriques pour soutenir l'hypothèse selon laquelle de meilleures décisions sont prises à long terme. Nous sommes convaincus que nos recherches serviront de base à de futures études sur la conception et la mise en œuvre de frameworks visant à relever des défis industriels.

Title : Supporting decision-making for solving design issues in the development phase of automotive vehicles

Keywords : decision analysis, modeling and simulation, problem-solving, automotive industry

Abstract : The purpose of this research is to support decision-making for solving design issues in the development phase of complex systems supported by numerical simulation. We conducted our studies in a multinational car manufacturer.
The first part of the research was devoted to identifying the difficulties encountered in the issue resolution process, with a particular focus on decision-making issues, methods and tools. A qualitative study done with 11 experts and on 40 decision problems highlighted that the decision-makers choose from a set of process alternatives rather than artifact alternatives. The consequences of these process alternatives such as recalculating, integrating information, waiting for the technical definition of the vehicle to evolve, etc. are not explicit. We identified the lack of a rigorous framework as an opportunity for improvement.
The second part was therefore to propose a framework to support design decisions. Concurrent engineering, resources constraints and project management issues have been often overlooked in the Decision Based Design literature. Attempting to bridge this gap, we designed IRDS framework.
Through IRDS, we propose to make explicit the process alternatives, to gather economic data and expert forecasts in adecision model based on the prescriptive decision theory, including the maximization of the expected utility and the economic value of imperfect information.
The third part of the research is related to the impact of uncertainty on the data collection process and on the overall decision outcomes. This has been done through proposing a sensitivity analysis that is performed with available data, before data gathering through elicitation process. The impacts on the decision-making process and information exchanges between stakeholders, as well as the resources consumed by the new practices we proposed have also been studied on a more superficial level. This work was in particular deployed and tested on 5 cases studies. The validation of this approach requires to collect further empirical evidence to support the hypothesis that better decisions are made on the long run. We are confident that our research will serve as a base for future studies on the design and the implementation of frameworks addressing industrial challenges.

Université Paris-Saclay
Espace Technologique / Immeuble Discovery
Route de l'Orme aux Merisiers RD 128 / 91190 Saint-Aubin, France

Abstract

In the development phase of a vehicle, when a technical problem occurs, an issue resolution process is initiated. The technical solutions are designed and evaluated on the basis of performance extracted from simulation results interpreted by experts and specialists. These practitioners benefit from knowledge specific to simulation and engineering. The resolution of issues requires the formulation of decision problems and decision making. Ideally, experienced engineers, comprehensive simulation processes, and well-informed decision makers would lead to efficient decision making. However, the top management of a multinational automobile manufacturing company observed a tendency for decision makers to postpone decisions, exposing projects to penalties, and sometimes poorly justified choices that led to the implementation of sub-optimal solutions. Making well informed decisions is widely considered to be the most important challenge in industries designing increasingly complex products in increasingly complex environments. The purpose of this research is to support decision making in this context.

The first part of the research was devoted to identifying the difficulties encountered in the issue resolution process, with a particular focus on decision-making issues, methods and tools. A qualitative study done with 11 experts and on 40 decision problems highlighted that the decision makers choose from a set of process alternatives rather than artifact alternatives. The consequences of these process alternatives such as recalculating, integrating information, waiting for the technical definition of the vehicle to evolve, etc. are not explicit. The uncertainty regarding the product and process leads to postponing the selection and implementation of countermeasures, and postponing without fully understanding the impacts can lead to delay and cost overruns. We observed that decisions are trans-hierarchical and transdisciplinary, and that sub-optimal communication can lead to ignoring certain parameters or questioning sources of information (e.g. certain types of simulation). This can lead to design issues being corrected late and urgently, involving additional costs. We identified the lack of a rigorous framework as an opportunity for improvement.

The second objective of this research was therefore to develop and propose a framework to support design decisions. Decision Based Design researchers have been investigating decision analytic issues in engineering design. However, most of the literature focuses on the decision analysis of the design artifact rather than the design process. Moreover, authors seldom tested decision analytic models on real industrial problems. Concurrent engineering, resources constraints and project management issues have been therefore often overlooked. Attempting to bridge this gap, we extended a model based on the work started by Thompson and Paredis. We designed IRDS, a framework including a decision model, a computing tool, and a definition of the roles and information flows. Through IRDS, we propose to make explicit the process alternatives, to gather economic data and expert forecasts in a decision model based on the prescriptive decision theory, including the maximization of the expected utility and the economic value of imperfect information. Acknowledging the effort involved in modeling decision problems, we have designed a generic and flexible model that aims to cover the majority of the problems encountered during the development phase of vehicles and platforms. To operate this model and in order to facilitate its integration into the company, we have tailored a commercial tool integrating in spreadsheets. The ambition is to make it an

interactive tool that allows one not only to analyze decision problems as formulated by specialists, but also to explore other configurations of the decision problem (technical alternatives still non-existent, other types of complementary analyses by simulation, etc.).

The third part of the research is related to the impact of uncertainty on the data collection process and on the overall decision outcomes. This has been done through proposing a sensitivity analysis that is performed with available data, before data gathering through elicitation process. The impacts on the decision-making process and information exchanges between stakeholders, as well as the resources consumed by the new practices we proposed have also been studied on a more superficial level. This work was in particular deployed and tested on 5 cases studies. The validation of this approach requires to collect further empirical evidence to support the hypothesis that better decisions are made on the long run. We are confident that our research will serve as a base for future studies on the design and the implementation of frameworks addressing industrial challenges.

Résumé en Français

Dans la phase de développement d'un véhicule, lorsqu'un problème technique survient, un processus de résolution du problème est déclenché. Les solutions techniques sont conçues et évaluées sur la base de performances extraites de résultats de simulation interprétés par des experts et des spécialistes. Ces praticiens bénéficient de connaissances spécifiques à la simulation et à l'ingénierie. La résolution des problèmes nécessite la formulation de problèmes de décision et la prise de décision. Idéalement, des ingénieurs expérimentés, des processus de simulation complets et des décideurs bien informés devraient permettre une prise de décision efficace. Cependant, la direction générale d'une multinationale de l'automobile a observé une tendance des décideurs à reporter les décisions, exposant les projets à des pénalités, et parfois à des choix mal justifiés qui conduisent à la mise en œuvre de solutions non optimales. La prise de décisions bien informées est largement considérée comme le défi le plus important dans les industries qui conçoivent des produits de plus en plus complexes dans des environnements de plus en plus complexes. L'objectif de cette recherche est de soutenir la prise de décision dans ce contexte.

La première partie de la recherche a été consacrée à l'identification des difficultés rencontrées dans le processus de résolution des problèmes, avec un accent particulier sur les questions, méthodes et outils de prise de décision. Une étude qualitative réalisée avec 11 experts et portant sur 40 problèmes de décision a mis en évidence que les décideurs choisissent parmi un ensemble d'alternatives liées processus plutôt qu'aux artefacts. Les conséquences de ces alternatives liées au processus telles que le recalcul, l'intégration d'informations, l'attente de l'évolution de la définition technique du véhicule, etc. ne sont pas explicites. L'incertitude concernant le produit et le processus conduit à différer la sélection et la mise en œuvre des contre-mesures, et le fait de différer sans en comprendre pleinement les impacts peut entraîner des retards et des dépassements de coûts. Nous avons observé que les décisions sont trans-hiérarchiques et transdisciplinaires, et qu'une communication sous-optimale peut conduire à ignorer certains paramètres ou à remettre en cause des sources d'information (par exemple certains types de simulation). Cela peut conduire à corriger tardivement et de manière urgente des problèmes de conception, ce qui entraîne des coûts supplémentaires. Nous avons identifié l'absence d'un cadre rigoureux comme une opportunité d'amélioration.

Le deuxième objectif de cette recherche était donc de développer et de proposer un cadre pour aider les décisions de conception. Les chercheurs en conception basée sur la décision (DBD) ont étudié les questions d'analyse de la décision dans la conception technique. Cependant, la plupart des publications se concentrent sur l'analyse décisionnelle de l'artefact de conception plutôt que sur le processus de conception. De plus, les auteurs ont rarement testé des modèles d'analyse décisionnelle sur des problèmes industriels réels. Les questions d'ingénierie simultanée, de contraintes de ressources et de gestion de projet ont donc souvent été occultées. Pour tenter de combler cette lacune, nous avons étendu un modèle basé sur les travaux de Thompson et Paredis. Nous avons conçu IRDS, un cadre comprenant un modèle de décision, un outil de calcul et une définition des rôles et des flux d'information. Grâce à IRDS, nous proposons d'expliciter les alternatives liées au processus, de rassembler des données économiques et des prévisions d'experts dans un modèle de décision basé sur la théorie

prescriptive de la décision, comprenant la maximisation de l'utilité espérée et la valeur économique de l'information imparfaite. Conscients de l'effort que représente la modélisation des problèmes de décision, nous avons conçu un modèle générique et flexible qui vise à couvrir la majorité des problèmes rencontrés pendant la phase de développement des véhicules et des plateformes. Pour exploiter ce modèle et pour faciliter son intégration dans l'entreprise, nous avons customisé un outil commercial s'intégrant dans les feuilles de calcul type Excel. L'ambition est d'en faire un outil interactif qui permet non seulement d'analyser les problèmes de décision tels que formulés par les spécialistes, mais aussi d'explorer d'autres configurations du problème de décision (alternatives techniques encore inexistantes, autres types d'analyses complémentaires par simulation, etc.)

La troisième partie de la recherche est liée à l'impact de l'incertitude sur le processus de collecte des données et sur les résultats de la décision. Cela a été fait en proposant une analyse de sensibilité qui est effectuée avec les données disponibles, avant la collecte des données par un processus d'élicitation. Les impacts sur le processus de décision et les échanges d'informations entre les parties prenantes, ainsi que les ressources consommées par les nouvelles pratiques que nous avons proposées ont également été étudiés à un niveau plus superficiel. Ce travail a notamment été déployé et testé sur cinq études de cas. La validation de cette approche nécessite de recueillir des preuves empiriques supplémentaires pour étayer l'hypothèse selon laquelle de meilleures décisions sont prises sur le long terme. Nous sommes convaincus que nos recherches serviront de base à de futures études sur la conception et la mise en œuvre de cadres répondant aux défis industriels.

Acknowledgements

Firstly, I would like to express my sincere gratitude to my advisors, Pr. Marija Jankovic, Pr. Chris Paredis, and Dr. Eric Landel. I would like to thank Marija for her guidance and support throughout the research. She cared about my progress in my journey, the quality of my research, and my welfare. Her renowned rigor and straight talk have helped me to forge a sound and structured mind. I thank Chris, one of the most brilliant individuals I had the chance to work with, for his patience, kindness, and expecting the best of me. I am grateful for his hospitality during my time at the Georgia Institute of Technology before he moved to Clemson University. I am especially thankful to Eric for his trust, precious insights, and for having introduced me to senior executive level practices.

Besides my advisors, I would like to thank the reporters of my dissertation, Pr. Eric Bonjour and Pr. Benoit Eynard, for the time they spent to review my work and for their insightful comments. I also thank the President of my thesis jury, Pr. Michael Kokkolaras, and Pr. Bernard Yannou, who served as an examiner. Pr. Bernard Yannou welcomed me to the reputable Industrial Engineering Department (LGI) of CentraleSupélec, Université Paris-Saclay. I express profound gratitude towards him for giving me the opportunity to flourish in this noble institution. I am also grateful to Pr. Vincent Mousseau for having authorized my application to the Interfaces Doctoral School.

I want to express my gratitude to Olivier Colmar, vice president of Renault's Simulation department, for his trust and for having given me the capability to work under exceptional conditions. André Barbe, chief of CAE at Renault, helped me to target and focus my investigation in the company as well as providing me valuable insight. I am appreciative of his support. I also want to thank Dr. Christine Royer, Jean Leung, Laurent Noyelle and all the people at Renault who directly and indirectly contributed to my research, with special mention to Stéphane Jacque, Dominique Bellot, and Selcuk Cura.

My doctoral research has been eased thanks to dedicated and reliable people technical and administrative personnel. In this way, I would like to express my sincere gratitude to LGI's Delphine Martin, Sylvie Guillemain, Corinne Ollivier, Carole Stoll, and Matthieu Tournadre. I also warmly thank Suzanne Thuron from Interfaces, Valérie Louchel from Renault, and Monifa Skelton from the Georgia Institute of Technology.

I want to thank my fellow labmates from LGI: Sarra Fakhfakh, Youssef Damak, Dr. Andreas Makoto Hein, Dr. Ouail Al Maghraoui, Dr. Reza Vosooghi, Dr. Abood Mourad, Dr. Mehdi Senouci, and all the members of the laboratory. I thank Alexander Murphy, Felix Ocker, Johannes Rist, and Dr. Bill Binder for the insightful moments we had together at Georgia Tech. Amongst my colleagues, my deepest appreciation goes to Naouress Fatfouta and Lara Qasim who have been precious devoted and supportive friends. Dr. Tanguy Loreau has been a valuable brother-in-arms and friend, I want to express my heartfelt gratefulness to him.

My sincere thanks also go to Dr. Göknur Sirin who was the first person I interacted with when applying to this Ph.D. program, and who guided me towards my recruitment. I thank my dear friends Dr. Thomas Gurriet, Xavier Loret, and Dr. Matthieu Le for helping me to get in shape to pass the selection tests. Dr. Thomas Gurriet, at this time Ph.D. candidate at the California Institute of Technology, supported me during my research throughout though

technical challenges, I am grateful for this. Thanks to Youssef Idelcaid for his wise words that helped me to overcome a difficulty that could have keep me stuck for a while.

Last but not the least, I would like to thank my closest friends and family. Dr. Thibault Guicherd shared with me his experience as a researcher and Chaker Alouni has long been an informal motivational coach. I am thankful to them. I want to warmly thank Alexandra Akosa and her adorable family. Alexandra made my life easier and more pleasant. She showed love, support, and consistency, which helped me to stay focused and perform. I am highly appreciative of the consideration and kindness of her parents, Marleen Van Hulle and Dr. Amechi Akosa, and her lovely sister Amanda. I am more than ever grateful to my family: Emma, who helped me step back from my research by often asking me relevant questions; Maëlle, who has always been loving; and Maxime, who is not only my brother but my best friend and with whom I had pleasant daily conversations. Finally, the people I cherish and respect the most on this planet, my parents. I thank my mother, Marie-Noëlle Sissoko, for all the sacrifices she made, and all the love and support she provided me since I was born and especially throughout this wonderful experience. I thank my father, Benjamin Sissoko, who overcame the lack of opportunity and resources growing up in a low income country, battled diseases with bravery, and gave his sweat and tears to always keep us on the road to success. He made the pursuit of knowledge his obsession, and he is the one to whom I dedicate this dissertation.

Table of Contents

List of Figures

List of Tables

Nomenclature

The nomenclature of the opposites of the following variables and functions can be easily derived and is not expanded in this section.

$pITDC(t)$	Probability that later or current but not represented changes in the technical definition of the vehicle will impact the outcomes of the current decision. *ITDC*: Impacting Technical Definition Change.
$P(OK\|ITDC)$	Probability that the vehicle passes the physical test given that changes affected the attributes of the decision.
$P(OK\|\overline{ITDC})$	Probability that the vehicle passes the physical test given that changes did not affect the attributes of the decision.
$P(Fav\|OK)$	True positive rate: the results of the analyses were favorable, and the vehicle passed the physical test.
$Cost_{delay}(t)$	Cost incurred by the delay in the project: delay propagation on other activities, speeding up, increasing resources to respect the project deadline, likelihood to pay penalties.
Dc_1	Cost incurred by the design necessary to implement in the vehicle a technical solution developed to solve a design issue in the development phase.
Dc_2	Cost incurred by testing a technical solution being implemented in the vehicle during the development phase.
Ic_1	Vendor tooling cost committed for the industrialization phase.
Ic_2	Manufacturing cost incurred by manufacturing a unit (material, labor, charges) times the number of units in the industrialization phase.
Ic_3	Supplier engineering cost committed for the industrialization phase.

Ic_4	Corrective design cost. Cost incurred by designing and implementing in the vehicle a technical solution developed to solve a design issue in the industrialization phase.
Ic_5	Corrective testing cost. Cost incurred by testing a technical solution developed to solve a design issue in the industrialization phase.
VP_i	Cost or gain incurred by any situation that causes penalty or adds value (weight addition or reduction of the technical solution on the vehicle, carry-over of a technical solution for other projects, production launch delay, etc.).
Ac	Cost incurred by additional analyses of a technical solution as a process alternative.
At	Time between two decision meetings when additional analyses are performed.
Process alternative	In a process-focused approach of the decision, course of actions that include technical modifications, data gathering or delaying other actions. It directly impacts the planning and resources of the design process.
Artifact alternative	In an artifact-focused approach of the decision, course of actions that include technical modifications of the product (the artifact). In a process-focused approach of the decision, artifact alternatives are process alternatives, since modifications impact the planning and resources of the design process.
DM	Decision maker
DA	Decision analyst
DaP	Data provider

1. Introduction

1.1. Dissertation motivation

1.1.1. Design decisions and use of Modeling and Simulation in the development phase of vehicles

In the automotive industry, as in many complex systems design industries, the development process can be seen as a series of decisions largely supported by modeling and simulation (M&S). A product development process can take different forms, such as V-models [1], spiral [2], or stage-gate [3], and vary across industries and companies. It is generally an iterative process [4,5] that is composed of design and testing cycles repeated several times [6]. In the context of vehicle development projects, the vehicle development process (VDP) is a well-planned process that transforms the strategic vision of a vehicle into a tangible product for the customer [7]. In the early decades of the automotive industry, the VDP was *sequential* and primarily relied on physical M&S capabilities (physical prototypes) [8]. However, this process has progressively become *concurrent* while increasingly leveraging information technology [9]. Specifically, the introduction of computer aided engineering (CAE) has reduced development costs and lead times [10] by accelerating the execution of tasks, the incorporation of design changes, and the information exchanges [11,12]. CAE enables numerical M&S, and therefore facilitates rework on numerical models instead of physical prototypes. In this respect, numerical M&S has triggered profound changes [9] in an activity that is inherent to product development: **problem-solving** [10,13–15]. Solving problems, in this context, supposes the design and selection of "solutions" or course of actions, and necessarily involves **decision making** [16,17].

In the **development phase** of a vehicle development project, a vehicle needs to be delivered at the right time, the right level of performance and the right cost [7]. In this phase, the vehicle is designed and tested through numerical M&S [18,19]. Models enable the investigation and prediction of architectural consistency and overall vehicle performances [20]. The corresponding design decisions are often based on these M&S results [21]. Through an iterative process a vehicle synthesis model is refined by adding detail to the specifications until a physical prototype can be manufactured.

The increasing use of numerical M&S – lately simply referred as M&S, given the current context – has impacted, amongst others, problem-solving and ultimately the decision-making processes in industry. Although significant research has been performed in decision support systems [22–24] and the decision-based design researchers have investigated decision theory applied to engineering design (as further developed in Chapter 2), the interaction between M&S and decision-making processes and the industrial applications of decision supports in the automotive industry are poorly explored. The motivation for our research was identified in this context.

Our research has been conducted at Renault, a carmaker founded in 1898 which sold more than 2.8 million vehicles in 125 countries in 2015 – the year before we started our investigations. At this time, Renault made 45 327 M€ revenues – 2 960 M€ net income – and

was employing over 120 000 people. Renault designs innovative goods and services in the perspective to be accessible to the greatest number. It fosters sustainable mobility, through its range of all-electric vehicles among others, and develops profitable international growth, notably through its alliance with Nissan in 1999, Mitsubishi in 2017, and many other partnerships. The company has been manufacturing vehicles and powertrain components at its 36 production sites, in 2015 [25].

At Renault, the overall logic of vehicle projects can be resumed in 3 phases (Figure 1): upstream, development, industrialization. The construction of this logic was carried out on the hypothesis of a " mother " pattern (i.e. a reference vehicle model in a specific segment), then declined for the other patterns (brother vehicle, child vehicle). For convenience purpose, let us focus on the simple case of a mother vehicle (from which other vehicles are derived). A vehicle is composed of a platform, a powertrain, and an upper body. Of course, several powertrains are available for one vehicle, for diversity purposes. Each of these elements are developed in parallel projects that are resynchronized at different times so that the complete vehicle can be commercialized.

Figure 1 – Renault's logic of vehicle project

The upstream phase consists in establishing vehicle concepts, requirements that differentiate the company from the competition (the Unique Selling Propositions), style, and lead to demonstrators that are clear enough to ensure cost-value trade-offs and robust choices. The development phase starts with a milestone called Vehicle Pre-Contract (VPC) and ends with the Tooling Go Ahead (TGA) milestone. During this phase, the design specifications of the vehicle are gradually refined through several digital loops punctuated by milestones. These loops involve design and testing activities, and are called "digital" on purpose. Indeed, during the development phase, the vehicle only exist in the form of numerical models that are assembled in a synthesis model. Arrived at TGA milestone, the digital vehicle is ready to be manufactured and enters the industrialization phase. In the latter, parts are manufactured and physical prototypes are assembled and tested. The manufacturing facilities are transferred to the final production site and the vehicle is mass-produced.

After this overview of the company and the overall design process, let us now take a closer look at what was observed in the development phase and what motivated our research.

1.1.2. Preliminary observations : decision-making issues

The numerical M&S tests performed all along the development phase allow the simulations analysts to detect the performance discrepancies and architectural interferences. When a technical problem is detected, an issue resolution process is initiated. The technical solutions are designed and evaluated on the basis of performance extracted from simulation results interpreted by experts and specialists. These practitioners benefit from knowledge specific to simulation and engineering. The resolution of issues requires the formulation of decision problems and decision making.

Ideally, experienced engineers, comprehensive simulation processes, and well-informed decision makers would lead to efficient decision making. However, the top management of the company observed a tendency for decision makers to postpone the technical solution selection and implementation, exposing projects to penalties, and sometimes poorly justified choices that lead to the implementation of sub-optimal solutions. The *postponement of decisions* – more precisely, artifact decisions, i.e. technical solution selection – consumes resources such as full time equivalent employees, computing costs, and project time. Also, it happens that new, but also predicted, issues appear in the industrialization phase, whereas it is supposed to be prevented by M&S and issue resolution decisions. Once rework is performed in the industrialization phase, the costs are generally important since they can involve changing tooling, manufacturing new physical prototypes, and creating task forces. These situations are undesirable, and the company asked our research team to investigate the decision-making process in this context and propose improvements.

1.2. Research objective and questions

Based upon the preliminary observations made in the company and the research background, our research objective is to support decision making for solving design issues in the development phase of a complex system. To fulfill this research objective, we first need to understand the current decision-making processes in a context of design supported by M&S. In order better support decision making, it is important to examine how M&S contributes to problem-solving, which information is considered, how results are used and interpreted. In this respect, we are able to assess the current difficulties and needs. Since implementing new frameworks requires tradeoffs between resources available, capacities, and effectiveness, it is important to explore the opportunities and difficulties in deploying a decision support framework.

Hence, in order to achieve the aforementioned objective, we identified and addressed two research questions in the corresponding chapters of this dissertation. The research questions are formulated as follows.

1) ***In practice, how does decision making unfold in a M&S environment?***

2) ***To which extent can a method based on normative decision theory enhance the decision-making process supported by simulation?***

To address these questions, we applied a methodology inspired form the well-established Design Research Methodology and divided our research into three main studies including their own literature reviews. These literature reviews are reported and synthetized in the next chapter.

1.3. Dissertation architecture

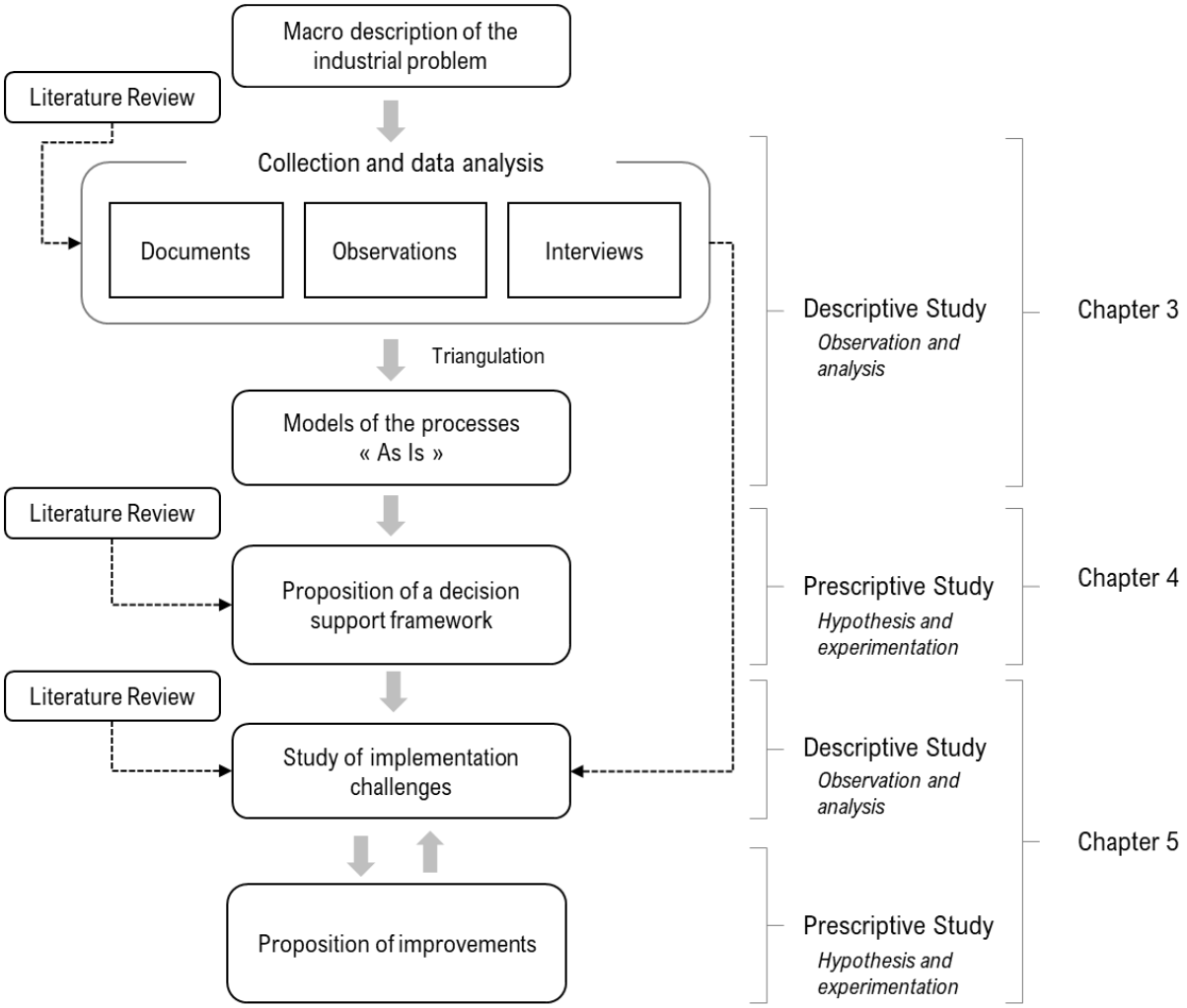


Figure 2 - Overall research methodology

We used a methodological framework strongly inspired by the Design Research Methodology (DRM) introduced by Blessing and Chakrabarti [26]. DRM consists of four stages: Research Clarification, Descriptive Study I, Prescriptive Study, Descriptive Study II. We chose DRM as the supporting framework of our research since its approach is coherent with the objective we defined: understanding the current situation, proposing a decision support framework, and examining the changes brought by our action on the situation. The particularity of our methodology is that the stage Descriptive Study II proposed by DRM has

been changed into a hybrid one: a study where descriptive and prescriptive approaches are interrelated. Figure 2 depicts the stages of the framework we used.

The dissertation presents three studies conducted to address the research objective in three chapters. These chapters are derived from articles which contain their own literature reviews that sometimes overlap between each other. To avoid redundancies and improve the reader experience, we extracted the literature review from the articles and rearranged it in a unique literature review chapter.

Chapter 2, the literature review, aims to: (1) provide the reader with an overview of the knowledge that has fueled our work, (2) highlight the research gaps that we identified, and (3) guide the reader by establishing connections with other chapters.

The next chapters of the dissertation correspond to the contributions addressing the research questions. It can be noted that the contributions as a whole are both prescriptive and descriptive in nature, in accordance with the research methodology we have articulated.

In practice, how does decision making unfold in a M&S environment?

This question is addressed in the **Chapter 3**. It corresponds to an empirical study that we conducted in the company. Through this descriptive approach involving qualitative data analysis, we:

- Mapped out the decision-making process as-is and its interactions with the modeling and simulation process
- Identify the challenges faced by the organization and the reasons that contribute to lengthening problem solving and leading to costly and urgent late resolutions

To which extent can a method based on normative decision theory enhance the decision-making process supported by simulation?

Through the prescriptive study reported in **Chapter 4** we:

- Designed a model based on normative decision theory that incorporate process alternatives based upon industrial cases and experts contributions
- Proposed a definition of roles and information flows, and a method to support decisions through the decision model

The descriptive-prescriptive study presented in **Chapter 5** allowed us to:

- Test the proposed framework on 5 real cases to identify the difficulties associated with data gathering and experts' beliefs modeling
- Estimate the resources consumed by using the proposed framework and the differences in terms of decision on a more superficial level

In the conclusion (**Chapter 6**), Section 6.1 provides a more detailed summary of the contributions and explains more into detail how they contribute to fulfilling the research objective. The limitations of the overall research are highlighted in Section 6.2. Finally, Section 6.3 provides recommendations for future works in the light of the contributions brought by this dissertation.

2. Literature Review

The following literature review introduces to the reader the overarching concept of decision theory and briefly discusses its applications in engineering design in Section 2.1. More details are provided about one practical application of decision theory, named decision analysis, in Section 2.2. In Section 2.3, we further narrow the scope of the literature to our research context by discussing the use of decision analysis for engineering design through Decision Based Design (DBD). We then examine, in Section 2.4, the research that extends classical approaches of DBD by studying the consequences of incorporating additional information to the decision analysis (the Value of Information). In Section 2.5, we consider analysis and design decisions from a process-focused perspective and review the work on the integration of process-related data. Since producing and manipulating information addresses some extent the need to tackle uncertainty, we review in Section 2.6. the literature on uncertainty and uncertainty management in engineering. Closely related to this subject, the elicitation of experts' beliefs when considering the use of models is discussed in Section 2.7. We consider that the acquisition of information – whether through expert elicitation or by performing numerical simulation – and how the search for precision involves the consumption of resources. Analyzing how a decision problem is sensitive to input parameters can help determine whether it is valuable or not to increase the precision of inputs. Hence, the last section of this literature review, Section 2.8, aims to provide the reader the knowledge about sensitivity analysis and its use in the analysis of design decisions.

What is a decision?

> Before diving into the theory, let us first define what a *decision is*, from its etymological roots and common sense to the most common definition used in decision theory. The noun "decision" comes from the Latin "decisio" which mean "a settlement, agreement," action noun of the verb "decidere" literally meaning "to cut off". In modern English, the Merriam-Webster dictionary [27] defines a *decision* as (1.a) the act or process of *deciding*, (1.b) a determination arrived at after consideration, (2) a report of a conclusion (in the sense of "conclusion"), (3) promptness and firmness in deciding (in the sense of "determination"), and one can find other sports-related meanings. *To decide*, in common language means (1.a) to make a final choice or judgment, (1.b) to select as a course of action, (1.c) to infer on the basis of evidence, (2) to bring to a definitive, and (3) to induce to come to a choice. These definitions used in common language may be appropriate to our approach, but they overlook a notion that is important in design: the notion of resources. In the decision theory literature, a more comprehensive definition has been proposed, and this is the one we will refer to in our research: *a choice between several alternatives that involves an irrevocable allocation of resources* [28].

2.1. Decision theory and its applications to Engineering Design

Decision theory can be split into three approaches: descriptive, normative and prescriptive. The *descriptive* approach focuses on how people actually make decisions in real-world settings. The research fields of human factors and cognition are generally based on the

study of decision making from a descriptive perspective. The Naturalistic Decision Making (NDM) community emphasized the role of experience in enabling people to rapidly match situations with patterns they have learned and make effective decisions [29]. Researchers observed that people rely on heuristics as opposed to algorithmic strategies and deviate from the principles of optimal performance as defined in the normative approach. On the other hand, the *normative* approach prescribes how people should make decisions, assuming that the decision maker is fully informed, fully rational and able to compute with perfect accuracy. These assumptions are idealistic and seldom encountered in real-world situations. Indeed, even assuming that decision makers have bounded rationality [30], they have to deal with uncertainty. This is the purpose of the prescriptive approach [31]. It consists of guiding decision makers by following principles of rationality and supporting them in their decision making in practice while dealing with uncertainty and biases. A formal method and practical application of decision theory is *Decision Analysis*. We discuss its development and contributions to engineering design through Decision Based Design in the next subsections.

Several methods other methods, related to the prescriptive approach of decision theory have been devised and applied in the literature across many fields (Multi-Criteria Decision-Making methods, Problem Structuring Methods [32], Theory of Inventive Problem-Solving method [33], Analytic Hierarchy Process [34,35], Multi-Attribute Utility Theory [36], etc.). In the field of engineering design for the automotive industry, Renzi et al. [16] recently investigated how decision-making methods can be used by automotive designers to solve the most common engineering problems associated with the design process. To do so, they analyzed studies in the literature and matched methods of decision making with design phases in automotive industry. Their research emphasizes that for the vast majority of the methods tested in the literature the conclusions of the authors are not objectively evaluated through a comparison with other methods, and that the proposed methods are applied with illustrative examples with simple models far removed from the complex design cases for which they are intended. Moreover, investigations demonstrated that very often designers prefer tested procedures and experience-based approaches [37]. However, to our knowledge, few studies investigate how, in complex systems industries, these heuristic approaches practically influence the decision-making processes deployed to solve design issues. Moreover, while the product development process is increasingly supported by modeling and simulation, the interaction between the decision-making processes and modeling and simulation have seldom been addressed. This led us to identify the first research gap.

Research gap 1: We currently lack a deep understanding of the actual practices and challenges associated with decision-making processes in a vehicle development process supported by simulation.

> This research gap is addressed in **Chapter 3**. In the latter, we explain how we have conducted an empirical study in the company to understand the relationships between as-is decision-making and simulation processes and present our observations. We map out the as-is decision-making process and identify the challenges encountered by the company when formulating and making decisions to solve design issues.

2.2. Decision Analysis

The literature on decision making under uncertainty and risk has been growing at least since Bernoulli [38] presented a theory on risk measurement 280 years ago. Decision Analysis has emerged from this literature. It has been widely explored, and is the subject of several text books. This prescriptive method is based on utility theory [39] and aims to support decision makers by systematically exploring possible decision alternatives. The methodology have been extensively discussed into detail in the literature [28,40–42], notably in books by Raiffa [42], Schlaifer [43], Tribus [44], Winkler [45], Brown et al. [46], Keeney and Raiffa [47], Moore and Thomas [48], Kaufman and Thomas [49], LaValle [50], Holloway [51], Edwards et al. [41] and very recently, Howard and Abbas [52]. The overall procedure consists of identifying the decision alternatives, predicting their associated outcomes, eliciting decision maker preferences with respect to outcomes, and computing the expected utility of each alternative.

2.3. Decision Based Design

A specific domain called Decision Based Design (DBD) has been investigating the development of prescriptive approaches, such as decision analysis, in engineering design [17]. In the late 80's, Shupe et al. [53] have been defining DBD as a heterarchical set of constructs that embodies developer's perceptions of the design environment and the real world. They asserted that the principal role of an engineer is to make decisions associated with the design of an artifact. The decade later, while proposing a framework for Decision-Based Engineering Design, Hazelrigg [54] defined DBD as a normative approach that prescribes a methodology to make unambiguous design alternative selection under uncertainty and risk wherein the design is optimized in terms of the expected utility. He underlined that DBD seeks to base engineering design decisions on information obtained from a variety of sources going well beyond the engineering disciplines. Indeed, in a decision analysis perspective, predicting outcomes associated with decision alternatives requires incorporating information and expressing beliefs about attributes that impact the outcomes. Such actions ultimately involve resources consumptions. However, until recently, the vast majority of research in DBD focused decision problems formulation on the design artifact and overlooked the tradeoffs involved when gaining additional information in a process-focused perspective. The study of these tradeoffs is, among others, the purpose of Value of Information.

2.4. Value of Information and Decision Analysis

Value of Information (VOI) was first introduced in 60's by Howard [55]. He emphasized that attempts of applications of Shannon's information theory [45] only considering the probability of outcomes but overlooking consequences were unsuccessful for problems beyond communication processes. He discussed the value of information that arises from considering jointly the probabilistic and economic factors that affect decisions.

The principle of VOI is that one can value the improvement in decision-making ability enabled by additional information by comparing the decision outcomes with and without the additional information. VOI helps to determine whether the decision maker should access an information source or not. In this respect, Matheson [56] used VOI to determine which computational and analytical procedure is the most economic for analyzing a decision problem in greater detail and yielding to a "better" decision. Various strategies based on the value of information used with normative decision theory have been discussed [57–59]. Bradley and Agogino [57] proposed a method incorporating the VOI along with a decision analytic approach to guide the information collection in the component selection process. Their method allows for reducing the uncertainty to select the best component. In the decision analysis and engineering design literature, design can be considered as series of decisions made by the designer. The latter creates and uses models to depict and predict the nature and behavior of an artifact, and some researchers studied the VOI for selecting and refining models. For instance, Radhakrishnan and McAdams [60] considered model selection as a design decision and applied utility theory to model selection for guiding decisions in engineering design. They proposed a method to select the best (or most useful) model according to different model selection criteria and ultimately model utilities. The author did not analyze the VOI associated with a specific model and did not consider the impact of model selection on design decisions. Panchal et al. [61] proposed a VOI-based approach for determining the appropriate extent of refinement of simulation models. They introduced a method utilizing a metric called "improvement potential" for supporting model refinement decisions. The metric measures the VOI by considering both models' imprecision and variability. The method they proposed supports defining a simple simulation model and gradually refining it until the value of further refinement on design decisions is small. Although it is reasonable to assume that highly refined simulation models are costlier to develop and execute, authors did not explicitly include the cost of the development of the new simulation models, nor the cost of analysis associated with running the simulations and interpreting the results. In these research studies, Bayes' theorem [62,63] is generally used to model how the beliefs are updated when new information is incorporated.

2.5. Integration of process-related data into design decisions

Although in the engineering context normative decision theory applications generally focus on artifact decisions about product features, some researchers stressed that all design decisions are actually process decisions. They argue that resources spent in the refinement of information should be also taken into consideration [57–59]. For instance, Bradley and Agogino [57] proposed the Intelligent Real Time Design Methodology (IRTD) to guide the information collection when selecting components from a catalog while reducing uncertainty. In their decision analytic approach to assisting catalog selection, they consider explicitly process related data such as the cost of resources consumed during design, and in particular the time of the designer. To have a comprehensive approach of design decisions, actions such as "modify a design specification" or "collect more information about a potential design modification" must coexist in the decision alternatives set and must be considered when analyzing the decision problem. However, many of the previous studies considered the

information gathering decision as a separate sub-decision that is formulated separately from the artifact decision. To bridge this gap, when investigating the decision analysis of design process decisions, Thompson and Paredis [59] proposed to formulate the decision problem in terms of the design process and included the alternative of gathering additional information along with the artifact parameter decision. The aim of their research is to provide a more comprehensive model of the problem when multiple sources of information can sequentially be used. However, the authors did not test their methods on a real industrial case and did not consider a tradeoff – which is often encountered in industrial settings – between waiting that new information is available to make the most profitable artifact decision and potentially exposing the project to penalty. Hence, we identified a second research gap.

Research gap 2: We do not yet have a thorough grasp of the integration of process-related data into decision analysis of design decisions in an industrial context.

> This research gap is addressed in both **Chapters 4** and **5**. Indeed, in Chapter 4 we propose to integrate process alternatives within the decision alternatives set of decision problems. In our approach, defining process alternatives include integrating beliefs and uncertainties related to product definition evolutions, industrial project time constraints, and model characteristics addressing industrial complexity. In real-world settings, gathering these process-related data demands effort and sometimes further resources consuming investigations. Hence, in Chapter 5 we review what process-related data are already available in the company and those that should be obtained.

Thompson and Paredis studied the gain of additional information from sequential analyses but did not address the case where analyses can be performed concurrently. Indeed, current complex system design is often based on concurrent engineering. Concurrent engineering is known to be a source of interactions between a decision situation and the outcomes of other decisions. Hence, in complex system design, decisions are interdependent and can have propagating impacts. Indeed, a decision situation about a sub-system can evolve because of the impacts of other design teams' decisions working on other subsystems.

Research gap 3: The integration of concurrent engineering considerations into the decision alternatives is still poorly explored.

> As discussed in **Chapter 5**, we aimed to bridge this gap by enabling the decision analyst to study the consequences of performing analyses concurrently. Furthermore, we proposed that a decision analysis of a design problem should account for current or later changes in the product technical definitions that are one of the results of concurrent design and testing activities.

In real-world settings, integrating process-related data – as for any data produced by systems or information communicated by humans – does not come without tackling the issue of uncertainty. Although uncertainty can deliberately be ignored when computing problems deterministically, those who manipulate models and interprets results ultimately have to deal with it. Uncertainty and its management in engineering is the purpose of the next section.

2.6. Uncertainty management in engineering

Uncertainty has been highlighted in the literature as an important challenge of decision making [52,64,65]. It can be defined as a lack of information [66], a state of mind characterized by a conscious lack of knowledge [67], or a lack of numerical probabilities of various outcomes [68]. Closer to our research interest, in the field of model-based decision supports, Walker et al. adopted a general definition of uncertainty as being *"any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system"* [58]. Uncertainty has been the subject of many classifications and theories and methods have been developed to address its issues.

2.6.1. Classifications of uncertainty

Several classifications have been proposed and discussed by researchers across many fields:

- ***Objective*** *(ambiguity) or* ***subjective*** *(vagueness)* according to Ayyub and Chao [69] and Klir and Yuan[70] among others.
- ***Aleatory*** *(irreducible, variability) or* ***epistemic*** *(reducible), or* ***error*** according to Oberkampf et al. [71], Haukaas [72], Isukapalli et al. [73], Der Kiureghian [74].

Recently, Hassanzadeh proposed two approaches to define uncertainty [75]in the context of R&D projects:

- ***Object-based approach***: related to the lack of information about the project. This approach is used in mathematics and economics and refers to Thiry [66], Galbraith [76], Klir [77], Zadeh [78], and Knight [68].
- ***Subject-based approach***: related to individuals' sense of doubt and perception of the inability to predict something. This approach, used in psychology, refers to Head [67], Lipshitz et al. [79], Milliken [80], and Thompson [81]. De Finetti [82], Ramsey [83], and Savage [84], among others, proposed a representation of uncertainty through subjective probabilities.

In the field of *complex and multidisciplinary systems design and development*, Thunnissen [85] proposed a four categories classification of uncertainty that recalls taxonomies mentioned above:

Ambiguity: also called imprecision, design imprecision, linguistic imprecision and vagueness, it causes misunderstanding between individuals sharing verbal information.

Epistemic: also called reducible uncertainty, subjective uncertainty, model form uncertainty, state of knowledge, type B uncertainty. It is characterized by incomplete knowledge or information of some characteristic of the system of the environment. It can be further classified into model, phenomenological, behavioral, volitional uncertainty and human errors.

Aleatory: also called variability, irreducible uncertainty, inherent uncertainty, stochastic uncertainty, intrinsic uncertainty, underlying uncertainty, physical uncertainty, probabilistic uncertainty, noise, risk, type A uncertainty, and *de re*. It is characterized by the inherent variation associated with a physical system or environment. A common example includes the

exact dimension of a component where the manufacturing processes are understood but variable.

Should we talk about an "aleatory" uncertainty?

> We disagree with the above-mentioned distinction between aleatory and epistemic uncertainty brought by several authors. "Aleatory uncertainty" is a misnomer because it does not apply to a single empirical quantity, but only to a population of empirical quantities. The "aleatory uncertainty" is not uncertainty at all but variation across the population. We believe that uncertainty is ultimately subjective and epistemic, i.e., a lack of knowledge. At the macroscopic and microscopic scales, phenomena are considered aleatory due to a lack knowledge about the interactions and initial conditions of the systems under consideration. For instance, a chaotic system, highly sensitive to initial conditions (e.g. double pendulum), can be the subject of "aleatory uncertainty" but is actually predictable. The most common mathematical representation for the "aleatory uncertainty" is a probability distribution. Treating "aleatory uncertainty" as epistemic uncertainty supposes deploying resources that can be substantial to refine the knowledge about a system. Considering the uncertainty as "aleatory" can therefore be convenient and cost-saving, depending on the model used and its sensitivity to the variable under consideration.

Interaction: this type of uncertainty, that we relate to the epistemic uncertainty, is assumed to arise from unanticipated interaction of many events and/or disciplines, each of which might be or should have been – in principle - predictable. According to Thunnissen, this uncertainty is significant in complex multidisciplinary systems, when many experts, variables and subsystems are involved, and when mostly when only subjective estimates are possible and lead to disagreement between experts.

In the perspective of *uncertainty management in model-based decision support*, Walker et al. [86] proposed to distinguish three dimensions of the uncertainty:

- ***Location***– where the uncertainty manifests itself within the model complex.
- ***Level*** – where the uncertainty manifests itself along the spectrum between deterministic knowledge and total ignorance.
- ***Nature*** – whether the uncertainty is due to the imperfection of our knowledge or is due to the inherent variability of the phenomena being described (therefore agreeing to an "aleatory" uncertainty, as discussed above).

Literature is extensive when it comes to classify uncertainty, but the actual difficulties associated with uncertainty when implementing a decision support framework based on a computational model have been seldom discussed. Introducing a new framework in a company can impact practices and even the company organizational structure [87–89]. In this respect, identifying the difficulties related to uncertainty when providing model inputs and interpreting results can help to establish better practices. This lack reveals another gap.

Research gap 4: The difficulties related to uncertainty when implementing a decision support framework in a company have been little investigated.

> We explore this gap in **Chapter 5**. After proposing a framework in Chapter 4, we study its implementation in the company. Our study highlights some of the difficulties related to the data gathering and the management of uncertainty that is associated with this activity.

2.6.2. Theories and methods used for managing uncertainty

According to researchers who proposed comprehensive taxonomies of uncertainty, these classifications are relevant since they allow guidance for uncertainty management. In that respect, several theories have been devised to tackle these different aspects of uncertainty: for example, probabilistic methods, Fuzzy sets, interval analysis, and other methods have been applied to determine uncertainty in engineering design [59,90–92].

***Probability theory*:** the most used and well-established theory for representing uncertainty. However criticisms have been made regarding its capacity to represent epistemic uncertainty for two reasons [93–95]: defining a probability distribution require more information that an expert is able to provide, and experts prefer supplying intervals rather than point-values because their knowledge both of limited reliability and imprecise. Authors have demonstrated that the classical probability framework needs additional information to quantify epistemic uncertainty that lead to unjustified results. These authors often support other theories such as Evidence theory and Fuzzy set theory.

***Evidence theory**:* also referred to as Dempster–Shafer theory [96], this theory introduces belief and plausibility measures for reasoning with uncertainty. It is assumed to deal with both aleatory and epistemic uncertainties, but considered as misleading by some researchers [97,98]. Evidence theory notably increased the popularity of the use of imprecise probabilities [58].

Possibility theory: subclass of Evidence theory, it provides an alternative to probability theory for characterizing epistemic uncertainty when incomplete data is available. Possibility theory involves two specifications of likelihood, a necessity and a possibility. Possibility is closely tied to Fuzzy set theory [99,100].

Fuzzy set theory: appears to be most suited for qualitative reasoning. It aims at dealing with ambiguity due to linguistic imprecisions [101], handling the concept of partial truth [102]. This theory defined a function describing the degree to which a statement is true [99].

Interval analysis: in this collection of methods [103–106], uncertainty on a variable is represented by intervals of possible values. Interval analysis proposes to represent the uncertainty in a different perspective that the theories mentioned above. It does not attempt to infer an uncertainty structure on the model outcome based on an uncertainty structure assumed for the input.

Probability theory is the only theory that is mathematically self-consistent and supports rational decision making. It remains the most used theory in methodological frameworks that

address uncertainty in industry. A leading European network of experts representing a cross section of industries present a common framework in [79].

We assume that in the vehicle development phase, where requirements or performance targets are rigorously defined enough to pass the clarity test [52], probability theory suitable and mathematically solid to represent the uncertainty about input values – that we consider ultimately epistemic. Furthermore, estimates provided by experts can be imprecise (considering that the precision sought is relative to its influence on the decision). In this respect, the elicitation of experts' belief can be critical. The next section reviews the literature that tackles this issue.

2.7. Expert elicitation for decision analysis

As discussed in the previous section, the most common way to represent uncertainty is in the form of probabilities. These probabilities are generated by modeling and simulation or expressed by experts as a part of decision analysis [40,42,52]. In the development of complex systems, numerical models are often not sufficient and comprehensive enough to gather all the information about the system under consideration [107] – about its current and potential future definition and behavior. Even synthesis models that aim at considering the interactions of multiple subsystems through different disciplines need data that are provided by both numerical and non-numerical sources, i.e. experts. In that respect, when conducting an analysis on a decision problem regarding a complex system, the data required to execute the computation can sometimes only be supplied – at a reasonable cost – by subjective estimates [85,107,108].

Eliciting and quantifying experts beliefs have been examined, in particular by meteorologists, for more than a century, following Cooke [109] groundbreaking contribution. *Expert elicitation* refers to obtaining and combining expert beliefs through formal procedures. When several individuals contribute their knowledge to a problem, combining their judgments or obtaining a consensus can be challenging. To address this issue, a method has been developed in the early 1950's by a group of investigators at the RAND Corporation: the ***Delphi method*** [110]. First used in classified studies carried for the US Air Force, the method started to become popular the decade later (after the work has been declassified). It aims at developing group consensus about parameter values or more qualitative questions through a structured communication process. This method has however been criticized [111,112] since researchers did not find compelling evidence supporting that Delphi outperforms other methods. suggest that the consensus is achieved mainly by group pressure to conformity. Approaches based on ***Bayesian inference*** have been proposed and tested [113–115], but they focus more combination of probabilities already provided by individuals on rather than how to obtain the probabilities from the individuals. Researchers from different fields – economics [116], medicine [117,118], environmental issues [119,120], etc. – proposed and discussed models and techniques to elicit beliefs in different forms.

Elicitation rules have been proposed and increasingly used in economics. These rules, in their most simple version, suit for predictions of binary events (*success* or *failure*). We later

highlight their relevance in engineering design when formulating possibilities in a decision analysis perspective (Chapter 5).

- ***Lottery Rule***: this procedure has been known for long [121] but seldom put in practice. Let us consider an event that can either be characterized by a success or a failure. The subjects (also called *assessors*) are asked to report their beliefs about the probability of success and a mechanism based on rewards is used as incentive for the subject to truthfully report their best estimates. An advantage of the Lottery Rule is that incentives are provided regardless of assessors' risk attitude [122]. However, the main drawback of this rule that it is quite complicated and cognitively demanding. Further details are provided about its principle and applications are given in [42,45,50,122].
- ***Quadratic Scoring Rule*** *(QSR)*: this rule has been imported from meteorology [123] – where it has been for long the most popular rule – to economics [124–126] . Also using an incentivization mechanism, this rule rests on a reward of $1 - P^2_{failure}$ if "success" is the true state of nature, and on a reward of $1 - P^2_{success}$ if "failure" is. Kadan et al. [127] highlighted that QSR is an incentive-compatible method only under risk neutrality and the no-stake condition. More recent research attempted to correct deviations due to risk aversion [128,129].
- ***Free Rule***: widely used in neurosciences and psychology, the Free Rule is particularly simple and time-efficient compared to those mentioned above. The assessors are simply asked to report their beliefs and are not confronted with an incentive mechanism.

Hollard et al. [130] assessed the performances of these elicitation rules – in a binary outcome event model – and found consistent evidence in favor of the Lottery Rule. It provides more accurate beliefs and is not risk attitude sensitive. They also reported that the Free Rule outperforms the QSR.

When designing a product, engineers often have to consider or predict quantities that they assume to be continuous. Merkhofer [131] proposed a protocol for judgmentally determining a cumulative distribution function for a continuous uncertain quantity. It includes 5 elicitation stages followed by 2 analysis stages. The five elicitation stages are (1) motivating, (2) structuring, (3) conditioning, (4) encoding, and (5) verifying. Further details are given in the reference [132] about its application to a senior executive of a large aerospace company. Of course, applying this protocol requires time and managing interpersonal interactions.

Glenn and Kirkwood [132] emphasized the fact that although the theoretical basis for judgmental probabilities is well established, in practice, the analyst must balance the need for a rigorous elicitation process and the resource constraints. Also, the analyst must take into account both verbal and non-verbal information and retain the interest of the expert. Indeed, completing a time and cost-efficient decision analysis requires to make tradeoffs among a variety of objectives when conducting an elicitation process. Seeking for precision can be costly and sometimes unnecessary, mostly if the decision is hardly sensitive to certain input variables. Sensitivity analysis can be used to guide beliefs elicitation [133], as well as information gathering involving multiple sources [134]. Section 2.8 explores this concept.

2.8. Sensitivity analysis in decision analysis

Sensitivity Analysis (SA) is strongly tied to decision analysis literature. Indeed, the vast majority of textbooks dedicate a chapter on this subject ([52] and other references in Section 2.2). SA consists in studying the effects of the variation of input parameters of a mathematical model on its outcomes. Hence, when small changes in the value of some input parameter lead to large fluctuations in output, one can consider that the model is sensitive to the input parameter into consideration. Respectively, the model will be considered insensitive to some input parameter if the large variation of the latter only shows slight output variation. One can distinguish two approaches to SA:

The local approach was the first to appear in the literature. In the spirit of what is mentioned above, it consists in studying the impact small perturbations around nominal values on the model outcomes. It is a deterministic approach in which the partial derivatives of the model are calculated or estimated at a specific point. The most simple and common method is referred as the self-explanatory name *one-factor-at-a-time* (OFAT/OAT) [135]. Local methods lie on the assumptions of linearity and normality of the model and concern local variations. To process models with a large number of input parameters, adjoint-based methods are generally used [136].

The global approach has been developed to overcome the limitations of local methods. It considers the whole variation range of the inputs [135]. The global sensitivity analysis methods generally require statistical and probabilistic tools (regression, Monte Carlo, Latin Hypercube, graphical and smoothing techniques, etc.). Rocquigny et al. [137] prescribed what global SA method to use when treating uncertainty in industrial practice – with regard to the linearity of the model, the number of inputs, the computational cost, etc.. Further details on global sensitivity analysis methods are given in [135,138]

The models used in Decision Analysis aim to predict what is the expected value (or utility) of a decision. Accordingly, the decision corresponds to the selection of the alternative that has the maximum expected value. In this respect, a distinction worth being established between *value sensitivity* and *decision sensitivity* [139]. It is possible for the expected value of decision alternatives to vary significantly without affecting the decision: i.e. the preferred alternative does not change. In this case, one considers that the *value sensitivity* is high whereas the *decision sensitivity* is inexistent. In some other case, the output variation for the decision alternatives can be slight, but the alternative that has the maximum expected value can change: a *decision sensitivity* is observed.

When conducting a decision analysis, SA can help to determine on which input parameter the elicitation or computational effort should be concentrated. To our knowledge few studies tackle the question of the impacts of sensitivity analysis on data gathering efforts practically in a company. That lead us to consider a last research gap.

Research gap 5: Few studies have considered the influence of sensitivity analysis on data collection for computing decision problems in a company.

> We address this research gap in **Chapter 5**. In the latter, we investigate how sensitivity analysis performed on a model informed with rough estimates rather than precise input

parameter can affect the data collection and the exchanges between entities in the company.

3. An Empirical Study of a Decision-Making Process Supported by Simulation

The design process can be considered as series of decisions supported by modeling and simulation (M&S). Current developments aim at supporting this decision making with regard to increasing resources committed in the M&S process. To understand possible decision support, we conducted an empirical study in a car manufacturing company to map out the decision-making process during the development phase. A qualitative data analysis was performed to understand the difficulties and the needs expressed by decision makers. Industrial preliminary observations have shown that decisions regarding design issues are often postponed, causing iterations, and time and cost overruns in the development process. The study revealed that decisions are escalated to upper hierarchical levels as complexity and uncertainty increase and as the tradeoffs become impactful. A lack of knowledge about the M&S performance and limits, a lack of clarity due to design ambiguity, and uncertainty are more likely to cause iterations and delay. In addition, decision makers and stakeholders are sometimes unadvised of the influence of the decision under consideration on subsequent decisions and on the profit. These findings are interesting as they shed light in terms of decision supports needed in the future.

3.1. Introduction

The principal role of an engineer is to make decisions associated with the design of an artifact [53]. Designing is changing existing situations into preferred ones [140]. Decision-based design [53] has been extensively studied and established the strong foundation of the decision theory to design methodology research [17,54,141]. Modeling and Simulation is used to facilitate decision making, and aeronautical and automotive industries are the major users of multidisciplinary design optimization (MDO) to solve design issues incorporating multiple disciplines [18,19]. Recent research has underlined that resources engaged in modeling and simulation activity can reach up to 50 % of overall development costs [142]. However, very few methods exist in the literature that support decision in design evaluating resources engaged in simulation process. A better understanding of the decision-making processes supported by simulation could help to improve practices by enhancing the use of simulation; allowing strategical choice of model granularity and precision regarding the decision situation needs; and, from a management perspective, better assigning workload of simulation activity and solution research with an issue resolution planning.

Performed in a multinational car manufacturing company, our research aims to support decision-making processes for vehicle development based on modeling and simulation. A first step, covered in this chapter, consists in understanding the current decision-making processes and their challenges. This research aims to analyze the decision-making process and related issues. We conducted a qualitative study to map out the decision-making process in the development phase and to identify the difficulties and the needs of the actors of the decision in a multinational car company. Our empirical research methodology is presented in Section 3.2, and the results are reported in Section 3.3. Relationships between the results and the literature, as well as propositions about requirements for a decision support framework are discussed in Section 3.4. This section discusses possible future work: after the present descriptive approach, we will analyze decision through a prescriptive approach. Finally, Section 3.5 draws together the most important difficulties observed, and the room for improvement in the current decision-making process.

3.2. Research methodology

In order to better understand the decision-making process in design supported by simulation, we conducted an empirical study consisting of observing decision meetings, interviewing stakeholders of the decision (project managers, architects, experts, M&S practitioners, etc.) and analyzing internal reference documents (Figure 3). This data was used to propose an “as is” process that was observed. This process was afterwards presented to several engineers in order to identify possible discrepancies and validate our understanding of the process. Various qualitative data analysis techniques such as coding, jotting and analytic memo-writing were used on the transcripts of the qualitative interviews, on the field notes, and on the reference documents [143]. Sections 3.2.1 to 3.2.3 provide details about methodology for each source of information. A final report was sent for reviewing to all the interviewees and people involved in the study, and final validation was made in a meeting gathering 10 major experts of the company.

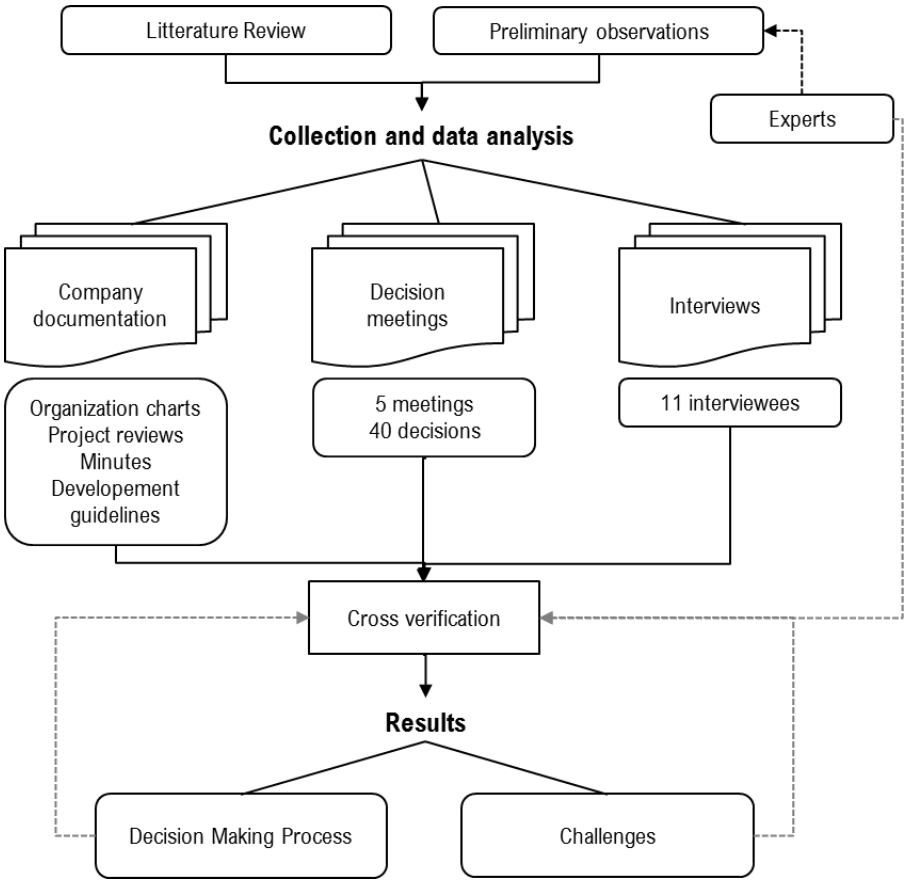


Figure 3 - Empirical research methodology

3.2.1. Decision meeting observation

We observed decision meetings and collected related information in mail conversations during the development phase of a vehicle platform (i.e. a chassis and a set of non-visible parts shared over distinct models of cars) for two vehicles. 40 decision situations were observed in 5 decision meetings led by a vehicle platform project manager. The decisions observed concerned design issue resolution, e.g. *decide design modifications for solving dash intrusions discrepancies for a frontal crash test*. We built a template for data collection and analysis with several categories of data: context, decision under consideration, design scope of the decision, alternatives proposed, new coming information, decision meeting conclusion, type of information presented, credibility indicators for the information presented, actors involved in the decision process, duration of the session, and comments with regards to the course of the meeting (people attitudes, quotes, etc.). To some extent, we also captured "corridor" discussions: unofficial discussions held by people presenting a topic (issue and decision request) that usually happen before and after topic is treated in a meeting. Audio-recording was discouraged by internal experts; decision meetings are sometimes tense, and participants sometimes complain about the work of their colleagues. Moreover, sensitive material is discussed. The recording method was therefore note taking. For each decision,

minutes have been prepared that were further sent to the participants and System Architect for the validation.

Therefore, in order to better understand the issues and challenges a coding was proposed with the aim to identify different types of problems. The taxonomy used has been built progressively, through several iterations between authors but also 3 company members participating in the project.

Once the coding was done with initial analysis of frequency of the problems identified with several details and quotes, the overall synthesis was presented and discussed during a group meeting with all strategic members of the process (for instance General manager of the M&S process of the company), where all elements have been looked at as well as the details of the challenges identified.

3.2.2. Qualitative interviewing

Main actors of the decision process were also interviewed. The interviewees were selected with regard to their role in the decision-making process and their expertise of the simulation process. The 2 vehicle program managers (and former project managers) and the 2 vehicle project managers interviewed were involved in 10% of the vehicle projects of the company. The other interviewees included: 1 synthesis architect (or technical synthesis engineer, i.e. an engineer responsible of the technical and economic convergence of the whole vehicle), 1 technical director (former program and project manager), 1 expert director of M&S, 1 expert director of durability (former director of customer performance, former program manager), 1 head of Computer Assisted Engineering, 1 expert in M&S, and 1 project manager of a model creation team. As the experience of the interviewees in the company ranged from 5 years to more than 40 years, some of them could speak of the different positions they previously held.

Qualitative interviews are potentially powerful to explore complex experiences [144] and subjective and complex decision-making processes [145]. We chose an in-depth interview style with descriptive questions. Although this method is time consuming, it reduces the possibility of influencing the interviewees (like in multiple-choice questions in quantitative interviews). We conducted semi-structured interviews with a set of 14 initial open and specific targeted questions used as the skeleton of the interview [146]. The overall structure of the interview guide used in the study followed a commonly used sequence [147]: introduction, warm up, main body of interview, cool off, closure. The average length of each interview was about 60 minutes. Since the subjects were likely to disclose confidential and sensitive material and remarks about colleagues, note taking was preferred compared to audio-recording so that the interviewees felt more comfortable. Declarations of the interviewees were clustered into 11 categories, covering both decision and M&S themes, and also a short biography and additional remarks (Table 1).

The two first interviews showed that interviewees sometimes anticipate the next questions while answering one question. For the transcription of the data, coding was used to analyze and identify different types of the problems. This was done iteratively with 3 company members participating in the project. Once the coding was validated this taxonomy

was used to analyze interview data. The analysis was also cross-checked by other two members of the research team. This was used to sort the data and evaluate the weight of the concepts raised in the answers. Spreadsheets documents were used for the analysis and storage of data.

	Categories	Example of question (translated)
1	Short biography	What is your background?
2	Role	What is your role within the development stage?
3	Decision process	How would you describe the decision-making process during the development of a vehicle/platform?
4	Favorable conditions	What are the favorable conditions to a good decision making?
5	Barriers and difficulties	What difficulties do you face in the decision-making process?
6	Type of information	What type of information do you deal with?
7	Uncertainty	What are the uncertainties related to decision making and what are their influence?
8	M&S support and decision support tools	Do you use decision support tools (which ones, advantages, drawbacks)?
9	Credibility and difficulties related to M&S	How do you assess the reliability of M&S results?
10	Knowledge about M&S processes	What do you know about M&S processes?
11	Additional remarks	***

Table 1 - Examples of questions related to the categories of answers

3.2.3. Analyzing company documentation

Internal reference process documents, best practices, the development guidelines, the organization charts, were analyzed as well as minutes of various decision and project review meetings that we did not attend. This was done in order to better understand the process as imagined and the process “as is”, i.e. implemented concretely in the design process. A coding technique very similar to the one described above was used on documents when it was possible.

3.3. Case study and results

3.3.1. Context

We performed the empirical study in the context of the development phase of a vehicle and vehicle platform project. A vehicle embodies an upper-body (i.e. cabin, body-shell and visible parts), a platform (rolling chassis and non-visible parts) and a powertrain. Platform and powertrain are common to different upper-bodies, and are developed in different projects, starting generally before the development of a new upper-body. In our context, we refer to *vehicle project* as the development of an upper-body, which is the element used by the company to distinguish vehicles, and we refer to *vehicle platform project* as the development of a platform. We generically refer to a *project manager* as a manager of a vehicle project or a vehicle platform project.

In the development phase, a vehicle needs to be delivered at a specific downstream milestone at the right time, the right level of performance and the right cost. This milestone is a stage-gate that separate the development phase from the manufacturing phase. The development phase consists of iteratively refining design specifications, testing the performance of vehicles with regards to predefined requirements, and fixing the issues while increasing the profit of the company. At this stage, the vehicle under development exists in the form of a digital model, and testing activities are therefore mostly digital, until a physical model can be manufactured. Digital models enable investigation and prediction of architectural consistency and overall vehicle performances. The model of the vehicle is based upon a design reference. The design reference corresponds to the state of knowledge about the vehicle under development, it contains all the product specifications. With different markets in mind, several versions of the vehicle usually exist at the same time. Design activity consists in refining the design reference. When design flaws are revealed by simulation, an issue resolution process, consisting in analyzing the causes and searching for solutions that will fix the issue, is put in place. This process involves decisions: choices between different paths of investigation (for the analyses) or design solutions. For example, a design flaw, or design issue, can be a yoke intrusion of 143mm instead of the 130mm required for a frontal crash test. The corresponding design decision can be about designing modifications for solving dash intrusions discrepancies. A resolution of the issue can be designing an add-on item tied to the existing structure that leads to a yoke intrusion of 128mm.

Our preliminary industrial observations have shown that although a considerable amount of resources is spent in M&S, decision makers often do not trust M&S results. Consequently, among other factors determined later in this section, difficult decisions to solve issues are often postponed and iterated many times, sometimes until the physical test phase. Moreover, new design issues are sometimes discovered on physical prototypes, when the cost of solving these issues is considerable. These observations reveal that there are issues related to the decision-making process itself.

The following paragraphs present the results of our empirical study. The decision-making process described, and the challenges identified are based upon our analysis of the data collected through the three sources of information mentioned in Section 3.2.

3.3.2. Decision-making process

3.3.2.1. Escalation of decisions

Decisions can be made at a different level in the hierarchical organization of the project. The issues identified by simulation concern both architectural and performance discrepancy. At first sight, most of the issues involve artifact-focused decisions with cost, technical, and customer performance considerations. Hence, a simple decision can be made locally by designers and analysts from an artifact perspective. However, when the potential outcomes of a decision have significant consequences in terms of process, the decision must be escalated to upper management (e.g. designing an add-on item would affect the manufacturing and assembly strategy, or additional analyses would push the delay up to 3 months for the whole project). Similarly, as the development of a vehicle is a complex system, a decision concerning a subsystem can have an impact on other subsystems. Therefore, the designers and analysts (solution providers) must refer to synthesis architects, who have a systemic and functional view, when making a decision. When a decision involves significant tradeoffs in terms of cost, quality, time, and affects the coherence between parallel projects, the project manager is asked to decide. More generally, if solving an issue may lead to collateral effects, extra cost, or require out of scope information, the related decision must be escalated to an upper level of hierarchy. The more the issues are complex and people are uncertain, the more they will collect information, reframe, and escalate the decisions (Figure 4). When a decision is made, actions are taken to update the design reference of the vehicle, until the next testing phase (validation). Such iterations (called digital loops in Figure 4) lead to a gradual refinement of the specification of the vehicle until is it ready to be manufactured as a prototype for physical tests.

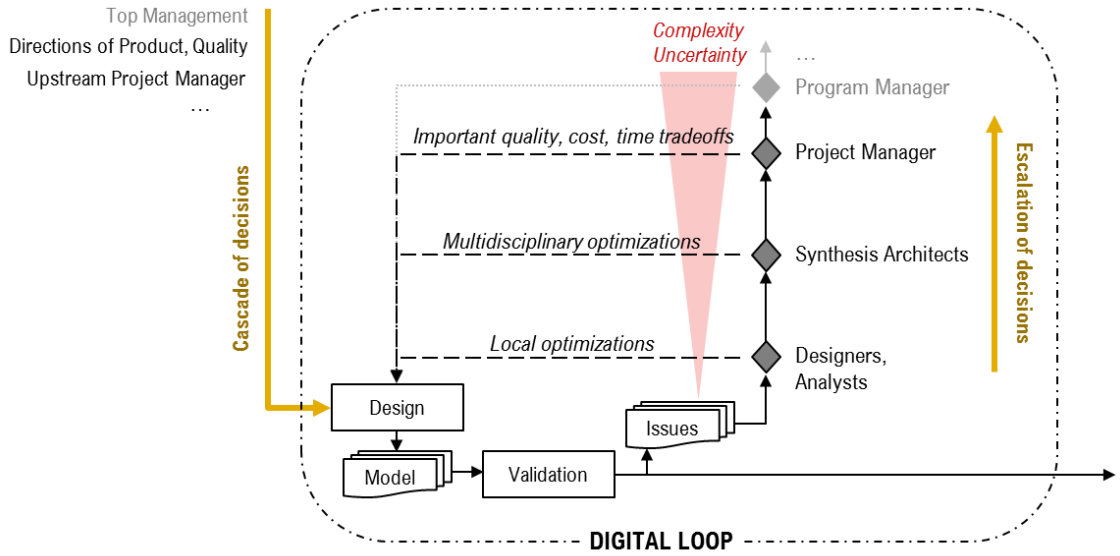


Figure 4 - Escalation of decisions in a digital loop

3.3.2.2. An issue resolution process supported by simulation

Models of different subsystems are created from the design reference (Figure 5). They are prepared (e.g., meshing for finite element analysis), and assembled in a synthesis model of the vehicle. According to a validation plan specifying the testing conditions, numerical simulations are made to evaluate the performance of the vehicle according to the specified requirements.

When a performance does not reach the target, an issue is created. Simulation analysts, customer performance specialists, and designers responsible of the affected subsystem or domain (métier), establish a plan to solve the issue. This plan consists of identifying paths of investigations for corrective actions (countermeasures) that will solve the issue. Once the plan is executed, potential countermeasures (alternatives) are tested. For each "métier" (e.g., passive safety), project review meetings are organized weekly. Designers, simulation analysts and architects exchange information about the progress of issue resolutions, and decisions are made at their level, in their scope, to refine design alternatives, to deepen the analyses or to escalate decisions.

If an alternative is expected to solve the issue at an acceptable cost, that particular countermeasure is chosen, and the design reference is updated with the modifications prescribed by the countermeasure.

Solving an issue might require several iterations in design and test to achieve the desired performance. If the alternatives are unsatisfactory and analyses prove that the issue presents the characteristics set out in the paragraph *Escalation of decisions* (costly solution, out of scope information, negative impacts on other subsystems, etc.), then a *decision dossier* is created and escalated to upper levels of hierarchy (such as synthesis architect level or project manager level).

To create a decision dossier, information is collected and abstracted according to the requirements of the decision maker. The decision maker might not be specific on the information he or she needs to decide in the best conditions; although he or she does not know in advance what information would be the most valuable, basic key data like cost, mass and effects are required. To select the information to communicate, engineers (designers, simulation practitioners, customer performance specialists) proceed according to standard practices and common sense. The information is presented in a decision meeting to the decision maker by representatives of the domains concerned by the design issue. Miscommunication between the decision maker and the engineers about their respective expectations often lead to incomplete decision dossiers. This often causes the decision to be postponed.

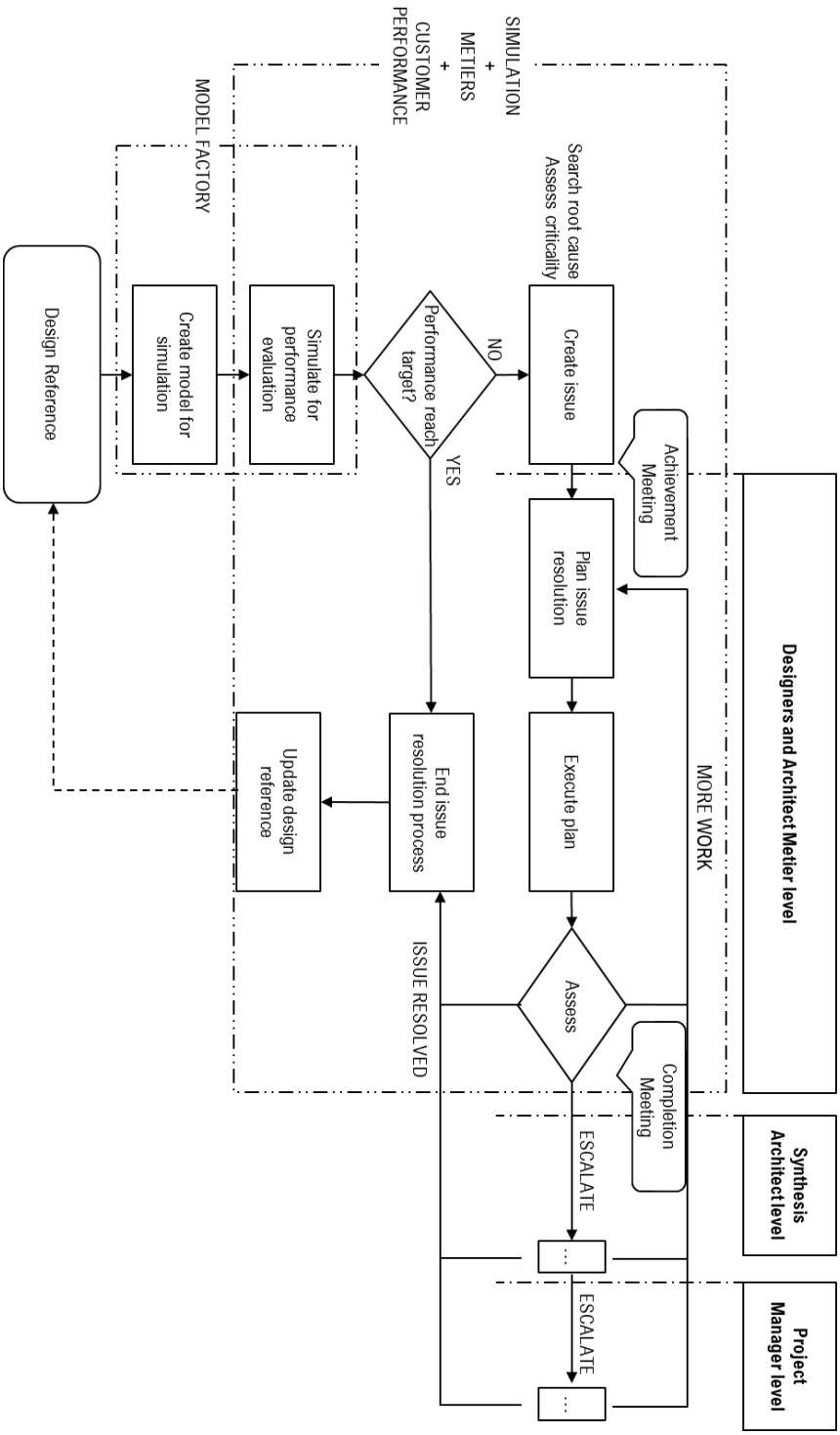


Figure 5 - Design issue detection and resolution process supported by modeling and simulation

3.3.2.3. Focus on project manager level decisions

The role of the project manager

The project manager is appointed at an upstream milestone when the concept of the vehicle and its unique selling propositions are defined, and match with the customer requirements. At this upstream milestone, the technical solutions are consistent with the economic target. The project manager is responsible in the company for the compliance to engineering entry ticket commitments for his project. The engineering entry ticket is the valuation of the engineering resources that are required to design the product end the process of a new vehicle or component. He or she makes decisions all along the development phase of the vehicle when the prototype is digital, and during the physical testing phase, when the prototype is manufactured. The more the design issues are solved during the digital phase, the less resources and effort are consumed. As several vehicle projects with different status are running in parallel for a same range, the project manager exchanges information with other project managers and is accountable to the program manager (Figure 4).

The course of a decision meeting

Once a decision is escalated to the level of a project manager, the decision dossier is presented in a decision meeting. A decision meeting is a meeting where several decision dossiers are presented. A specific time frame is allocated to review each dossier with the representatives concerned. Like the project manager has to make tradeoffs between cost, quality, delay and customer performance, he or she debates with two principal actors: the technical synthesis engineer, a synthesis architect, who is focused on objectives in the technical engineering (such as lowering the mass, the cost, etc.), and the synthesis customer performance engineer, who is focused on the customer performance requirements (i.e. what the customer perceives and values, such as the thermal comfort, the acoustics, the ergonomics, etc.). Of course, these objectives can be divergent.

The project manager actions usually follow the pattern illustrated in Figure 6. For a decision dossier examined, the possible outcomes fall into two categories: either the decision is finalized, and a countermeasure is selected, either the decision is postponed. Whether the project manager decides to choose a design alternative as a countermeasure or to collect more information about one or several alternatives (or about the frame of the decision problem itself), his or her decision is later cascaded (i.e. reframed into specific decisions at lower hierarchical levels to take a set of actions) as shown in Figure 4.

The use of decision-making methods

In the company, at the development phase, there is no standard practice including rigorous methods or analyses to support decision making when solving design issues. Weighted-sum methods are sometimes used by project managers, but the additive utility assumption is often violated, and the results are equivalent to “adding apples and oranges”. People are generally not trained to multiple-criteria decision methods and decision analysis.

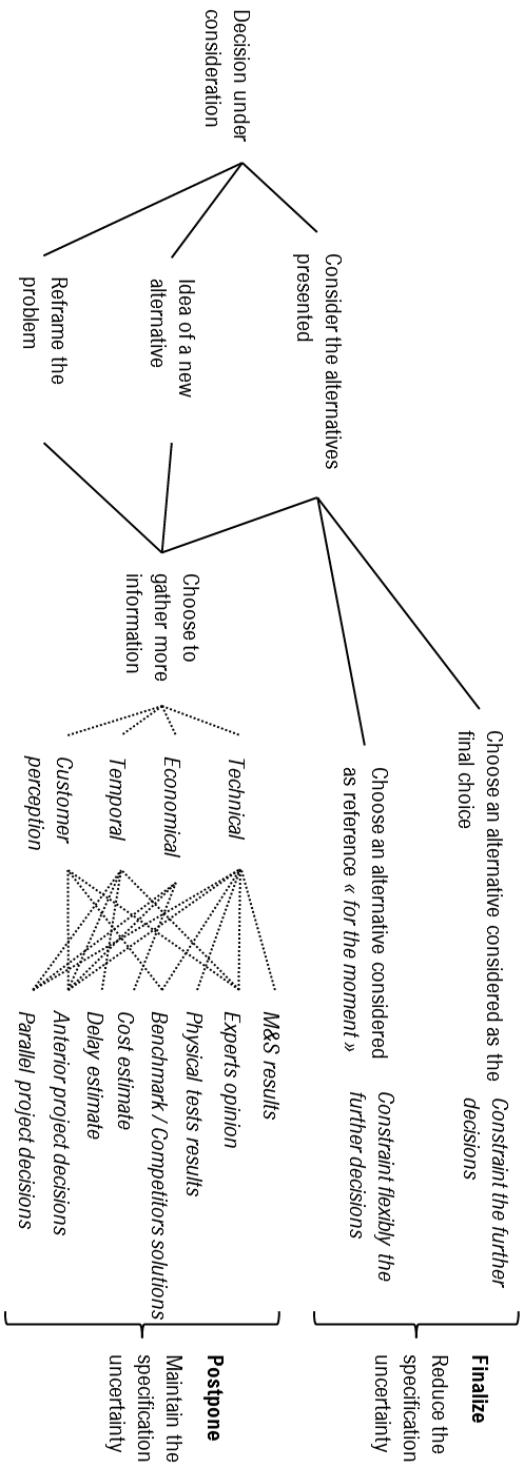


Figure 6 - Possibilities for a project manager in a decision meeting

3.3.3. Challenges

3.3.3.1. Difficulties with design decision-making

Consistency of the data

Whereas management prescribes that design and testing activities should be sequential, in practice, when issues are identified, they are solved while designers continue to refine the product specification (or technical definition). The results of the testing phase which revealed the issue under consideration can become outdated. Decision makers can become uncertain about the consistency of the data: they wonder whether the results are based on the latest technical definition and whether the last countermeasures (the previous decisions) are taken into consideration.

Feasibility of alternatives

Some alternatives presented are not analyzed enough in a product-process perspective. The project manager needs to rely on experts that, despite the rules of core competencies and experience, might not have certain answers, or do not communicate their uncertainty about the information they provide.

Validity of simulation assumptions

The results of simulation are based on assumptions that are supposed to reflect the reality; despite the history, knowledge, and rules about tests. Numerical calculations are made with nominal values whereas there is variability within the physical prototypes. The project managers are aware of these types of deviations but are usually not informed about a confidence interval which could be provided by probabilistic calculations.

Framing of the decision problem

Some presenters attend decision meetings without a well framed decision problem. The project manager is uncertain about what he is expected to decide. Either the question, the alternatives, or the criteria can be missing. Although any choice can be made between inexistent design alternatives or investigations, the decision maker usually postpones a decision and demands the presenters to work on their request until the decision is framed and informed. These iterations are inconvenient for the decision makers since they consume time that could have been used to treat another issue. This also reflects a lack of preparation or an error of decision escalation. “If you come up with a problem without any solution, you are the problem” (said an interviewee). Decision makers and stakeholders are often unadvised of the influence of the decision under consideration on subsequent decisions and on the profit. This information comes with a good framing that shows the problem, the alternatives, the preferences and the potential outcomes on the design process and ultimately on the profit.

Quality Cost Delay impacts

For a specific alternative, one or multiple dimensions of the QCD impacts can be unknown. Modeling and Simulation results alone do not cover cost and time aspects. Rules exist to determine the cost impacts at the designer levels, but the cost modeling is ideally made by the purchasing teams. Sometimes the cost information has not been gathered before the meeting due to the lack of time. Delays encompass both analyses, and design and manufacturing lead times. Iterating on an issue resolution or postponing the decision until the time is critical can have severe consequences on the overall timeline. Subsequent decisions on the project and sometimes parallel projects can be affected since they share some specifications. QCD data are sometimes estimated or collected during the decision meeting. In these cases, the decision maker prefers to be sure and usually postpones the decision until he or she has a clear view of the QCD estimations. The cost of inaction is seldom explicit.

Risk management

QCD impacts, or outcomes of a decision more generally, can be quantified with probabilities. If the risk is sometimes communicated, it is either informal or expressed as a guess work, since probabilistic approach are not used as routine methods. For some issues, a risk management is considered by developing solutions that can be modular (kits): if the issue identified by digital simulation appears during the physical tests, the kit designed beforehand is ready to be manufactured to solve the issue. The decision to create a kit or not requires risk information.

The "right time" to decide

In the same vein of the delay impact, to remain cost-effective, a decision must be made at an optimal moment, or before a given moment. That moment is not certain and depends on several factors (milestones, other design specifications, availability of information, etc.). The project manager often asks, "until when do we have to decide?", meaning "when will the value of the payoff drop if we do nothing?". Assuming that there is a "right time to decide", some decision problems are discussed too early, while others are discussed late, when the cost of solving is higher.

3.3.3.2. Modeling and simulation use

Knowledge and trust about M&S

M&S results are considered as not predictive enough for some domains such as acoustics and ground links. In such domains, to be relevant, simulations need to consider the entire vehicle synthesis model since only a holistic approach can best address these issues. Even if late in the digital phase, the vehicle is detailed enough to perform representative synthesis tests; interviewees agree that, in the company culture, physical testing is considered as more credible than digital testing for decision makers. This was also observed in decision meetings, mostly for acoustics, for example when the decision maker preferred to wait for the physical test instead of taking actions to solve a customer performance issue highlighted by acoustics simulation. People often do not question the protocol, the technical definition, and the

relevance of physical tests. Whereas in M&S, the update of the technical definition, the accuracy, the simulation assumptions are questioned. Sometimes data are presented without a clear definition of pedigree and accuracy; and lack of explanation. M&S results characteristics are also more likely to be discussed when they are unsatisfactory: when they do not confirm the alternative that would has been considered as the most cost and effort saving. The room for the doubt and the lack of knowledge about M&S quality and limits allow the actors of the decision the possibility to steer decision making to their own interests. Indeed, although M&S is intended to support design decisions, it is sometimes used in the company as a means to off-load responsibilities and workload.

3.4. Discussion and future work

The internal validity of this study was carefully treated by methodology and data triangulation as well as an internal reviewing. The external validity must be relativized with cultural differences that might exist in other companies in a global context [148,149]. Indeed, it is important to take into consideration that our study was conducted in a specific automotive company where people are imbued with French culture. This company has a strong partnership with a Japanese car manufacturing company. Among other things, they share knowledge, designs and exchange about processes. During the interviews and the meeting observations, people emphasized multiple times that cultural differences exist in terms of management and about the issue resolution process between the two companies.

In the scope considered (vehicle development projects) people of the company refer to artifact decisions when they speak about decisions. An *artifact decision* must be understood as "the choice between the design alternatives that solves the issue". Note that choosing to postpone an artifact decision implies choosing between finalizing the issue resolution at that time or finalizing later; it is a *process decision*. It is important to recognize that a decision about an artifact – here, the car – influences and is influenced by decisions made about the process, and decisions made about the process influence and are influenced by decisions made about the organization [150].

Postponing an artifact decision causes a delay in the issue resolution process. The delay related to one artifact decision can be propagated to other subsequent decisions and cause a delay in the overall process or involve cost overrun to respect the timeline.

The causes of delay in collaborative decision making under uncertainty have been studied by Hassanzadeh [75] in the context of pharmaceutical R&D projects. The author has stressed the 3 most mentioned causes of delay over 252 key factors that affect decision making: the fear of uncertainty [68,77], the fear of hierarchy and the difficulty of Go/ No Go decisions. Her research is focused on pharmaceutical R&D, where projects last more than ten years. As the consequences of Go/ No Go decisions are not immediate, delays of several months may be ignored or tolerated. However, in the automotive industry, the time allocated to make decision is significantly shorter since the projects of new vehicle development last about 3 years.

In the development process, when an issue is being solved, the product specification keeps evolving since designing of several subsystems is performed concurrently. This

overlapping of testing and design activities can create uncertainties about the consistency of the data and can block out the opportunity to respond to emerging issues. For generic overlapping, research has been done on understanding the format and timing [151] and on effective communication and close coordination among different specialists [152,153]. Tahera et al. [20] developed a method validated in a case study in the automotive sector. The objective is to avoid unnecessary rework and iteration. Their method consists in integrating digital and physical testing to support overlapping between upstream testing and downstream redesign. In our case, testing and design activity are mainly both digital for the upper body. The digital prototype is supposed to meet the requirements before starting the physical testing. Some early physical tests are performed upstream for platforms (i.e. a chassis and a set of non-visible parts shared over distinct models and even type of cars). For a specific model of vehicle, a hybrid prototype (platform under development and tinkered upper body) is created and physically tested. The relevance of that type of test remains questionable in terms predictability and representativeness. Indeed, how representative are the results of a real vehicle obtained from a single or very few crash tests of an early hybrid prototype? Would those results be more predictive than a probabilistic simulation where tremendous digital prototypes are crashed multiple times to incorporate design ambiguities and manufacturing deviations? However, early physical tests allow the analysts to observe phenomena that are not covered by numerical simulation, such as rupture.

The projects managers usually rely on the analysts to interpret the results and to communicate them with their inferences. The value of the M&S results partly depends on the credibility granted to them by the decision makers. The NASA [154] developed a standard method to assess the credibility of the M&S results presented to the decision maker; and established a common set of terms and a uniform way for M&S practitioners to communicate the credibility of M&S. A challenge is to adapt and implement such a method in a company with its own M&S process history.

Towards a prescriptive approach

Our results show that decision makers struggle with poorly informed decision problems, whether it is in terms of cost, quality, times attributes or in terms of the expression of the uncertainty about the information provided. We consider testing a method based on normative decision theory (NDT) on real decision problems encountered in the company. This will consist of identifying influential decision attributes and expressing explicitly and numerically how of these attributes affect the payoff of the decision. The Value of information approach will be used to consider whether additional information should be collected or not. That could provide clarity on when finalizing the artifact decision and avoid endless loops of simulations. A challenge lies in gathering input data for our method. Indeed, as the practice is mainly based on guesswork and heuristics, specific data could lack or be difficult to access. Cost and effort of using a NDT-based method should be evaluated, recorded and compared with the current practice, as well as the difference in terms of benefits. This comparative analysis is considered as one of the steps in the future work.

3.5. Conclusion

In this chapter, we have investigated the decision-making process and its challenges in the development phase of vehicle projects in an automotive company. We focused on the decisions made to solve design issues (technical, related to the customer performance). Irrevocably, solving design issues involve resources for collecting information to frame the decision problem, to develop solutions and analyze their consequences.

The level at which decisions are made depends upon the control that the decision maker has with regard to the technical and economic constraints and depends upon his or her access to information. Decisions to solve design issues are often escalated to upper hierarchical levels when the alternatives considered involve a risk of cost and time overruns (including impacts on the design activity of other subsystems).

We described the process of design issue resolution supported by simulation, and the way a decision dossier is treated in a project manager level decision meeting. The lack of conclusive information is the main reason for postponing an artifact decision. Project managers make process decisions; they choose between finalizing the issue resolution by selecting a design solution and waiting and collecting information to finalize the issue resolution later. Considering the continuous evolution of the product specification the multiple interactions between decisions made at different levels and in different interrelated projects, defining the optimal moment and the valuable information to make a decision is challenging.

Our descriptive approach enabled us to identify the difficulties encountered by the decision makers and the type of information they need. The decision makers lack of clarity about: the consistency of the data; the feasibility of the alternatives; the cost, quality and delay impacts; risk information; the optimal time to treat an issue in the development process; and knowledge about modeling and simulation process, validity and limits. Some decisions are risk informed, but this is often not explicit; and engineers are generally not well trained to deal with uncertainty involving mathematical methods. We also observed that the lack of knowledge about modeling and simulation, and the lack of trust about the results, are likely to facilitate irrational behavior such as off-loading responsibilities and workload.

The objective of this work is to propose a decision support in design with regard to M&S process utilization. Therefore, next steps will include a prescriptive approach to devise a decision support framework based on normative decision theory.

4. A Proposal for a Decision Support Framework to Solve Design Problems

Decision makers in the industrial context often rely on heuristics and experience to make complex decisions. Often, integrating implicit or expert knowledge as well as uncertainties can lead to decisions that are not necessarily the best ones. Moreover, in engineering design, the decision-making approaches focus on the product itself and do not investigate necessary effort that is needed to gather additional data in order to devise more precise decision-making models. In our research, we propose to integrate this estimation of additional effort needed for data gathering and decision making refinement in order to support design teams. This research has been conducted in collaboration with a major car manufacturing company, and in particular in the development process through Modeling and Simulation. The objective is to propose a decision-making model that integrates data-gathering estimation, integrating also the estimation of postponing one decision. A decision problem model based upon expected utility combined with the value of information theory is proposed to address this issue. The model has been developed and tested on 4 case studies. We define a decision support framework by integrating the model into a tool and by proposing roles in the decision-making process. We finally present its application on a concrete example.

4.1. Introduction

Normative decision theory has been devised in order to support the decision making. The underlying hypothesis of this theory is that the decision maker is considered fully rational and that all data necessary for the decision making is available. However, in industry, these approaches have been used on a smaller scale. Several reasons have been identified as possible causes such as that these approaches are computationally challenging, there is a lack of data, conflicting objectives of the decision makers, high cost of implementation [37,155,156], etc.. In Engineering Design, proposed approaches in decision making have been mostly focused on the product itself; not necessarily taking into account the time needed for additional data gathering or modelling one decision.

Previous empirical studies [107] aimed at understanding the causes that hinder the use of decision making approaches in automotive industry. Some of the major reasons that have been identified are: 1) a lack of clarity due to the uncertainty about potential changes (because of concurrent design and testing activities) as well as cost, quality and delay; 2) lack of knowledge and trust in M&S performance and limits; 3) miscommunication between decision actors partly due to the fact that complex decisions are *trans-hierarchical* (i.e. decisions are escalated at higher hierarchical levels). This decision escalation may result from: (a) a need for additional information that is out of the scope for a given subsystem or a component; (b) the fact that the decision problem involves adding extra cost to the development process; or (c) the possibility of impacting heavily another subsystem or process. The study also underlined that decision makers and stakeholders are sometimes unaware about how their decision influence subsequent decisions and ultimately the profit of the company.

Interestingly and contrary to what has been usually proposed in decision making in engineering design, observations from industry underline the fact that decision makers (project manager, synthesis architect, etc.) tend to have a process-focused approach. For instance, they consider the fact that the technical definition for a given subsystem or component will in time be more refined and less likely to change over time. When deciding, they tend to make an intuitive trade-off between the probability that changes in the technical definition will affect their decision about technical solutions and the costs incurred by the delay. However, outcomes related to actions such as data gathering and postponing the issue resolution are not explicitly integrated in the decision-making process.

In this chapter, we propose to bridge this gap by proposing to integrate process related data, hence proposing a decision-making framework entitled IRDS (Issue Resolution Decision Support). This research is done in collaboration with a major multinational car manufacturing company and concerns Modeling and Simulation (M&S) process. The decision problems considered in this research refer to decisions made to solve the "*design issues"* in the vehicle Development phase. This phase is characterized by design and numerical testing iterations refining the vehicle technical definitions in order to comply with vehicle requirements. *Issue resolution* in this chapter is the process of defining solutions and gathering information to ultimately incorporate a technical solution (i.e. modifying the vehicle technical definition). For instance, a *design issue* can be that a noise, vibration or harshness performance does not meet the requirements. The corresponding decision can be to make a choice between two or more alternatives that will ultimately lead to solving the design issue. The alternatives are

courses of actions like “changing the current material X to material Y on the same design” or “analyzing the consequences of incorporating an add-on”. Ultimately, the choice of an alternative leads to an irrevocable allocation of resources.

IRDS includes a generic model of common decision problems addressing design issues, a customized tool that enables to compute decision problems, a definition of the roles in the decision-making process, and specification of the information flow between these roles. Its decision problem. The model relies is based upon the expected utility maximization and value of information theory. In this chapter, we focus on the decision problem model, its structure, variables, and conceptual features.

Related scientific background for this research are given in Sections 2.1 to 2.5: they focus on decision making in engineering design, value of information theory as well as approaches that have been integrating design process information in the decision-making models. We propose the following structure of the chapter. Section 4.2 details the proposed decision-making model. Industrial cases are given in Section 4.3. In Sections 4.4 and 4.5 we discuss limitations of the proposed approach and discuss future research.

4.2. IRDS’ generic decision problem model

Decision makers struggle with poorly informed decision problems in terms of cost, quality, and time attributes about process alternatives such as: modify design now, analyze a design modification considering the current beliefs about the decision situation, postpone to analyze and modify design at a later time (in a different the decision situation). In order to support Issue resolution process we propose a an issue resolution decision support (IRDS) that aims at answering the following general questions: *What are the artifact alternatives (technical solutions)?, What if the decision maker chooses to incorporate a technical solution now?, What if he/she decides to collect information about a technical solution?, and What if he/she postpones the issue resolution finalization?*. The IRDS model is based upon the expected utility defined for each decision alternative and the Bayes inference to update the beliefs in case of information gathering (for the alternatives consisting in performing an analysis). IRDS aims at integrating information pertaining to the development process; the model itself includes an industrial cost breakdown and takes into consideration the evolution of the design refinement. Depending on the accuracy expected, the data required can be extracted from expert or non-expert estimates; and simulation analyses results. The model was defined and tested progressively. Several feedback loops have been done in order to refine the model and ensure its genericity.

4.2.1. Case studies used for model building

In order to propose a generic decision-making model, four case studies have been identified and discussed with industry experts:

- RC1: Tunnel
- RC2: Fairing thermal protection

- TC1: Reinforcer
- TC2: Analyses for reinforcer

Two of them are real design issues that have been extracted from history and discussions with two experts and two analysts *("real cases",* RC1 and RC2), and the two others are synthetic design issues (*"toy cases"*, TC1 and TC2), that we designed in accordance with experts with the aim to represent common situations.

Two of them are real design issues that have been extracted from previous projects and in discussions with two experts and two analysts *("real cases",* RC1 and RC2); and the two others are synthetic design issues (*"toy cases"*, TC1 and TC2), that we designed in accordance with experts with the aim to represent common situations encountered in projects.

The two *real cases* consider two different stages in the development process. At the upstream edge of the process (RC1), the design maturity is very low, and the decision problem information is scarce. In other terms, the technical definition of the vehicle is imprecise and the probability that changes can occur and affect the problem settings is high. Moreover, no numerical simulation results on technical performance are yet available, and the cost estimate is very imprecise. Conversely, downstream (RC2), closer to the manufacturing milestone, the design maturity is high, and the information is prolific. In other terms, simulation results for technical performance already exist and simulations can be performed with reasonable accuracy. There is also more clarity about the economic and time constraints related to the potential actions. As for the two *toy cases,* they were designed to represent the decision problems encountered between these two different ends of the process. One of these *toy cases* helped us to determine the cost breakdown and the influence of the design maturity on the decision (TC1). The other case (TC2) helped us to model the influence of the analyses about the beliefs about the chances of success of one or several technical solutions.

4.2.2. Structure and principles

The Issue Resolution Decision Support model proposed is represented as a pseudo-recursive tree. Decision Alternatives in this context that have been identified (see Figure 7) are the following ones:

1. *Incorporating a technical solution at the current moment*: This alternative corresponds to modifying the design of a part, changing the material, or adding a new part (eg. a reinforcer). In its broad sense, this alternative also includes sticking to the current technical definition.
2. *Analyzing one or several technical solutions concurrently and wait for the results before selecting which technical solution should be incorporated (cf 1.)*: In other terms, this alternative consists of gathering additional information about the chances of success of incorporating a technical solution.
3. *Postponing the finalization of the issue resolution at a later moment, to then decide whether incorporating a technical solution (cf 1.) or perform analyses (cf 2.)*: This alternative reflects the case when the decision maker looks for the most favorable moment to choose to integrate a technical solution. He/she targets a time when the architecture is less likely to evolve and affect the outcomes of the decision.

These alternatives can be linked to the notion of different situations represented in the model (see Figure 7). The current situation (S1) includes the three categories of alternatives. The situation S2 corresponds to the moment when the analysis results are available and when the decision maker will have to choose which technical solution to incorporate. S1' corresponds the moment when the decision maker will have to choose between incorporating or performing analyses, after having postponed the finalization of the issue resolution. If in the future, in S1', the decision maker chooses to perform analyses about one or several technical solutions, he/she will end up to S2'. S2' has the same structure as S2 but has a different time coordinate (and potentially different decision attributes). At each decision node of the tree, the maximum expected value is used to calculate which is the most profitable alternative.

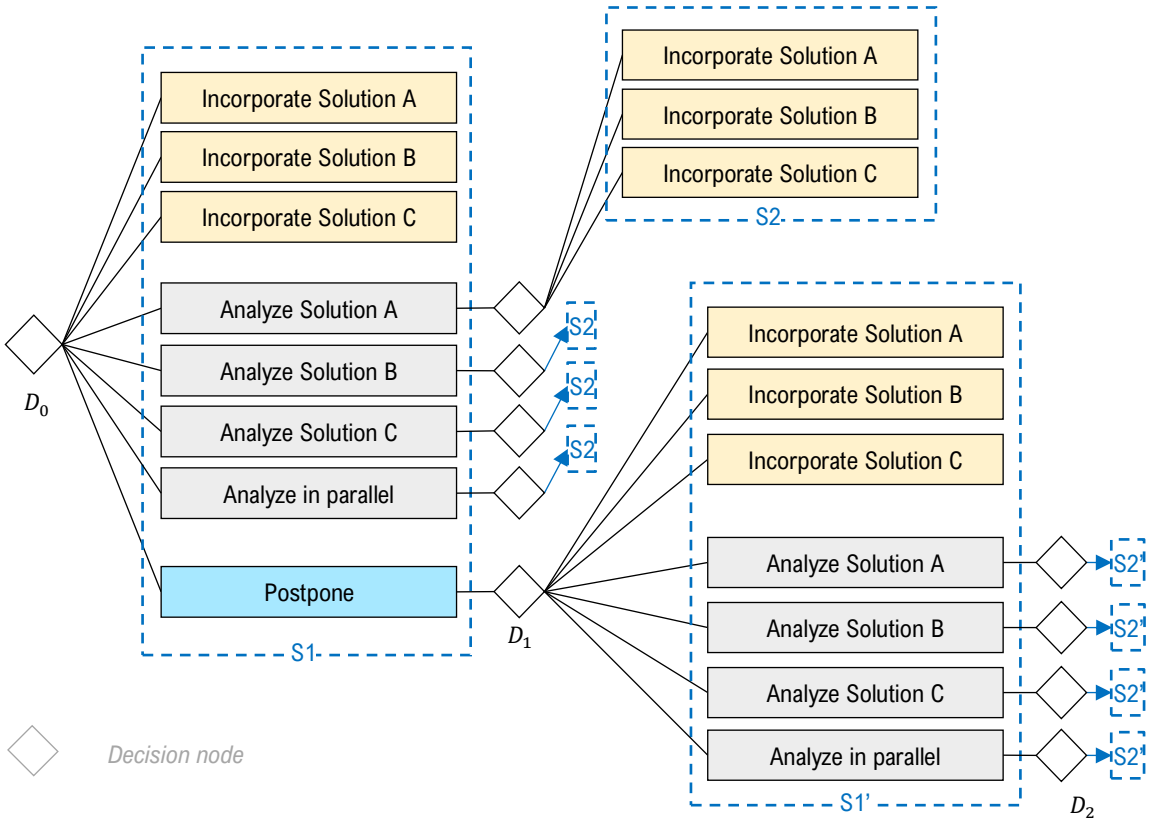


Figure 7 - Structure of IRDS' generic decision problem model

4.2.3. Variables, functions and conceptual features

To comply with the company risk policy, we assume that decision making is risk neutral. Decisions are made to ensure that performance meets the requirement that was defined in a perspective of demand maximization and regulatory compliance upstream. Also, we consider that in the development phase, a decision addressing a design issue ultimately involves an expense. This expense can result from the implementation of a design change, the performance of analyses or, indirectly, a delay in planning (due to the cost of accelerating

subsequent activities to meet the deadline). These two reasons (risk profile and expense-focus) lead us to assimilate the expected utility to an expected cost. The preferred alternative is considered to be the one that has the minimum *expected cost*. Figure 8 provides an overview of the relationships between the variables involved in IRDS. More details about the functional use of these variables are given in the next subsections.

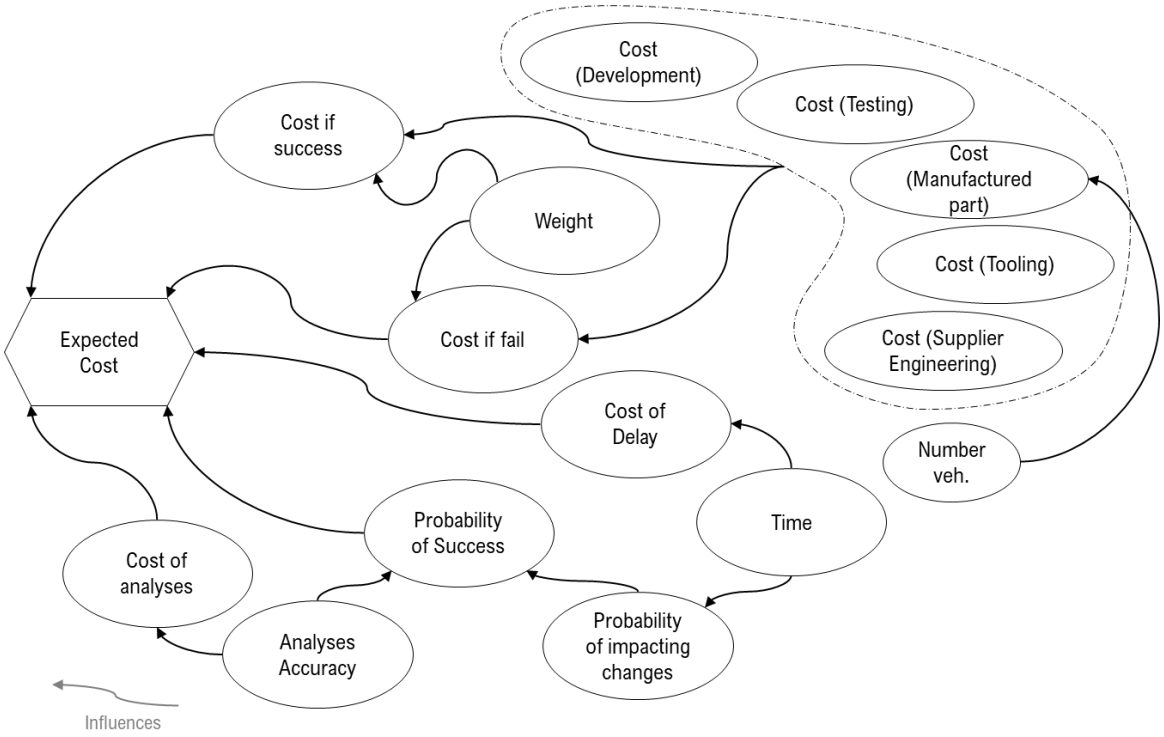


Figure 8 - Variables relationships in IRDS

4.2.3.1. Incorporate Solution

The expected cost of an *Incorporate Solution* alternative is computed with (Figure 9):

- The probability that current or later changes in the technical definition of the vehicle will affect the outcome of the decision, $pITDC(t)$; and its opposite, $p\overline{ITDC}(t)$. This probability is time-dependent as the technical definition of the vehicle becomes more and more detailed as the development phase progresses.
- The probabilities that the vehicle passes the physical tests with the solution implemented whether changes occurred or not $P(OK|ITDC)$ and $P(OK|\overline{ITDC})$; and their opposites, $P(\overline{OK}|ITDC)$ and $P(\overline{OK}|\overline{ITDC})$. Note that during the development phase all the tests are numerical until the vehicle can be manufactured and physically tested in the next phase.
- The cost actually committed in case of the success of the solution, composed by the development and analysis costs, the vendor tooling cost, the manufacturing cost (influenced by the number of vehicles manufactured), the supplier engineering cost, and the eventual added value or penalty (e.g. because of addition or subtraction of

material weight, or savings for other vehicle projects that would require the same tooling).

- The cost actually committed in case of failure of the solution. The design issue discovered on physical prototypes is supposed to be solved before the mass production phase. A resolution of this problem may require changes in the manufacturing process. In this case, the manufacturing costs in case of failure of the initial solution replace the manufacturing costs in case of success.

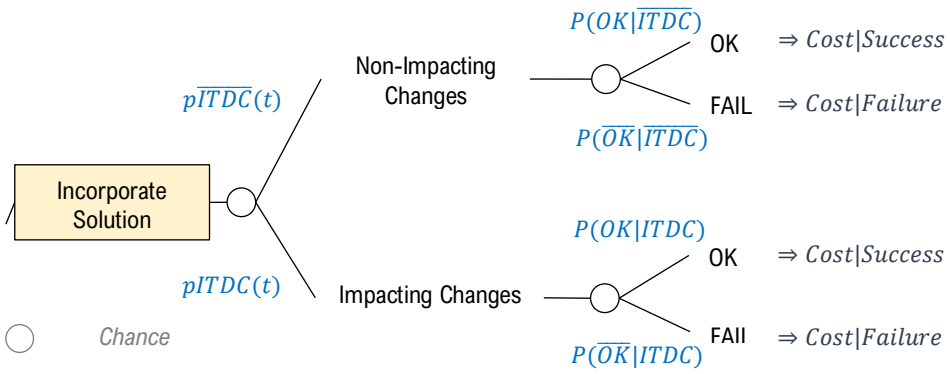


Figure 9 - Structure of "Incorporate Solution" alternative

The cost breakdown structure for a technical solution when its implementation leads to a success or a failure can be seen in Table 2.

		Costs for a Solution
Development phase	A_1	Design
	A_2	Testing/Analysis
Industrialization phase *(manufacturing)*	B_1	Vendor Tooling
	B_2	Per-unit manufacturing × number of units
	B_3	Supplier Engineering
	B_4	Corrective Design
	B_5	Corrective Testing/Analysis
Added value/Penalty	C_1	Weight increase/reduction
	C_2	Carry-over for other projects
	C_3	Production launch delay
	C_n	…

Table 2 - Technical solution cost breakdown

The costs in case of success and failure (also represented in Figure 9) are defined as following:

$$Cost|Success = \sum_1^2 A_i + \sum_1^3 B_i + \sum_1^n C_i \qquad Equation\ 1$$

$$Cost|Failure = \sum_1^2 A_i + \sum_1^3 B'_i + \sum_4^5 B_i + \sum_1^n C'_i \quad Equation\ 2$$

The B'_i represents the new costs that are involved if the solution chosen fails when the physical prototype is manufactured. For instance, in case of failure, corrective actions can lead to change the per-unit manufacturing cost (it generally increases). Hence, B'_2 will be involved instead of B_2. The corrective actions, involving design and testing, incur their corresponding expenses, B_4 and B_5. In both cases of success or failure, the expenses of design and testing, $\sum_1^2 A_i$, have been committed in the development phase. Depending of the decision situation, Vendor Tooling and Supplier Engineering costs can be sunk or not. In the case where they are sunk, $Cost|Failure$ becomes (2) + $\sum_1^2 B_i$.

As mentioned earlier, $pITDC(t)$ is used for computing the expected cost of an *Incorporate Solution* alternative. The introduction of this function offers a new feature compared to current practice. Indeed, because the evolution of design maturity is not explicit in the decision problems, the simulation results that are presented to the decision maker only reflect what will happen to the physical prototypes with a certain vehicle technical definition. This vehicle technical definition corresponds to a specific stage of evolution in the development process. Ignoring this notion would imply that the vehicle technical definition would not evolve or that its evolution would not affect the outcomes of the decision. From the probability perspective, this would mean that the probability that changes occur in the vehicle technical definition due to interrelated design decisions and affect the decision outcomes is assumed to be 0. By introducing this function, we aim at making explicit these time related process considerations. $pITDC(t)$ plays an important role in the *Postpone* alternative (Section 4.2.3.3) and will be discussed in the case of *Analyze Solution, Analyze in parallel* alternatives (Section 4.2.3.2).

4.2.3.2. Analyze Solution, Analyze in parallel

In the case of *Analyze Solution* and *Analyze in parallel* alternatives, the analyses results can be favorable or not regarding one or several technical solutions. "Favorable" means that, considering the accuracy of the analysis, the result ensures that the incorporation of the technical solution will allow the vehicle to pass the physical test. The accuracy of an analysis is broken down by assigning a sensitivity and a specificity. This corresponds respectively to the *true positive rate,* $P(Fav|OK)$ and the *true negative rate,* $P(\overline{Fav}|\overline{OK})$*.* Whether the analyses results are favorable or not, using sensitivity, specificity and the prior probability about the chance of success, Bayes' rule allows to compute the posterior probability that the vehicle will pass the test. For example, Equation 3 represents the posterior probability that the vehicle passes the physical test given that the analysis was favorable. An analysis is performed at a given t_j to which corresponds a $p\overline{ITDC}(t_j)$. Therefore, the analysis allows to update only the belief in the case of $\overline{ITDC}$, i.e. assuming that no changes in the technical definition of the vehicle will have an impact on the results of the decision, $P(OK \cap \overline{ITDC} \cap Fav_B)$. The analysis is based on an already known technical definition and does not yet take

into account all possible changes that may occur during the period before the manufacturing phase.

$$P(OK|Fav) = \frac{P(Fav|OK)P(OK)}{P(Fav|OK)P(OK)+P\left(Fav|\overline{OK}\right)P(\overline{OK})} \quad Equation\ 3$$

Figure 10 shows how an analysis on the solution B affects the values in the decision tree. In this case, only the chances of success of the alternative Incorporate Solution B is impacted (in the case of non-impacting changes in the technical definition).

The analyses can be performed in parallel for several technical solutions, and the posterior probability that the vehicle passes the test is computed with the product of $P(Fav)$ (and its opposite) for each technical solution. Figure 11 gives an example of parallel analyses for Solution A and Solution B. One can see in the decision tree that the beliefs concerning Solution C are not updated by the alternative *Analyze A+B.*

Finally, in a value of information perspective, the cost of performing analyses must be considered as well as the cost of the delay incurred in the project. The delay created in the *Analyze Solution* alternative not only takes into account the actual time required to obtain analysis results but also the time at which it will be possible for the project team to meet to address the problem while respecting the company's practices and the project schedule. The notion of *cost of delay* will be discussed along with the *Postpone* alternative in the coming subsection.

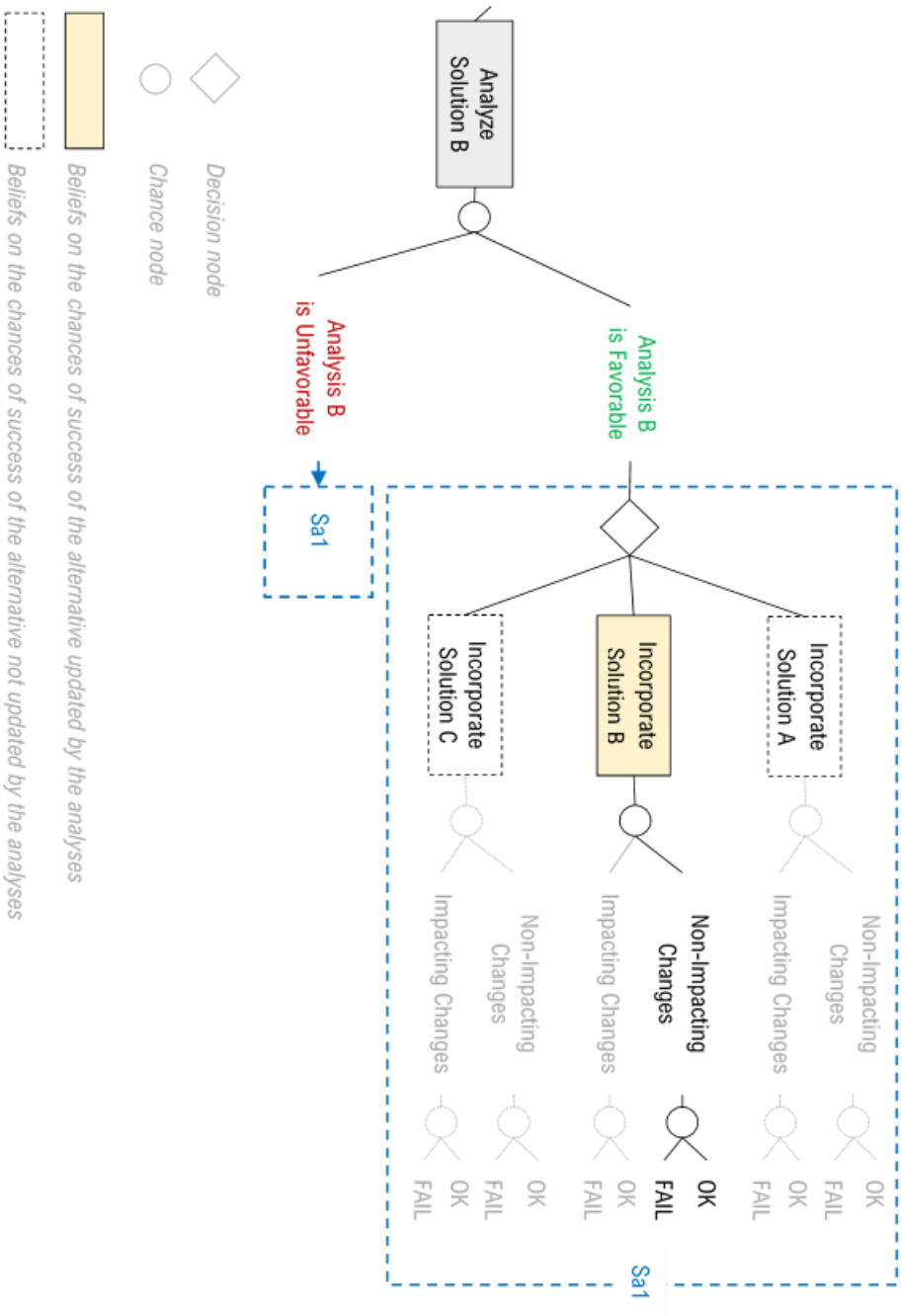


Figure 10 - Structure of "Analyze Solution" alternative: e.g. Solution B

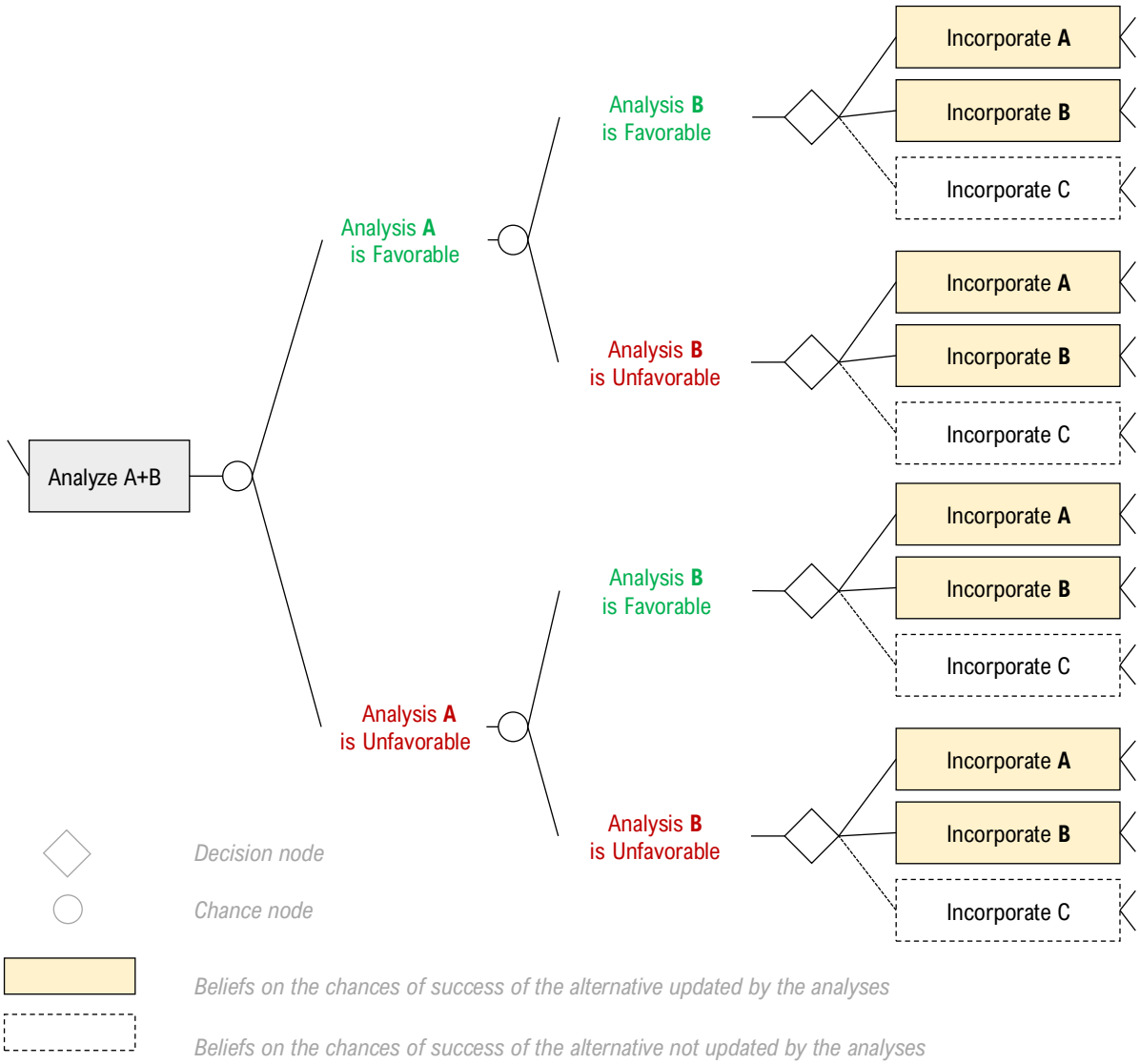


Figure 11 - Structure of "Analyze in parallel" alternative: example with Solutions A and B

4.2.3.3. Postpone

The *Postpone* alternative corresponds to waiting for the technical definition of the vehicle to be more detailed before deciding on the technical solution to be implemented. Three main reasons motivate decision makers to postpone the finalization of the issue resolution:

- The belief at any time that the data could be inconsistent, i.e. the simulation results considered at any given time may not correspond to the latest technical definition.
- At the time the decision is considered, at t_0, changes may have occurred; project team already know what these changes are, even if they do not appear in the simulation results, or project team do not know what these changes are, but they know that the technical definition has already been affected.
- Changes may occur later in the development process; project team knows what they will be (through heuristics or knowing that process instructions require that the design of certain types of parts be specified only at a given milestone), or they do not know what they will be, but they know that changes will appear.

In all mentioned cases, changes of the technical definition of the vehicle may require the design issue to be reworked and resolved late and at a higher cost. When postponing, the decision maker expect fewer subsequent (or current and unaddressed) changes in the technical definition of the vehicle that could affect the outcomes of the decision under consideration (cf. $pITDC(t)$). In the light of the reasons mentioned above, Figure 12 illustrates what influences this function. In general, there are fewer changes over time, hence we propose to consider that the likelihood of reworking on the design issue will decrease and that the expected costs incurred by this rework will also decrease.

It is important to note that we assume that existing technical solutions will be modified according to the evolution of the vehicle technical definition. With regard to the alternative *Postpone*, technical solutions should be considered as "types of technical solutions" (which lead to their respective expenses). Considering that the decision situation may change over time, a new and better technical solution may be designed later; the design issue may even disappear because some further changes can help to meet the target performance. But at the time the decision is considered, at t_0, it is difficult to know. Therefore, we consider that in the worst-case scenario, it is the type of existing technical solution that is the most successful that will be incorporated later when the outcomes of the decision will be less likely to be affected by external changes.

To illustrate the *Postpone* alternative concept, let us consider an example with the following the probabilities applied to Figure 9: $p\overline{ITDC}(t_0) = 0.3$, $P(OK|\overline{ITDC}) = 0.9$, $P(OK|ITDC) = 0.5$, $P(OK) = P(OK \cap \overline{ITDC}) + P(OK \cap ITDC)$, there is 62% chance that the vehicle actually passes the test at the moment the decision is considered, t_0. If the decision maker chooses to postpone at t_2, $p\overline{ITDC}(t_2) = 0.9$, $P(OK|\overline{ITDC}) = 0.9$, $P(OK|ITDC) = 0.5$, $P(OK) = P(OK \cap \overline{ITDC}) + P(OK \cap ITDC)$. At t_2 there will be 86% chance that the vehicle actually passes the test. Without any consideration of the cost related to the delay in the project caused by a postponement, it is preferable to wait before finalizing the resolution of the problem.

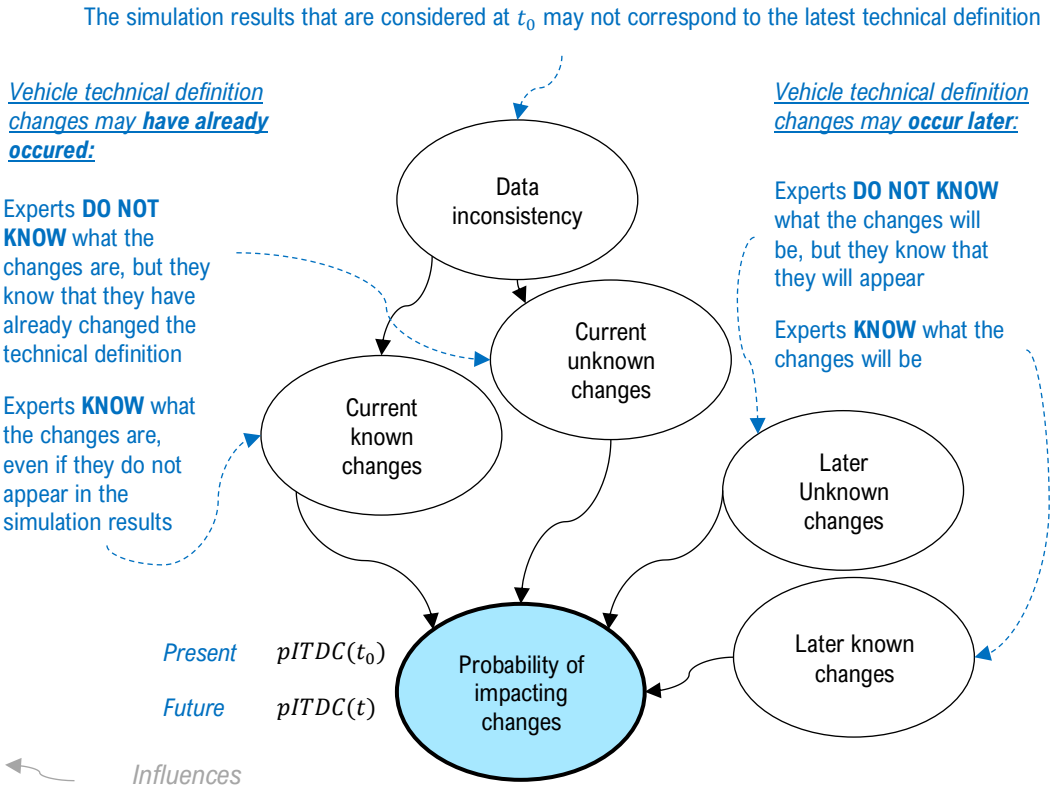


Figure 12 - Influence diagram related to $pITDC(t)$

However, the *cost of delay* needs to be taken into account when considering postponing the finalization of an issue resolution. If the project team postpones the finalization of the issue resolution, the technical solution will need to be implemented in the shorter period, demanding more resources to respect the deadline of the project. This will also require solving subsequent and depending design issues faster, prioritize these issue resolutions over other activities (designing, testing, optimizing for manufacturing, etc.), and in both cases mobilize engineers. Moreover, the engineers are paid whereas they do not provide value to the project while they wait for the decision to be finalized. Finally, the chance to have to pay

directly or indirectly delay penalties increases. After discussing with experts and collecting the historical data, we propose to model the postponing trade-off with two functions: 1) $pITDC(t)$ that ultimately reflect the evolution of the expected cost committed in case of failure, and 2) $Cost_{delay}(t)$.

To illustrate this notion, consider Figure 9 with the example applied with *Figure 13*: "Now", at t_0, the decision outcomes have 70% chance to be impacted by changes. After *Impacting Change 2* is made, at t_2 , there will be 10% chance of impacts. At that moment, a long time will remain available to implement the decision and carry out the activities that depend on it. Once *Impacting Change 3* will be made, short time will remain available. With regard to project development, closer the to deadline, there is more effort needed to perform the remaining activities on time. Consequently, although postponing can decrease the expected cost of reworking a design issue**,** it also increases the chance of having to speed up activities to meet the deadline or to pay penalties; in short, to incur expenses. In cases where the project team does not know in advance which change will occur at which time, we propose to define $pITDC(t)$ as a linear function or a simple curve.

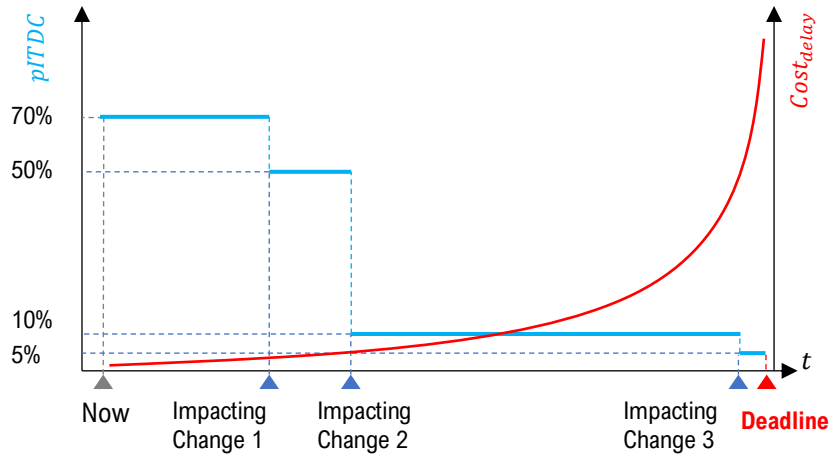


Figure 13 - Notional example of the relationship between time, pITDC and $Cost_{delay}$

Analyzing how the expected cost (or expected value) of the *Postpone* alternative varies when t varies can help to know whether and until when it is profitable to postpone the finalization of the issue resolution. This analysis has been used as a Value of Information analysis related to postponing one's decision. An illustration of this trade-off is presented in Section 3.3.3.

In industry, it is not always easy to define nominal probabilities and costs used. In this case, we propose to define distributions to represent the uncertainty about the input values and to use a sampling method to simulate the risk associated with the decision under consideration. In this respect, if being uncertain has a significant impact on the decision or if

risk-taking can create high value, then the decision maker must have the decision analyzed more thoroughly.

The conceptual features we have presented are derived from our observation of industrial issues and practices. Section 4.3 aims to explain how IRDS can be integrated into an industrial framework.

4.3. IRDS industry application

4.3.1. Proposition of roles in the decision-making process

In order to support the decision making, in discussion with the company we proposed that the decision analysis is done by a specific person, exchanging information with project team members and knows how to manage an IRDS tool. Hence, in the IRDS framework one can identify 3 different roles: the decision maker (DM), the decision analyst (DA) and the decision-problem data provider (DaP). DaP are generally numerous (experts, analysts and designers from different disciplines, working on different subsystems). They provide data for decision analysis while responding to DA requests, and provide complementary situational information to the DM. DA gathers decision problem data and *context* information by issuing *data queries*. These data can be *numeric values* obtained through numerical simulations or *quotes* from experts expressing their beliefs. DA analyses the decision while integrating DM's queries, and provides him/her *decision analysis results* and *suggestions*. DM receives and requests information from DA and DaP, and takes the decision to solve the issue. Figure 14 shows what data is conveyed between the 3 roles and the associated data flow in the decision-making process and supported by the IRDS tool.

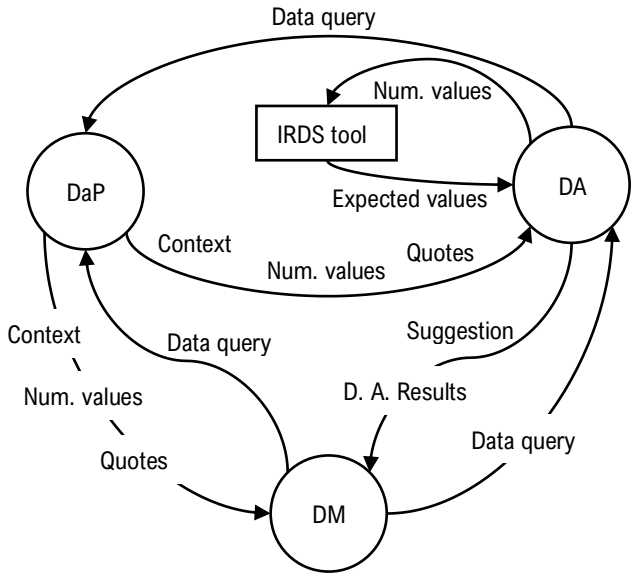


Figure 14 - Data flow diagram of the decision-making process supported with IRDS

4.3.2. Customized toolbox

In order to support design teams, we tailored *Palisade Decision Tools Suite* [157] to deploy IRDS. With *PrecisionTree 7.5*, a generic decision tree has been developed based upon the model previously discussed. 22 IRDS inputs have been defined with regard to the variables and functions mentioned in Section 4.2.3.. Design team can use automatically defined functions with regard to the type of alternatives selected. For a decision problem considering 3 technical solutions, the decision problem model is constituted of 644 end nodes. We also created tables to define $pITDC(t)$ and $Cost_{delay}(t)$. We propose to use *Palisade's @Risk* [157] to perform sampling distribution simulations. The decision analyst has to define the simulation settings according to the specificities of the decision problems. Our motivation was to simplify the use of the decision support tool so that the effort is concentrated on the data gathering and analysis rather than on modeling.

4.3.3. Noise Vibration and Harshness example

As it discussed in previous sections, several use cases were the basis for the IRDS development and validation. In order to illustrate, in this section we focus only on one industrial case where a vibration performance does not meet the requirement. Simulation results initially show that two measurement points do not reach the target. Simulation analysts identified the vehicle part involved in this defect and proposed, with designers, two technical solutions (design and material changes). They performed analyses on the efficacity of the technical solutions with regard to the vibration performances. As any design change can impact many performances, and passive safety success is a sine qua non condition to accept a design change, simulation analysts also tested passive safety performances.

In order to support the decision making, we deployed IRDS and fulfilled the role of DA. A DaP initially provided a $P(OK|\overline{ITDC})$ estimate for each technical solution (10% for Solution A, which is the current technical definition of the vehicle part, 70% for the Solution B, and 90% for the Solution C). To do so he relied on his own experience supported by numerical simulations. The simulations for performance assessment were performed with nominal values for two potential technical solutions. The differences between the 2 proposed technical solutions and the current technical definition in terms of *Manufacturing cost* | *Success*, and *Weight* | *Success* were provided in the decision dossier that was already prepared. To use IRDS, DA investigated with DaP to collect missing data.

It is important to note that not all missing data were worth gathering; for instance, development cost difference was supposed to be equal for the two solutions and was not necessary to estimate (more precisely: one estimation was sufficient for both solutions). DA assumed that costs estimates were accurate in the case of success; and the costs estimates in the case of failure were rough but plausible according to the experience of DaP. In this case, an order of magnitude was sufficient as an input data. Depending on the accuracy expected, this data can be easily available for low cost, but it is time consuming since DaPs are spread in different services. Sometimes it may require additional effort to estimate costs in the case of failure, since it requires history and/or cost estimates of backup solutions. In this case, DA and DaP assumed that in the case of failure, the technical solution that has the best chance to

succeed but that is the most expensive will be used as to develop a late solution. An additional weight is considered and corresponds to a penalty that is computed with the company *cost per kg model*. The scenario of failure involves extra-costs due to the late work and late negotiations with suppliers. In other words, the three technical solutions have the same manufacturing (MFG) cost in case of failure, as stated in Equation 4:

$$Per\text{-}unit\ MFG\ cost\ A,B,C \mid Failure\ = Per\text{-}unit\ MFG\ cost\ C \mid Success\ + Per\text{-}unit\ MFG\ extra\text{-}cost\ A,B,C \mid Failure \qquad Equation\ 4$$

DA performed analyses with rough approximates of $pITDC(t)$ and $Cost_{delay}(t)$, as in Figure 15 and Figure 16, to assess how sensitive the decision was about these functions, in order to eventually model them more accurately with the help of DaP.

Figure 15 shows 3 $pITDC(t)$ profiles. The *Linear* profile represents the simplest $pITDC(t)$ model that can be made. This profile is based on the obvious assumption that the more the project progresses, the more design parameters are fixed, and the less changes can occur. This *Linear* profile is the one that is used by the DA in the current example. To illustrate other possibilities, notably in the case where information about specific technical definition changes would be available, we defined two other profiles: *Step Early* and *Step Late*. They respectively represent scenarios where short and long remaining times available after main impacting changes have occurred. In the *Step Early* scenario, the second $pITDC$ drop happens 6 weeks earlier than in *Step Late* scenario. Figure 17 shows how these 2 beliefs models would have affected the expected value.

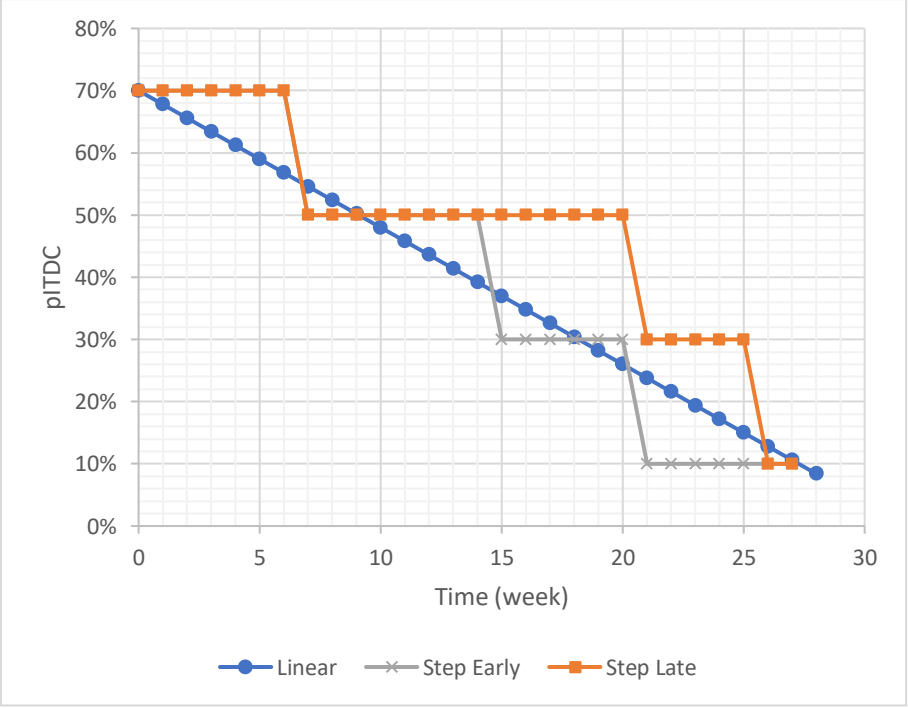


Figure 15 - Evolution of pITDC over time

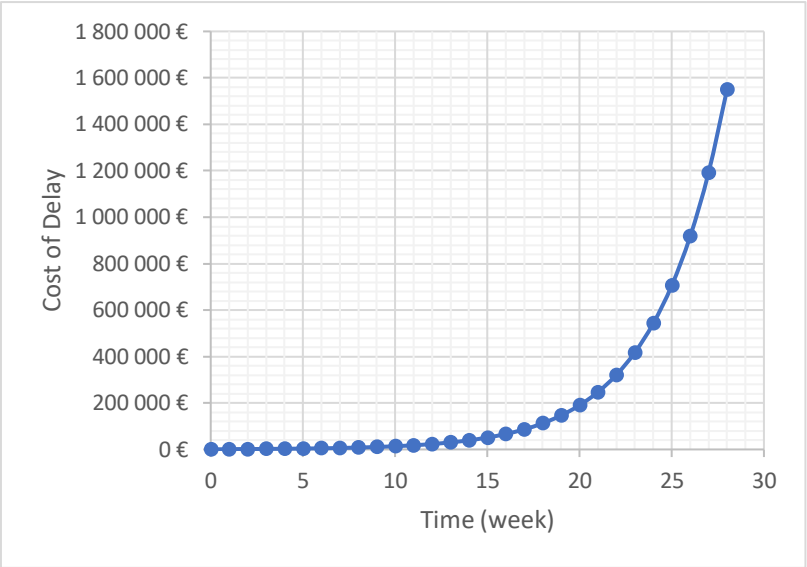


Figure 16 - Evolution of $Cost_{delay}$ over time

Once the IRDS process led to conclusive results, DA presented a report to DM. As shown in Table 3, excluding the *Postpone* alternative (that is time dependent), the alternative that has the maximum expected value (EV) is *Analyze A+B+C*. Although Solution A (current technical definition of the vehicle part) has only 10% chance of success (prior belief), it costs 1 220 000 € less than Solution B in case of success. Solution B (70% chance of success) costs 780 000 € less than Solution C in case of success. These two solutions worth investigating since they would lead to significant savings compared to Solution C if they ever succeed.

Alternative	Expected Value
Incorporate A	-2 880 000 €
Incorporate B	-2 091 200 €
Incorporate C	-2 456 000 €
Analyze A	-2 093 890 €
Analyze B	-2 086 498 €
Analyze C	-2 093 890 €
Analyze A+B	-2 077 100 €
Analyze A+C	-2 094 890 €
Analyze B+C	-2 078 775 €
Analyze A+B+C	-2 070 389 €

Table 3 - Expected values of decision alternatives

Involving $pITDC(t)$ and $Cost_{delay}(t)$, the EV of *Postpone* alternative varies over time, as shown in Figure 17 and Figure 18. It is important to remember that the *Postpone* alternative includes a later decision among the other decision alternatives. This later decision will involve a different probability of impacting changes. Figure 18 underlines the expected value of *Postpone* increases until week 15. At week 21, its EV is equal to the expected value of choosing

Analyze A+B+C at week 0. Between week 0 and week 21, an update of the situation will allow to make a better decision and avoid rework. Week 15 is the optimum date for postponing the decision, with a difference of EV of 221 058 €. Postponing until after week 21 will not be profitable, since the EV after week 21 is smaller than choosing *Analyze A+B+C* at week 0. Indeed, any choice after week 21 will be potentially more expensive since costs will be incurred by the delay. The DM should best postpone the decision.

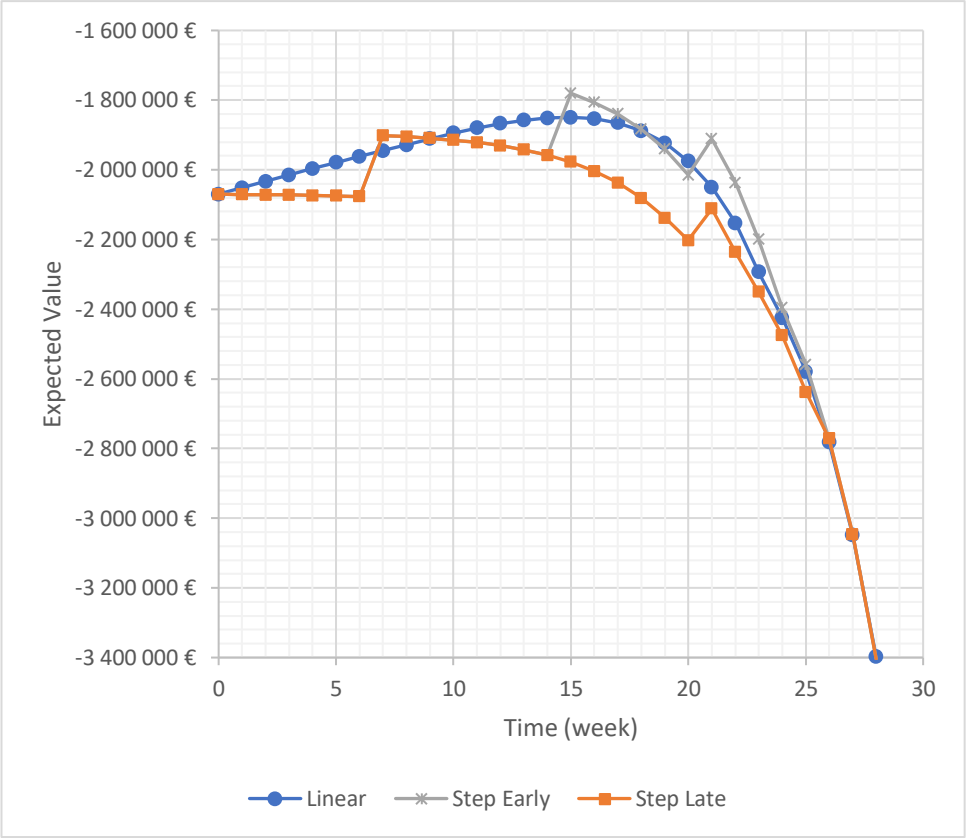


Figure 17 - Evolution of the expected value over time when postponing the issue resolution for three pITDC(t) profiles

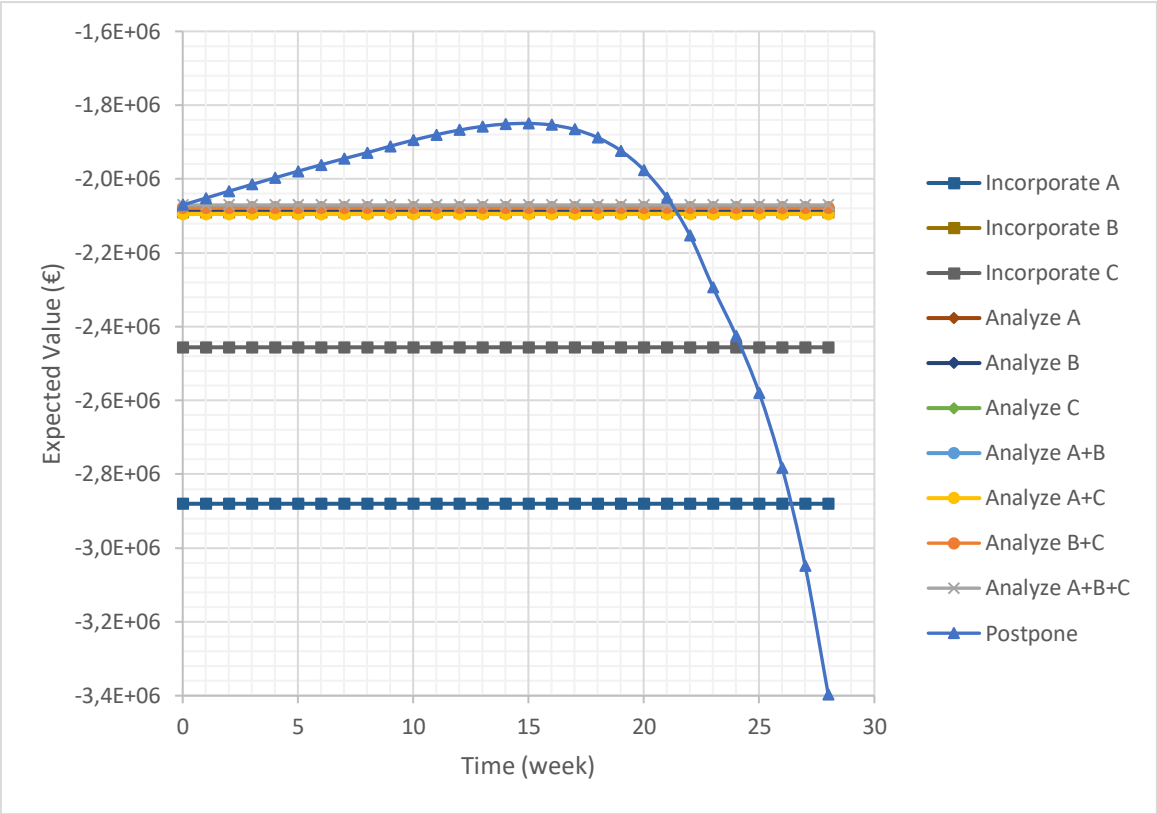


Figure 18 - Evolution of the Expected Value over time when postponing the issue resolution compared with Expected Values of other decision alternatives

In this example, the DA gathered data from DaPs for entering IRDS inputs. For convenience purposes, we performed the computation on a deterministic model, implicitly assuming that DaPs are certain about the data they provide. However, DaPs are uncertain about every input to some extent. For example, the person providing the costs can say "the per-unit cost difference for this solution is between 7 € and 11 €, but this is most likely 9 €". We have deepened the analysis of the decision problem by modeling uncertainties about costs. These inputs are worth investigating because they can change according to the moment they are estimated, the multiple information sources, and the assumptions made. DaP's are aware of this variability and generally are able to estimate the range and the modal value. In such situations, triangular distributions are convenient to represent beliefs since they are based upon scarce data. We therefore defined triangular distributions to describe DaP's beliefs and uncertainty about inputs and reported it in *Table 4*. According to the assumption made about the scenario of failure (Equation 4) we defined a triangular distribution only for $Per\text{-}unit\ MFG\ extra\text{-}cost\ A, B, C \mid Failure$. A distribution is also defined for the additional weight in case of failure.

Input	Lower limit	Mode	Upper limit
Vendor tooling cost C | Success (k€)	72	80	88
Per-unit MFG cost B |Success (€)	2	2,5	3
Per-unit MFG cost C | Success (€)	7,2	9	10,8
Per-unit MFG extra-cost A, B, C | Failure (€)	1,6	2	2,4
Additional weight (kg)	0,2	0,3	0,4

Table 4 - Input triangular distributions

Figure 19 shows the distributions of values for the *Postpone (until week 15)* alternative and the 3 artifact alternatives. We purposely plotted these distributions in order to compare the gain of the *Postpone* alternative against the alternatives that would only have been explicitly considered in current practice. These types of results allow us to observe how the uncertainty about IRDS inputs can affect the results of decision analysis. Given this additional analysis, depending on how the distribution intersects, project team members should be cautious about their beliefs.

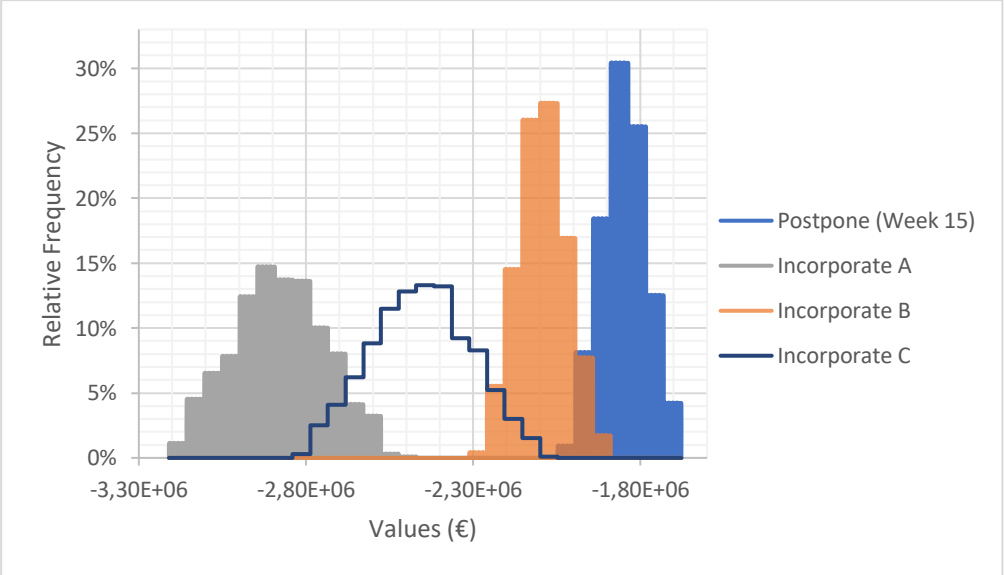


Figure 19 - Distributions of values for postpone alternative compared to incorporate alternatives

In the current practice of the company, the decision maker would not have been provided with such explicit information about the consequences of analyzing technical solutions or postponing the decision. This lack of clarity could have led the decision maker to iterate more often and mobilize engineers (slowing down other activities), or to choose to incorporate a technical solution right away and rework it later at a higher cost. The IRDS framework allows for structuring the process-focused approach for decision making and for informing the decision maker accordingly.

4.4. Discussion

Discussions with different actors in this process and in the company can highlight several benefits of the IRDS framework: IRDS framework allows to explicitly and systematically identify what the alternatives are, including the action of performing further analyses. It is also considered as an incentive to bring the team together to discuss the beliefs people have about the inputs of the decision problem. The decision is analyzed with a rigorous mathematical framework. The decision problem model is designed to address most of the decision problems that can be encountered in the development phase. Hence, it allows the project team not to spend resources to build new models for similar problems.

However, several limitations can be discussed as well. Using the IRDS requires time and efforts in terms of data gathering and beliefs modeling. In the case where IRDS would lead to the same decision as to the current practice, the use of IRDS would involve unnecessary expenses. In such case, by investigating decision alternatives, the organization can gain insights that can be useful for other purposes (such as improvement of processes and practices). However, this gain is difficult to quantify and out of our current research scope. We acknowledge that IRDS framework does not prevent the users from experiencing biases that can lead to poor decisions. Framing the problem and the actions explicitly can discourage the decision maker to think broader and reconsider the problem. Moreover, IRDS may not include all the alternatives that are actually available. Another bias is related to data gathering by beliefs elicitation and modeling: if the beliefs deviate too much from the truth, the computation can provide results that are mathematically correct but do not conform to the actual state of reality. Finally, IRDS decision problem model is the results of assumptions and modeling choices we have made. Consequently, the functional relationships that we impose through our model can also introduce biases as these assumptions may not reflect the beliefs of the people using IRDS.

4.5. Conclusion and future work

Decision making in industry context, and in particular in complex system design can be difficult. Often data gathering or additional time necessary for developing a more precise decision-making model is not considered explicitly. In this research, IRDS framework has been proposed in order to integrate process related data in the Modeling and Simulation based vehicle development process. IRDS allows for process-focused decision-making, incorporating the analysis of the consequences of actions such as information gathering and postponing the choice of artifact alternatives. The proposition of a decision-making model has been defined based upon 4 industry case studies and an additional case of Noise, Vibration and Harshness has been used for testing. This model has been designed in accordance with experts to reflect the possibilities and the constraints of the industrial process.

We observed that it is challenging to gather some of the data used for the computation of the decision problem. Engineers struggle to express subjective probabilities when numerical data is scarce or when numerical simulation results contradict their beliefs (e.g. when the numerical model of the system do not take into consideration attributes that are known by the expert). Hence, investigation of methods that allow for data identification that are critical

and change the decision (in the light of sensitivity analysis) will be considered as to permit to focus data gathering activities. This is considered by the experts as necessary in order to support decision making but also future resources consumption.

5. Exploring the Difficulties Related to Uncertainty when Implementing the Decision Support Framework in the Company

Decision support systems and frameworks are getting increasingly computerized and often based on mathematical models. In such cases, the decision problem is modeled, and users provide inputs and interpret outputs computed with the model to guide their actions. In company settings, when designing complex systems, several persons or entities contribute to the information collection. Hence deploying a decision support framework based on a model suppose tackling uncertainty about inputs and information collection difficulties. We focused this research on the Issue Resolution Decision Support (IRDS), a decision support framework tailored for solving design issues in the industrial development phase. We aimed at identifying difficulties and uncertainties encountered when implementing the framework in the industry. In a second time, we explored methods for addressing these implementation issues. When deploying IRDS, we identified the data that are scarce, mapped out how data are scattered among people, and identified the elicitation process as an important challenge for defining the values of model inputs. We proposed a sensitivity analysis-based method as a cost-saving method for handling data gathering difficulties and uncertainty. We present this research through 5 decision problems encountered by an automotive company. These results are interesting since they contribute to improving knowledge on industrial applications of a decision support framework in terms both of uncertainty management and data gathering efforts.

5.1. Introduction

When addressing design decisions for the development of complex systems, decision makers often face situations characterized by uncertainty. This uncertainty is both related to the design artifact and the design process that can be impacted by interrelated decisions. However, until recently, the vast majority of research in decision-based design (DBD) focused decision problems formulation on the design artifact and overlooked the tradeoffs involved when gaining additional information in a process-focused perspective. To expand this scope, Thompson and Paredis [59] established a new DBD perspective that represents the tradeoffs under consideration when analyses can be performed to incorporate additional information in the design phase. They show that the decision analysis of design process decisions provides a more comprehensive model of the problem when multiple information sources can sequentially be used.

In the context of decision making addressing design issues, we extended Thompson and Paredis' process-focused approach in a model that integrates concurrent analyses, impacts of potential changes related to the product definition evolution and project time constraints [108]. We proposed the IRDS (Issue Resolution Decision Support) framework to operate this model in an enterprise context. We highlighted that data gathering can be challenging, costly, and that biases can be introduced by beliefs modeling. The implementation of a decision support framework in a company implies to tackle difficulties and uncertainties related to the prioritization of data providers, the elicitation and modeling of their beliefs, and the representation and the interpretation of the results provided by the decision analysis. Managing the uncertainty when implementing IRDS in a company setting is necessary to perform valuable decision analysis and help the project team to gain insight and take actions. Sensitivity analysis has been used along with decision analysis in the literature to help to focus data-gathering effort. In the context of IRDS, sensitivity analysis is worth studying from a cost-efficient data collection perspective. In this respect, the chapter aims to address the following questions:

What are the difficulties related to the uncertainty encountered when implementing IRDS and how to manage them?

As we conducted our research, this general question lead to the followings:

- *How to incorporate various experts' beliefs that are sometimes contradicting each other and expressed in different forms in a numerical model?*
- *How can sensitivity analysis influence data collection strategy?*

In section 5.2, we briefly recall what is IRDS framework: its principles, the roles and information under consideration. Thereafter, in Section 5.3, we discuss the uncertainty and the related difficulties encountered when implementing IRDS framework. In Section 5.4, we introduce a sensitivity analysis-based method which aim to address these issues. In Section 5.5, we present case studies and insights we gained by deploying IRDS framework enhanced with sensitivity analysis. We end with discussion in Section 5.5, and conclusions and future work in Section 5.7.

5.2. IRDS framework fundamentals

In this section, we provide a synthetic recall of the fundamentals of the IRDS framework to better transition with the study presented in the next sections. IRDS framework [108] is based upon a decision problem model of the most common design issues occurring during the development phase of vehicles. The framework includes customized computational tools and definitions of roles and information exchange.

5.2.1. Decision problem model

The decision problem model can be represented as a pseudo-recursive binomial decision tree and relies on expected utility maximization and value of information theory. It includes 3 types of alternatives:

1. *Incorporating a technical solution at the current moment*. It is an artifact-focused alternative that corresponds to modifying the design or material of a part, adding a new part to the vehicle, or sticking to the current technical definition.
2. *Analyzing one or several technical solutions concurrently* and wait for the results before selecting which technical solution should be incorporated (cf 1.). It is a process-focused alternative which consists of gathering information about the chances of success of incorporating a technical solution.
3. *Postponing the finalization of the issue resolution* at a later moment, to then decide whether incorporating a technical solution (cf 1.) or perform analyses (cf 2.). It is a process-focused alternative that takes into consideration the evolution of the technical definition of the vehicle and the uncertainty about the variability of the design. Practically, the decision maker targets a time when the architecture is less likely to evolve and affect the outcomes of the decision.

5.2.2 Roles

Three roles are involved in IRDS framework: the decision-problem data provider (DaP), the decision analyst (DA) and the decision maker (DM).

- *DaP* (experts, analysts and designers from different disciplines, working on different subsystems), provides data for decision analysis while responding to DA requests, and provides complementary situational information to the DM.
- *DA* gathers decision problem data and context information by issuing data queries and integrates DM's queries. He/she analyses the decision and provides the DM with decision analysis results and suggestions.
- *DM* requests and receives information from DA and DaP, and finally makes a decision to solve the issue.

These roles exchange information in different forms and DA ultimately translate it into IRDS input data. to compute decision problems with IRDS computational tool.

5.2.3 Information

IRDS decision problem model involves 22 different inputs: 20 input data per technical solution, and 2 generic input data for the decision problem. All of them fall into 4 categories: costs, probabilities, times and rates.

- ***Costs*** includes the costs of design, manufacturing and analysis for each technical solution in case of success and in case of failure. Costs of delay due to a late implementation of the solutions and penalties or value added are also included (e.g. cost of additional weight).
- ***Probabilities*** reflect the chances of success or failure of the solutions, but also the chances that changes occur and affect the decision under consideration.
- ***Times*** are related to the duration necessary to acquire additional information.
- ***Rates*** correspond to statistical estimates or measures of sensitivity (true positive rate) and specificity (true negative rate) in case of performing single or concurrent analyses regarding the chances of success of technical solutions.

Table 5 gathers IRDS inputs. The class *weight performance* corresponds to the estimate of weight addition or loss. It is ultimately converted into a cost of weight that is included into the *Added value/Penalty* input data. For *Analysis time*, the time is incorporated in the overall cost of *Additional analysis* that incorporate the cost of performing analyses (e.g. numerical simulation) at any time plus the cost incurred by the delay that analyses generate in the project schedule.

These inputs ultimately reflect the modeling choices of the modelers. Simplifications from more complex versions of the decision problem model have been done to provide valuable results with minimal information and to be consistent with the company capacity to produce data.

Despite this simplification effort, gathering some data and modeling beliefs can be challenging. The next section focuses on discussing the challenges encountered when considering the implementation of IRDS, notably due to the management of uncertainty of information sources.

CATEGORY	N°	INPUT	NAME
Cost	1	Design	Dc_1
	2	Corrective Design	Ic_4
	3	Testing/Analysis	Dc_2
	4	Corrective Testing/Analysis	Ic_5
	5	Vendor Tooling	Ic_1
	6	Vendor Tooling | FAIL	$Ic_1{}'$
	7	Supplier Engineering	Ic_3
	8	Supplier Engineering | FAIL	$Ic_3{}'$
	9	Per-unit manufacturing × number of units	Ic_2
	10	Per-unit manufacturing × number of units | FAIL	$Ic_2{}'$
	11	Added value/Penalty	VP_i
	12	Added value/Penalty | FAIL	$VP_i{}'$
	13	Additional Analysis	Ac
	14	Delay	$Cost_{delay}(t)$
Weight performance	15	Weight	w
	16	Weight FAIL	w'
Probability	17	Probability of Success | Impacting Changes	$P(OK\|ITDC)$
	18	Probability of Success | Non-Impacting Changes	$P(OK\|\overline{ITDC})$
	19	Probability function of Impacting changes over time	$pITDC(t)$
Rate	20	Sensitiviy	$P(Fav\|OK)$
	21	Specificity	$P(\overline{Fav}\|\overline{OK})$
Time	22	Analysis time	At

Table 5 - IRDS input data

5.3. The uncertainty associated with gathering data

Implementing a decision support framework in a company suppose dealing with the actual company processes, practices, and to a bigger extent, its culture. The introduction of new methods and tools impact the current practice and organization and vice versa [87–89]. The objective was to identify the challenges of implementation from an operational perspective, so that the framework can be best integrated in the company without necessary transforming abruptly the organization and practices. We focused the research on the information collection for supplying model inputs.

5.3.1. Available data and access to information in company settings

To better identify the challenges of decision support framework implementation, we first compared the information already available in as-is decision dossiers and the information that is required to use IRDS. To do so, we referred to an empirical study that mapped-out the as-is decision-making process and extended it by interviewing more participants and observing five more decision dossiers. These decision dossiers will be used as case studies for the implementation of IRDS.

Hence, based on the empirical study presented in [107], we extended the observation to 45 decision dossiers brought to project manager level decision meetings and interviewed 15 more professionals. Table 6 shows the variety and number of participants considered for this extended study.

Interviewee Role	*Number*
Technical director	1
Vehicle program manager	2
Vehicle project manager	2
Synthesis architects	2
M&S expert leader	1
Durability expert leader	1
M&S expert	1
Head of CAE service	1
Head of Numerical Simulation Methods and Tools service	1
Crash simulation expert	1
Acoustics expert	1
CAE Synthesis Engineer	3
Validation synthesis leader	1
Simulation Analyst	4
Cost engineer	1
Customer Performance Leader	1
Optimization and Numerical methods team leader	1
Process-related data management referent	1
Model building project manager	1

Table 6 - Roles and number of interviewees for the extended empirical study

Interviews were semi-structured, conducted by one researcher, and analyses were cross-checked with two other members of the research team. Questions were designed to understand the as-is decision-making process and data gathering. For the present research, as we included new interviewees, we focused questions on data-gathering. For example:

- *What data are communicated in decision dossiers?*
- *Where do these data come from?*
- *How long does it take and how much does it cost to produce such data?*

This study allowed us to identify what type of information and through which means it is conveyed in decision meetings. There are three communication means:

- ***Decision dossier presentation documents**:* These are a PowerPoint documents composed of a dozen slides either presented by the Synthesis Architect, the Customer Performance Leader, the CAE Synthesis Engineer, or any knowledgeable person on the subject. It presents the issues and the artifact alternatives – also called hypotheses at the OEM – to solve it. It synthetizes the stakes, performance, cost and time data related to the design issue framed as a decision problem.
- ***Quotes from decision meeting participants**:* These exchanges aim to enrich the knowledge of the participants and, ultimately, influence the decision maker. Such quotes can relate to the simulation results or cost estimates presented, including the expression of uncertainty.
- ***Water cooler talk:*** These are discussions held aside from decision meetings where implicit knowledge and data that are not included in the presentation can be shared.

Figure 20 presents the roles that supply the information that is available in current decision dossiers. The fact that data included in decision dossiers may be supplied by various roles will be relevant when we will establish a parallel with the data gathering of IRDS inputs. For instance, the costs can be estimated by both designers (through heuristics), cost analysts (through cost simulation and further analyses), Engineering Leaders (who works closely together with designers, supplier, and manufacturer) and synthesis architects (through heuristics or gathering and interpreting other roles' estimates). The same applies to performance estimates with the corresponding roles. The timing data are seldom provided explicitly with regard to design process alternatives (analyzing further a solution, time between one decision meeting and another, etc.). However, the project team can agree on an estimate of the delay in the manufacturing of prototypes caused by the choice of a technical solution.

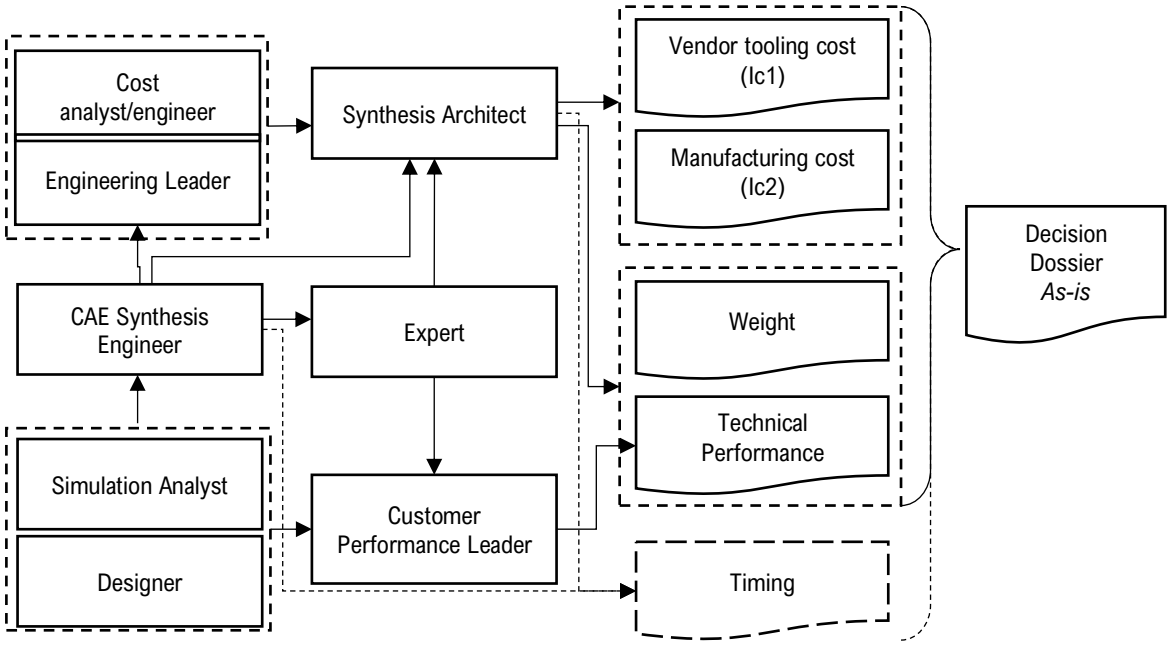


Figure 20 - Information sources in as-is decision dossiers

It is important to note that to date, the information contained in decision dossiers, and ultimately presented in decision meetings, only consider the *scenario of success*. It means that the costs considered only reflect the costs that will be committed if no rework is needed. The costs involved in case of failure are not explicated (e.g. corrective design, changing tooling, etc.). A corollary of this framing choice is that risk is not represented. Indeed, the probability of success – and its opposite – is not explicitly considered. The information also does not contain the evolution of the product and unknow changes considerations. It means that the way the decision problem is framed does not include the likelihood that changes may occur and affect the decision outcomes.

IRDS aims to provide a more comprehensive framing of decision problems. It computes the expected utility by incorporating costs involved in case of failure, probability of success/failure, and changes in the decision situation. Computing requires input data, and this is where it can become a challenge in an enterprise context.

We observed that 5% to 20% of IRDS inputs are already available in the current decision dossiers – this proportion varies because some decision dossiers do not contain enough information to compare technical solutions with each other. It corresponds to the data presented in Table 7. The Probability of Success is seldom communicated directly as a numerical probability. It can rather be inferred from a Boolean representation (OK/NOK) or a smiley rating scale (sad-red / sad-orange / happy-orange / happy-green). Due to subjective and therefore variable definitions and mental models, the inference and translation of performance data, qualitative ratings, and personal beliefs into numerical probabilities can be ambiguous. Other information that is lacking in current decision dossiers needs also to be elicited and translated into IRDS input data. This leads us to the consider the notion of belief modeling.

CATEGORY	INPUT	NAME
Cost	Vendor Tooling	Ic_1
	Per-unit manufacturing × number of units	Ic_2
Weight performance	Weight	w
Probability	Probability of Success | Non-Impacting Changes	$P(OK\|\overline{ITDC})$

Table 7 - IRDS input data available in as-is decision dossiers

5.3.2. Modeling data providers' beliefs

Data providers traditionally communicate their beliefs in decision dossiers in the form of written sentences associated with plots and 3D simulation screenshots, numerical values and smiley faces. These representations usually serve as basis for discussion between participants of the decision meetings.

When considering enhancing the information in a decision analysis perspective, these qualitative and quantitative representations of data providers' beliefs can be leveraged to infer quantities such as the probabilities of success and the costs (e.g. from "this solution is more expensive" to "likely 2€ more expensive"). In the current practice, statistical data are seldom provided for technical performance since it involves performing important numbers of simulations, which is time consuming and costly (durability performance and advanced driver-assistance systems are some exceptions). Simulations are usually done in relatively small numbers and integrate nominal parameters – i.e. seldom take into account variability due to changing design specifications and manufacturing process deviations.

Probabilities of success

Let us examine the input $\boldsymbol{P(OK|\overline{ITDC})}$. This input is a probability that reflects the chance that once the technical solution is incorporated in the vehicle, assuming that no changes will impact the decision, it will lead to a success when the prototype of the vehicle is tested in the manufacturing phase. One considers the state "success" if the performance target is met. In the current practice, information of various nature concerning the performance of a technical solution is provided to the decision maker. In our empirical study, decision makers indicated that they formulate their own beliefs about the chances of success of a technical solution based on the numbers, quotes of participants, etc. and by confronting them with their own experience and "intuition". Experts proceed the same way when they report their beliefs in the form of quotes. $P(OK|\overline{ITDC})$ takes a single value to capture the prediction about a binary event. For such a belief representation, as discussed in Section 2.7, a simple and time-efficient rule has been used in the literature of belief elicitation: the free rule. With this rule the decision analyst simply ask the experts to report their beliefs – without confronting them with an incentive mechanism. This elicitation can include the translation or interpretation of the beliefs representations already provided (such as smiley faces) by other data providers. This translation is made together with the decision analyst. It is useful from a knowledge capitalization perspective (capturing information from historical decision problems and performing analyses with ex-post information).

Figure 21 shows how experts translate the smiley faces already existing in decision dossiers into $P(OK|\overline{ITDC})$. These assumptions are made in accordance with the data providers interviewed; they assumed a variation on the responses depending on the problem considered, but also depending on the experts' subjectivities. For sad-red and happy-green, we observed in the case studies that experts tend to assess $P(OK|\overline{ITDC})$ that are closer to the extrema (0% or 100% chances of success). This can be explained by the fact that they are more comfortable with translating what they consider as strong statements, such as "sad-red means that there is very few chances to pass, therefore I would give a little 5%, even less" or "happy-green means that it is ok, I would give 95%, even more". The drawback of this approach is that the elicitation can be biased by the fact that experts assess a probability through a model that already is already an interpretation. Moreover, more effort is needed to combine the smiley faces across several disciplines to come to an overall estimate. A direct approach, consisting in eliciting the belief without the support of smiley faces could avoid this bias – we did elicit without smiley faces, but the comparison of the two approaches for the same case studies is not included in the ongoing research.

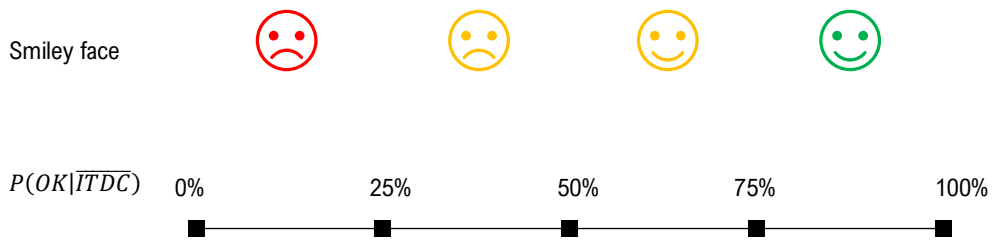


Figure 21 - Translation of smiley faces into $P(OK|\overline{ITDC})$

Let us now consider $\boldsymbol{P(OK|ITDC)}$. This probability is similar to the latter, with the difference that impacting changes are assumed to occur. This input variable is more challenging to elicit since it involves additional assumptions strongly related to the experience of the experts. For instance, some changes are known to be likely occur at specific milestones. In accordance with experts, we assumed that a default value of $P(OK|ITDC)$ is 50% (reflecting ignorance) for technical solutions that have $P(OK|\overline{ITDC}) \geq 50\%$ (i.e. the vast majority of the technical solutions that are considered to solve a design issue).

IRDS proposes a simple model for $P(OK|ITDC)$ and supposes that changes have negative impacts – in accordance with experts interviewed – even if it is not always true. Predicting whether the changes will impact positively or negatively the performance of the technical solution considered is more challenging. The impacts of changes can also change overtime. For instance, the changes that occur before a certain moment can have positive impact, and the changes occurring after can have negative impact. In that respect, $P(OK|ITDC)$ can be time-dependent. However, it is even more difficult to elicit beliefs for such a model since it requires additional assumptions not necessarily supported by empirical evidences. IRDS still enables the user to compute the problem with time-dependent $P(OK|ITDC)$ if enough information is available.

Both $P(OK|\overline{ITDC})$ and $P(OK|ITDC)$ are conditional to $\boldsymbol{pITDC(t)}$. This function represents the probability that later or current but not represented changes in the technical definition of the vehicle will impact the outcomes of the current decision. Its values depend on the design issue itself: whether the system under consideration is isolated or interacting with others, and whether the interactions affect the performances under consideration. Defining $pITDC(t)$ from empirical evidence is so far very difficult. It would imply to, at least, gather data about design modifications on a significant number of similar projects over time, and relate these design modifications to each other with regards to the technical performance under consideration to formulate assumptions based upon objective observations. Ideally, a synthesis model or influence diagram associated with historical data would help one to define $pITDC(t)$. These supports would involve investing in knowledge management systems development, which is the tendency in a digital transformation perspective, and the work towards this direction was not mature when we performed this research. However, experienced simulation practitioners who are among the first persons informed of design changes can formulate assumptions and provide $pITDC(t)$ profiles. These educated guesses are easy to elicit with a free rule. Simply asking them "at this time, what are the chances that

changes that impact the performance measured occur?" allows the decision analyst to collect values – cartesian coordinates used to build the function. A short iterative elicitation process where the data provider can readjust the profile of the function is sufficient to obtain an estimate of $pITDC(t)$ in less than 10 min. In the example shown in Figure 22, the data provider (a Simulation Analyst) reported his beliefs about *pITDC*, for a specific part, in function of the development process milestones – and the design specifications that are generally set at these moments.

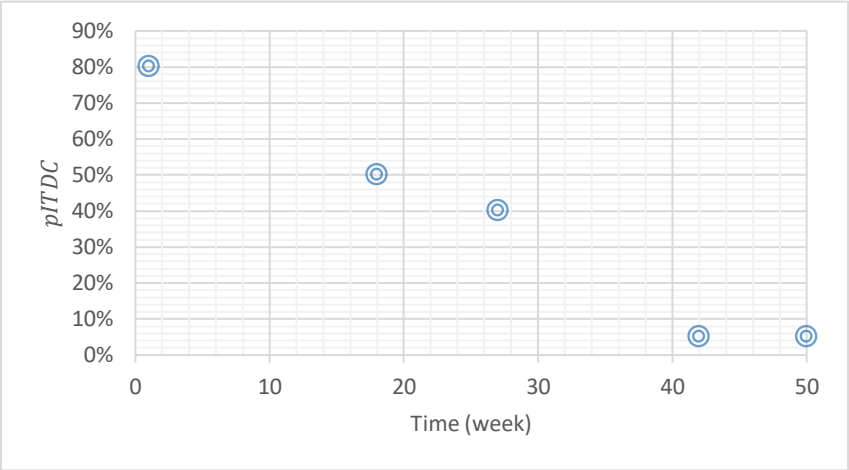


Figure 22 - Example of elicited pITDC coordinates in accordance with development process milestones

Costs

As shown in Table 5, IRDS' cost structure include costs committed during and related to the development phase (Dc_1, Dc_2, Ac), costs committed during the development phase and related to the industrialization phase (Ic_1, Ic_2, Ic_3), costs committed during and related to the industrialization phase ($Ic_1{}'$, $Ic_2{}'$, $Ic_3{}'$, Ic_4, Ic_5), and a cost of delay function.

The costs estimates can be supplied by different actors, as shown in Figure 20, with different precision and level of confidence. For instance, for industrialization costs, a synthesis architect can provide costs estimates based on heuristics and rules that do not really reflect the actual suppliers negotiated prices or specific manufacturing processes. Cost analysts perform simulations with a large number of inputs of various nature to support purchasers who negotiate with suppliers. Both the simulations outputs and negotiated prices can be used as estimates in as-is decision dossiers. In the fact, some interviewee reported that the persons who enter the costs estimates can deliberately choose to reveal one value over another to influence the decision maker for hidden interests.

Of course, it is difficult to provide costs estimates based on negotiated prices for newly designed technical solutions since the issue resolution process has to lead to the selection of a technical solution that will be used as an input for negotiations with suppliers. However, historical data of negotiated prices for similar technical solutions in similar project can help

to infer costs estimates. For costs related to vendor tooling or supplier engineering studies, some estimates based historical data are used as references.

Considering this setting, IRDS proposes to integrate probability distributions to represent the uncertainty of data providers regarding costs. We observed that, when interviewed, data providers spontaneously provide a variation range associated with a value that they consider as the most probable rather than providing a single value – like they do in the decision dossiers. This three-point estimation represents the less expensive, most likely, and most expensive estimates, and is convenient to build a triangular distribution, as shown in Figure 23.

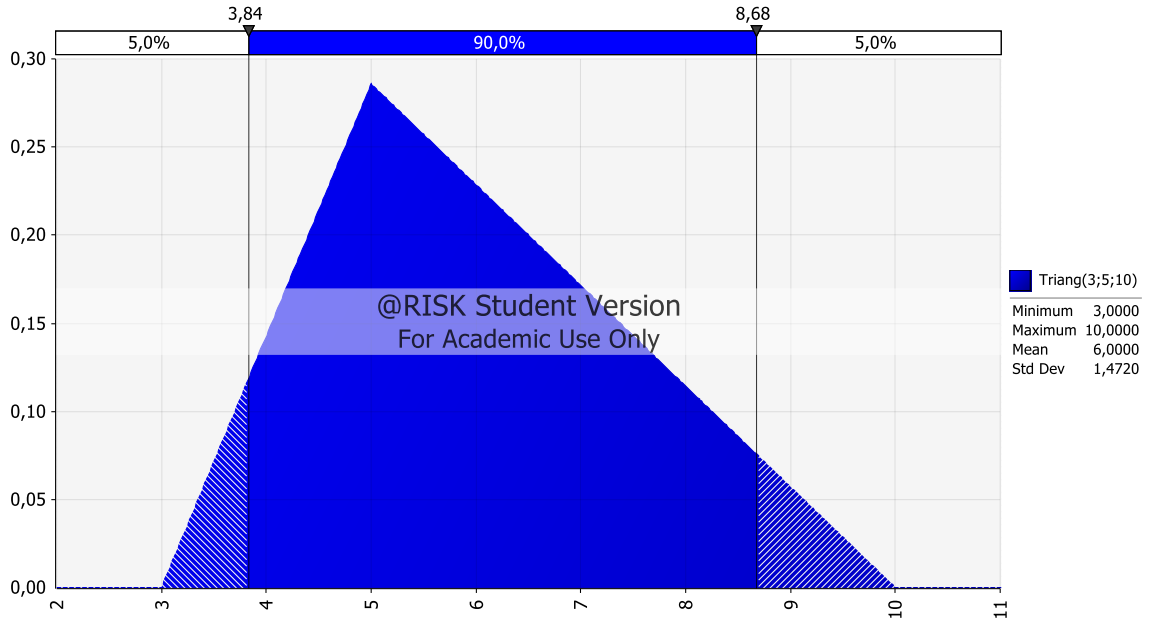


Figure 23 - Triangular distribution representing a per-unit manufacturing cost estimate based on a three-point estimation

As mentioned above in Section 5.3.1, only the costs engaged in case of success are provided in the current practice. Although the data providers traditionally do not explicit their beliefs about the costs incurred in case of failure, they do not struggle make assumptions about these costs when they have a backup plan in mind. For some design issues causing appearing in the manufacturing phase, Simulation Analysts and designers know what type of solution is more likely to be implemented, and what procedures it involves (e.g. designing a reinforcer, changing the tooling, manufacturing a new prototype, etc.). The costs associated with these interventions are estimated the same way as in the scenario of success, but involve to discuss further the assumptions. We observed that this effort help the data provider to anticipate the rework needed and related expenses, and consider risk more explicitly.

The penalty and added values quantities can be related to the cost of additional weight (established by the management control and straightforward to provide), the savings due to reusing tooling, etc. and are supplied as the costs mentioned above. It can be challenging to quantify these inputs when it comes to taking into consideration other projects that may be impacted by the decisions made for the one under consideration.

The cost of delay is a function that represent the cost incurred by the delay in the project over time. Due to a lack of measurements and tracking of delay, this function is difficult to define precisely. However, experts assume it to have an exponential profile. They consider the penalty related to postponement of the production launch – the management control provides estimates about the daily loss in such situations – and the increase of full-time equivalent staff requested in order to meet the deadlines. The latter consideration depends on the nature and the quantity of activities that depend on the design issue to be solved. The decision analyst can build $Cost_{delay}(t)$ by eliciting coordinates with a free rule (see Figure 24), in the same fashion as $pITDC(t)$. As some problems are similar and are detected at similar moments in the development process, $Cost_{delay}(t)$ reference profiles can be established over time and experience.

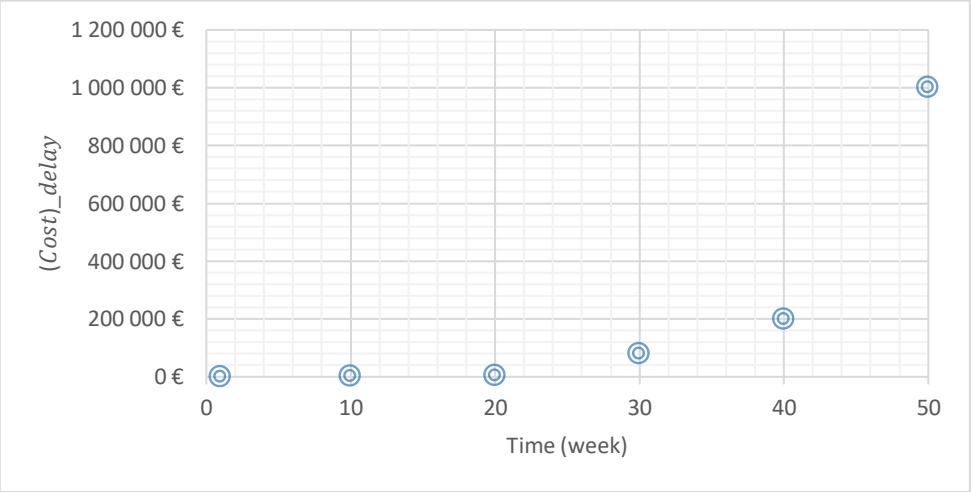


Figure 24 - Example of $Cost_{delay}$ coordinates based on the agreement of two experts

Accuracies of the analyses for technical solutions

The additional analyses can be either related to numerical simulations, early physical tests (when possible), studies conducted by suppliers, or experts judgments. The input variables that indicate the accuracy of the additional analyses are the *sensitivity* (true positive rate) $P(Fav|OK)$ and the *specificity* (true negative rate) $P(\overline{Fav}|\overline{OK})$. When considering the most common information source, i.e. numerical simulation, the simulation practitioners and methods specialists do not characterize the accuracy of numerical simulation analyses with true positive and true negative rates. Since only design specifications with favorable analyses results are normally brought to the manufacturing phase, correlation studies performed between numerical models and physical tests measurements and feedback from the manufacturing phase can provide insight to assess $P(Fav|\overline{OK})$. The specificity is more difficult to assess with this approach. However, data providers are asked to define these input variable with respect to the confidence they have into the processes that provide them additional information. Hence they provide estimates of these values through an free-rule elicitation.

Analysis times

Whether considering numerical simulation or other information source, in the current practice, simulation practitioners or other expert provide the time that is necessary to obtain informative results, and the project manager defines, on the basis of this estimate, at which meeting date the issue will be re-examine with new information. This difference between two decision meetings corresponds to At. Hence, in some situations, the project manager – who takes on the role of decision maker – can also be a data provider. Knowing the decision meetings are held weekly, the decision analyst can easily define together with data providers the value of At to make a recommendation before even meeting the project manager.

In conclusion, the decision analyst has to model data providers' beliefs when gathering data to use IRDS. He or she has to identify the data provider that is the most likely to supply accurate data, make a tradeoff between the time necessary to complete the elicitation process and the accuracy sought, and foster the commitment of data providers to carry out additional work. This is particularly the case in the early phase of implementation – the phase we focused our research on – in a situation where the new practices are not yet established.

5.4. Sensitivity analysis-based method

When testing the framework on historical design issues, it was difficult to enhance the available information through an elicitation process in a timeframe consistent with our project. Indeed, some of the individuals who are the more knowledgeable about certain data were unavailable. That led us to assume estimates together with non or less-expert data providers for some input data. We performed sensitivity analyses to examine whether seeking for more accuracy was actually necessary. Our observations prompted us to reconsider the data gathering strategy, as discussed in the next sections.

5.4.1. Model type: deterministic or probabilistic

The decision problem model can be either considered as *deterministic* or *probabilistic*. We investigated two approaches to perform a sensitivity analysis on a decision problem with IRDS.

In the ***deterministic approach***, input variables are nominal values and are varied one at a time. This approach is convenient when we gather data gather from existing information sources – i.e. as-is decision dossiers. This approach leverages sensitivity analysis to account for uncertainty. Sensitivity analysis yet requires determining variation ranges that should be consistent with data provider's uncertainty. Hence, an initial elicitation effort is necessary for each type of input, at least to formulate assumptions for common variation ranges. In the theoretical case where it would be impossible to elicit variation ranges, or the decision analyst wants to explore a problem briefly, we found reasonable to use 20% as a common variation ranges for costs, and a standard logistic function for the bounds of the probabilities of success ranges – as in the following equations and in Figure 25:

$$p_{min} = \frac{e^{n-r}}{1+e^{n-r}} \qquad Equation\ 5$$

$$p_{nominal} = \frac{e^{n}}{1+e^{n}} \qquad Equation\ 6$$

$$p_{max} = \frac{e^{n+r}}{1+e^{n+r}} \qquad Equation\ 7$$

$$n \in [-5; 5]$$

$$r = 1\ (default)$$

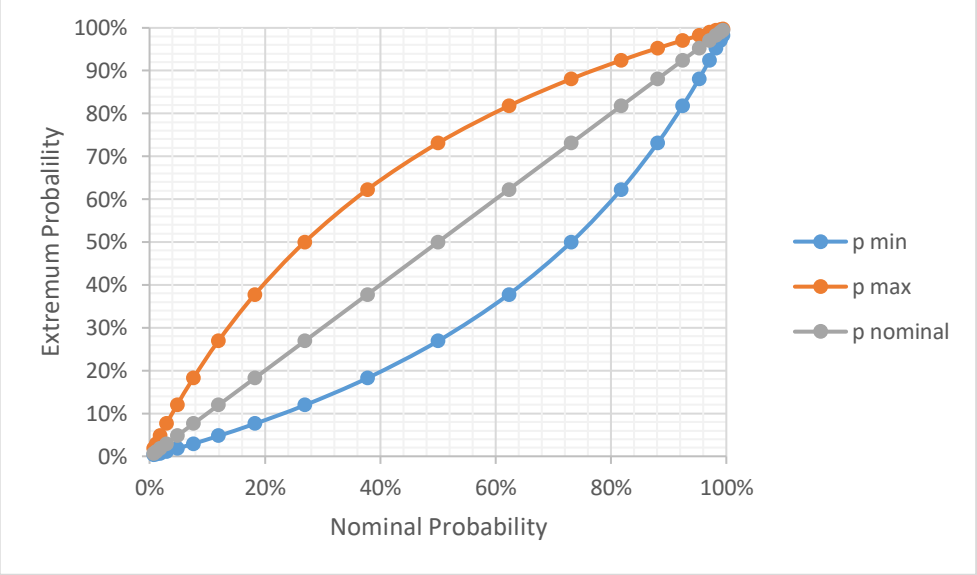


Figure 25 - Variation ranges for probabilities of success

As discussed in Section 5.4.2, tackling decision problems with this approach upfront can help to determine how a complementary probabilistic approach should be handled.

In the ***probabilistic approach***, inputs are provided in the form of probability distributions, after an elicitation process, as discussed in Section 5.3.2. In this case, the distribution parameters are varied, and not only the nominal value of the input. This allows the analyst to identify which input variation is likely to change the decision, and to determine whether further analyses should be performed on the beliefs modeled.

In Section 5.3.2 we stated that the simplest distributions used as cost inputs are triangular distributions. These distributions account for the most probable value (the mode) and upper and lower bounds. In the particular case of symmetric triangular distributions, the mean actually corresponds to the mode. . In this case, we think it is reasonable to use a variation range of 20% both for the variation of the mode and the variation of the lower and higher bounds. The same logistic function is used for the variation of the probabilities of success.

We observed that when considering a linear model – i.e. static in the case of IRDS, at a given t – the EV results tend to be similar whether symmetric triangular distributions are

provided with the deterministic approach or nominal values are provided with the deterministic approach. The underlying assumption is that the *deterministic-nominal values* entered correspond to the *probabilistic-means of triangular distributions*.

5.4.2. Impacts on the data gathering process

Analyzing a decision problem with IRDS requires to gather information related to a set of alternatives and to perform a computation that issue an expected value for each alternative. The preferred alternative is thus identified and communicated to the decision maker. We first considered rigorously collecting accurate input data, in order to accurately calculate the expected values and thus be able to correctly distinguish the outcomes of the alternatives while ranking them. We observed that an exhaustive and detailed information gathering process is both cognitively demanding and time consuming.

The efficiency of this process can be improved by conducting a sensitivity analysis in the early phase of data collection, on a model initially filled with rough estimates. The aim of this approach is to tend towards a cost efficient information enhancement – from a value of information optimization perspective. Indeed, SA conducted on a model incorporating rough estimate allow to roughly identify whether more accuracy is needed, i.e. if the alternatives have close expected values. When data is lacking and no elicitation is immediately possible, therefore in case of relative ignorance, the decision analyst can expand the variation range of the inputs under consideration and examine whether and how the inputs actually impact the decision. When conducting the sensitivity analysis with approximates (or rough estimates), the decision analysis process, shown in Figure 26 does not change in principle, it is only the data gathering effort that is more efficiently allocated.

While studying the implementation of IRDS in the company, the SA on approximates leverage effect has been useful when working on historical cases. Some case studies that illustrate both the difficulties associated with handling uncertainty and the benefit of SA are presented in the next section.

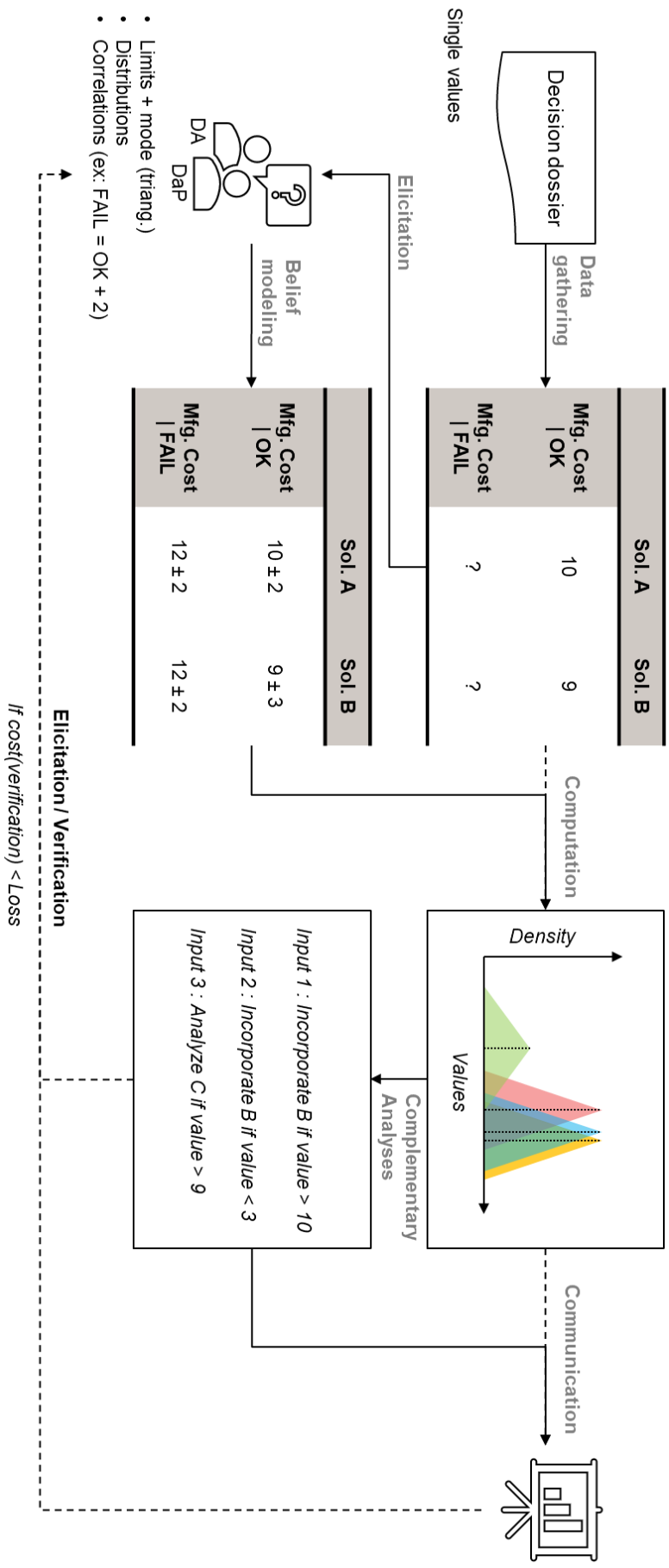


Figure 26 - Decision analysis process with IRDS, simple example with manufacturing cost

5.5. Case studies

The last section discussed the uncertainty associated with the data collection when using IRDS. We considered both the uncertainty of the data providers about the quantities they manipulate and the uncertainty of the decision analyst about the value of enhancing information.

To provide an illustration of these considerations, this section presents 5 case studies that we used to test the implementation of IRDS in the company. Because we were unable to enroll in ongoing projects and could not track their progress in a timeframe consistent with our own time constraints, we focused on historical cases. As data gathering issues and belief modeling have been introduced in Section 5.3.2, the case studies are interesting to show what time was necessary to gather data and elicit beliefs, and how sensitivity analysis on approximates can help saving resources. The case studies also reveals practical difficulties and biases that can affect the decision analysis if IRDS is not used carefully. As the studies have been performed on real industrial cases, some data have been concealed. Some numerical results of the sensitivity analyses are presented for illustrative purpose in the first case only. Moreover the aim of this section is to discuss the process and difficulties rather than the numerical outcomes of decisions analyses.

The 5 cases we considered are the following:

- *B-Pillar case*
- *Door Hinge case*
- *Bumper Beam case*
- *Front Subframe case*
- *Booming Noise case*

The role of DA (decision analyst) was assumed by the lead author of this research and the roles of DaP (data provider) were assumed by engineers, analysts, experts and deputy project managers who were formerly involved in the projects. The role of DM (decision maker) normally assumed by the project managers was not directly involved in the studies since we focused on the decision analysis prior to the recommendation to the DM, however we discussed the outcomes of the choices that would have been made by the DM. The cases have been provided by CAE Synthesis Engineers concern design issues and decision problems escalated to project managers. CAE Synthesis Engineers are the professionals who keep a track of the design issues and mostly gather performance data. They interact with Simulation Analysts who are specialized in specific customer performances (passive safety, acoustics, durability, etc.) and exchange with Customer Performance Leaders and Engineering Leaders. They escalate the information to synthesis architects, who complete decision dossiers with cost data collected from other sources.

5.5.1. B-pillar case

For illustrative purposes, we will provide numerical values that represent an order of magnitude of the quantities under consideration.

Context

The case has been communicated to the DA by a former Passive Safety Simulation Specialist (DaP^{SiAn}) – also referred to as "Simulation Analyst" in our research – who worked on the design issue. For this case, the decision dossier was not available in the usual form (a presentation document), therefore the decision problem has been explained by the initial DaP by email. The case concerns the choice of the technical definition, and ultimately the manufacturing process, of the B-pillar (Figure 27). According to DaP^{SiAn}, the decision problem has been examined at the end of the development phase, few weeks before the TGA milestone. The B-pillar is traditionally made of two materials that are welded together. One material considered brittle and the other ductile. This configuration is designed to withstand deformations in the event of a crash. Several parameters are taken into account when implementing such a solution into a new vehicle – the vehicle dimensions, weight, structure, etc. – and other solutions have been explored in view to reduce costs and optimize the performances. For the vehicle project under consideration, a solution proposed was to manufacture the B pillar with a single material. This solution would save a considerable amount of money by saving the cost of the welding operation per vehicle. As presented by DaP^{SiAn}, two decision alternatives were explicitly considered: “Incorporate A” which consists in implementing the traditional solution (two welded materials), and “Incorporate B”, which consist in manufacturing a B-pillar with a single material – the brittle one. “Incorporate B” was designed to save about 10€ per vehicle (for 200 000 units). this case is interesting insofar as the decision made led to unwanted consequences. Indeed, a fracture of the B-pillar has been observed through physical tests during the industrialization phase, and the traditional solution has been implemented to solve the problem. This required to spend 700 000 € to build a new prototype, and reintegrate the costs of welding.

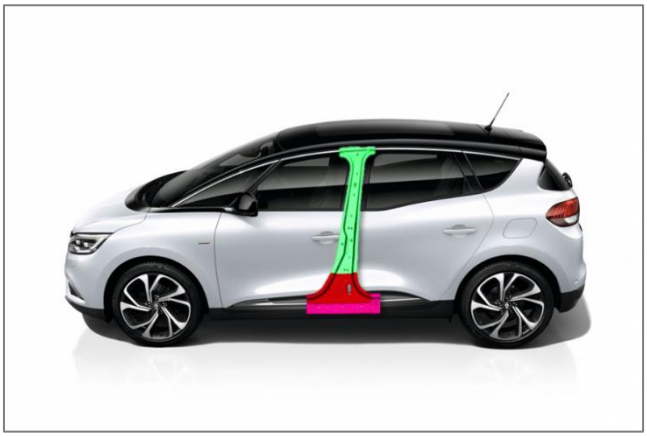


Figure 27 – Illustration of a B-pillar

Data collection

In the email sent by DaP^{SiAn}, amongst the costs, only the cost of the welding operation was provided, and estimated to be the only cost difference between the two technical solutions. Experienced to design decision problems, the DA asked whether other common data were estimated but not explicitly reported, such as the cost of material involved in the per-unit manufacturing cost, weight difference, the vendor tooling cost. Moreover, for the costs known a posteriori, whether other costs were "hidden", such as a per-unit manufacturing extra-cost (due to materials and late negotiations), delay penalties, etc. To use IRDS with the data known *a priori* – i.e. before knowing the outcomes –, the DA asked to DaP^{SiAn} (by email) whether a cost of rework was considered at the moment the decision was made. For instance, did the DM or other stakeholders communicate about a backup plan in case of a failure? Was the cost of building a new prototype estimated? The Simulation Analyst answered that, to his knowledge, the 10€ difference was the information that was mainly considered during the decision making. The email contained qualitative information, explaining that although the simulation results were favorable to "Incorporate B", the Synthesis Architect requested the opinion of DaP^{SiAn}. The latter expressed strong doubts about the validity of the simulation results, relying on his knowledge about mechanics. He was skeptical about the solution with a single material and suggested to choose to implement the traditional solution (A). This traditional solution allows a rotation movement that has been observed in physical tests and that is generally necessary to avoid fracture. DaP^{SiAn} reported $P(OK|\overline{ITDC})^A = 90\%$ (70% in case of impacting changes), $40\% < P(OK|\overline{ITDC})^B < 60\%$ (50% in case of impacting changes), and a constant $pITDC = 10\%$. As shown in Table 8, Table 9, and Table 10, deterministic sensitivity analysis showed a decision sensitivity to, amongst other, $P(OK|\overline{ITDC})^B$, the per unit manufacturing cost difference in case of success (Ic_2), the penalty in case of failure – which is actually the estimated cost of building a prototype – (VP_1^B).

Input value	Decision
14,0 €	B
13,2 €	B
12,4 €	B
11,6 €	B
10,8 €	B
10,0 €	*Ana. A+B*
9,2 €	Ana. A+B
8,4 €	Ana. A+B
7,6 €	Ana. A+B
6,8 €	Ana. A+B
6,0 €	Ana. A+B

Table 8 – Decision sensitivity for Ic_2^A, B-pillar case, DaP^{SiAn}

Input value	Decision
38%	Ana. A+B
40%	Ana. A+B
43%	Ana. A+B
45%	Ana. A+B
48%	Ana. A+B
50%	*Ana. A+B*
53%	B
55%	B
58%	B
60%	B
63%	B

Table 9 – Decision sensitivity for $P(OK|\overline{ITDC})^B$, B-pillar case, DaP^{SiAn}

Input value	Decision
910 000 €	Ana. A+B
868 000 €	Ana. A+B
826 000 €	Ana. A+B
784 000 €	Ana. A+B
742 000 €	Ana. A+B
700 000 €	*Ana. A+B*
658 000 €	B
616 000 €	B
574 000 €	B
532 000 €	B
490 000 €	B

Table 10 – Decision sensitivity for VP_1^B , B-pillar case, DaP^{SiAn}

Moreover, the decision is sensitive to the extra per-unit manufacturing cost in case of failure ("Incorporate B" if extra-cost inferior or equal to 1,92 €, i.e. $Ic_2{}'^B \leq 11{,}92$ €, "Analyze A+B" otherwise), the cost of additional analysis for solution B ("Incorporate B" if $Ac^B \geq$ 24 242€, "Analyze A+B" otherwise), and for most other IRDS input, the decision changes from "Analyze A+B" to "Incorporate B" at within the variation range. In conclusion, the decision prescribed is to further analyze both technical solutions or, in case of a small error for most inputs, incorporate the solution that lead to a bad consequence. A probabilistic approach confirmed these results - Table 11 shows for example the decision sensitivity to variations of parameters for a triangular distribution for Ic_2^A.

		Mode : c				
		8	9	10	11	12
Range : b - c	1,6	**An. A+B**	**An. A+B**	**An. A+B**	**B**	**B**
	1,8	**An. A+B**	**An. A+B**	**An. A+B**	**B**	**B**
	2	**An. A+B**	**An. A+B**	**An. A+B**	**B**	**B**
	2,2	**An. A+B**	**An. A+B**	**An. A+B**	**B**	**B**
	2,4	**An. A+B**	**An. A+B**	**An. A+B**	**B**	**B**

Table 11 - Summary of decisions prescribed for Ic_2^A, B-pillar case, DaP^{SiAn}

Intrigued by this situation, the DA arranged a 75 min meeting with the former Synthesis Architect (DaP^{SyAr}) and former CAE Synthesis Engineer (DaP^{CASE}). DaP^{SyAr} explained that solution B was considered to be the reference during the upstream phase, despite the company's lack of experience with this type of solution. Therefore there was a bias in favor of solution B when the development team handled the project. The dimensions of the vehicle were such that the "classical" rotation occurring on the pillar was not necessary in the case of a lateral impact. Moreover, the simulation results were favorable to a B-pillar with a single material. He still recognized that "the eventuality that a crack may occur at a certain location was suspected". The overall extra-cost per vehicle of solution A over solution B was, according to DaP^{SyAr}, closer to 25 € than to 10 €. Both DaP^{SyAr} and DaP^{CASE} agreed that the chances of success were similar for the two solutions, reporting $P(OK|\overline{ITDC})^A = P(OK|\overline{ITDC})^B = 90\%$. IRDS prescribes to "Incorporate B", when used with a combination of beliefs on which DaP^{SyAr} and DaP^{CASE} agreed, with a low decision sensitivity input variations and a small expected value difference (tilting to "Analyze A+B" if $P(OK|\overline{ITDC})^B \leq 57\%$).

To gain more insight about this case, the DA arranged a 45 min meeting with the Crash Simulation Expert (DaP^{CrSE}). DaP^{CrSE} did not participate in the decision making for the B-pillar case because she was not working for the company. In fact, there were nobody to fulfill this role at the time. Although her judgment is solely a posteriori, she provided interesting remarks. According to her, the simulation models at the time did not predict the fracture – it is a phenomenon that is still difficult to predict. She indicated that people were not aware of the limitations of simulation models and were confused about the assumptions and proxies used to read the results. In other terms "they did not know what they did not know". This conjunction of conditions, in addition to the strong incentive of money saving, may have led

them to not explore other analyses options. One analysis was available and could have provided valuable information: the metal supplier studies. Indeed, the supplier conduct studies to characterize the material they sell to the manufacturer. DaP^{CrSE} stated that the supplier had already done an analysis – that would have discarded solution B – at the time the decision was made, but the project team did not ask them. Assuming a priori information, she admit that it is difficult to predict the chance of success for both solution A and B, even if it was reasonable to assume that solution A had higher probabilities of success, due to empirical evidence. Solution B could have been as likely to be successful that unsuccessful ($P(OK|\overline{ITDC})^B = 50\%$) without the additional information obtained from the supplier. Using IRDS with DaP^{CrSE} leads to similar results as the ones with DaP^{SiAn} if the cost are the one believed by the latter. Associating the costs provided by DaP^{SyAr} to the beliefs of DaP^{CrSE} lead to "Analyze B" with a decision sensitivity that tilts to "Analyze A+B" with few expected value difference (640 €) in case of small error in the inputs.

Decision prescribed

As mentioned more into detail above, the decision prescribed by IRDS with the beliefs elicited with the former Simulation Analyst was "Analyze Solutions A and B". A high decision sensitivity can be observed for most inputs, and a tilt towards "Incorporate B". When IRDS is used with the beliefs elicited from the former Synthesis Architect and the former CAE Synthesis Engineer, the decision prescribed is to "Incorporate B", with no decision sensitivity to small inputs variations. The beliefs of the Crash Simulation Expert leads to "Analyze B" whether the costs are the ones provided by the former Simulation Analyst or the ones (more reliable) provided by the former Synthesis Architect.

Decision made at the time

Following the advice of the Synthesis Architect and the CAE Synthesis Engineer, the DM chose "Incorporate B", i.e. a B-pillar manufactured with a single material. As mentioned above, an issue appeared during the industrialization phase due to a fracture of the B-pillar. This led to building a new prototype incorporating the traditional solution (A). The monetary consequences are the loss of the expected saving, the cost of building a new prototype and the mobilization of a task force (not estimated in the scope of the case study).

Comments

This case is interesting since it shows that data providers can have divergent beliefs. Making them explicit and fostering communication can help stakeholders in their critical thinking with regard to a given decision problem. Cognitive biases associated with ad hoc judgment can have influenced the beliefs elicitations. Nevertheless, the case illustrates the fact that a rational decision based on expected value maximization can eventually lead to undesirable outcomes and vice versa. Indeed, considering a risk-neutral profile, the amount of money that could have been saved by incorporating the solution with the smaller probability of success was so considerable that pursuing this opportunity was the most rational decision (according to the Synthesis Architect's beliefs). The difference in expected value – computed with IRDS – between the decision prescribed and the decision made is 19 k€ in favor of the decision prescribed, with the beliefs elicited from DaP^{SiAn}. This difference is 83 k€ in favor of the decision prescribed with the combination of beliefs elicited from DaP^{CrSE} for the probabilities of success and additional analyses accuracy and DaP^{SyAr} for the costs.

5.5.2. Door Hinge case

Context

The decision dossier associated with this case study has been presented once to the project manager. The design issue, identified thanks to numerical tests, concerns a fold that is generated because of the weakness of a reinforcer for a door hinge. Two technical solutions were proposed: H1 ("Incorporate A"), consisting in augmenting the stiffness of the reinforcer, and H2 ("Incorporate B"), consisting in changing the grade of the steel (and adjusting the stiffness accordingly).

Data collection

The decision dossier includes, CAE screenshots, results of numerical tests for different stiffnesses and grades, and a synthesis of the alternatives proposed. Only the cost Ic_2 for each technical solutions are presented. Referring only to this cost, H2 is 3 times less expensive than H1. Intrigued by the fact that the classical other costs were not expressed in a decision dossier presented in a project manager's decision meeting, and willing to elicit beliefs about the success of these technical solutions, the DA interviewed the CAE Synthesis Engineer. He explained further the design issue and indicated that the "missing data" were assumed to be "equal", i.e. the cost differences were considered inexistent and the chances of success were considered as similar. We also asked why some performance results were missing in the simulation reports, he told us that such cases generally happen when the Simulation Analyst is confident enough to the performance of the design tested, and that further investigation do not add value – and are only used as "confirmation" to increase the confidence when necessary. This type of actions correspond to the IRDS alternatives "Analyze Solution". The CAE Synthesis Engineer gave us estimates about the time necessary to perform the simulations and post-treatment, and to fill the blanks in the reports. This allowed us to estimate the costs associated with additional analyses for this source of information. The sensitivity analysis showed a value sensitivity to the probabilities of success of H2, but no decision sensitivity for a reasonable variation range. Hence, further accuracy was not necessary to issue a robust recommendation.

Decision prescribed

The decision prescribed by IRDS was "Incorporate B", i.e. H2..

Decision made the time

The project manager selected H2 and asked for an optimization of Ic_2. Later on, a small change considered as "at no cost" (adding a welding point) has been discussed to ensure that the performance of the reinforcer is consistent with other manufacturing process constraints.

Comments

The need to add a welding point was predictable but the likelihood hard to quantify. Even if it is considered as "at no cost" it still involves engineering costs. However, this question could have happen for H1.

5.5.3. Bumper Beam case

Context

The design issue concerns the performance discrepancies of many targets that have been identified as being related to the bumper beam. The decisions alternatives presented to the DM are 3 technical solutions: ("Incorporate A") sticking to the current technical definition of the bumper beam, and incorporating different bumper beams, ("Incorporate B") and ("Incorporate C"). We have little information about this case, the DaPs to reach, the decision made, and the consequences of the decision. However, the case is interesting since it is an example of a dossier that includes a synthesis which consist of both quantitative and qualitative data in different forms, as shown in Figure 28.

Data collection

Figure 28 reports the data available in the decision dossier that are highlighted to advise the DM. The costs and the weights are presented for the European version of the vehicle – the version under consideration. The non-European version data are also presented for comparison. On the figure, we made the data correspond to IRDS inputs. We observe that $P(OK|\overline{ITDC})$ can be, at least partly, inferred from a section of the table. However, this inference requires extensive knowledge about the contribution of each data to $P(OK|\overline{ITDC})$. The CAE Synthesis Engineer, who provided this case, was ignorant about the design issue under consideration (i.e. he was not involved in this issue at the time) and was unable redirect the DA to knowledgeable DaPs. However, relying on the experience of the CAE Synthesis Engineer – the only available DaP – on similar issues within other projects, the DA still explored the decision problem.

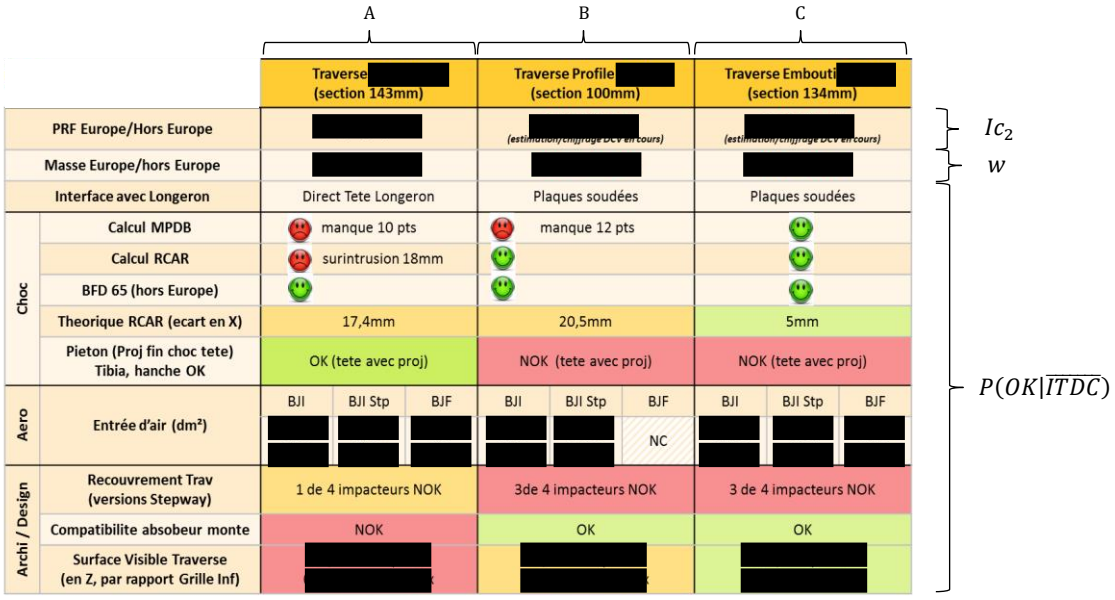


Figure 28 - Synthesis of the alternatives proposed in the Bumper Beam case

Decision prescribed

The decision prescribed by IRDS was to postpone the issue resolution until week 9. A deterministic sensitivity analysis performed with large ranges of variation showed a decision sensitivity to the input $P(OK|\overline{ITDC})$ for C. A classical approach which does not incorporate process alternatives (such as "postpone") would result in recommending C.

Decision made at the time

The decision that was made was unknown at the moment where the decision dossier was presented as-is to the DA. However, the only available DaP speculated that the DM asked to postpone the final decision while developing further the solution corresponding the alternative C.

Comments

Postponing an issue resolution lies on the assumptions that impacting changes in the vehicle technical definition would decrease over time. Hence, further developing a technical solution at a more favorable time would lead to better outcomes. This case illustrates this notion by recommending to postpone the issue resolution considering that the technical solution C has the highest expected value.

5.5.4. Front Subframe case

Context

The design issue concerns a noise, vibration and harshness (NVH) performance discrepancy and has been discovered 3 month before a decision was made to end the resolution process. The case has been presented in decision meetings 2 times because cost and collateral impacts were lacking in the decision dossier until the Synthesis Architect gathered the information and synthetized it into the table reported in the Figure 29. Three families of alternatives were presented. Three versions of the H1 (without a specific part), a H2 including a specific part in steel, and an H3 which includes a specific part in aluminum.

	Hypothèse 1	Hypothèse 1b	Hypothèse 1c	Hypothèse 2	Hypothèse 3
	DT REF = pas de MEC			Hyp 1c + MEC	Hyp 2 + Corne Alu
Périmètre technique	Berceau sans MEC		Berceau sans MEC (+optimisation design coquilles sup et inf)	Berceau avec MEC (+optimisation design coquille sup)	Berceau avec MEC (+optimisation design coquille sup)
	BIW BJA Europe			BIW BJA Corée (zone boitier)	
	Corne acier sans douille	Corne acier à douille soudée	Corne acier sans douille	Corne acier sans douille	Corne Alu DT1 = DW30 à Re+ (Contrainte archi) DT2 = autre BV Re-
Écart de masse	**REF**	Châssis = +0,4 kg BIW = sans impact **TOTAL = +0,4 kg**	Châssis = sans impact	**Châssis = +0,63 kg** (Optim. possible avec réduction ep coquille Berceau → -0,2kg TBC) **BIW = 0,66 kg** **TOTAL = +1,29 kg**	**Chassis = -0,6 kg** **BIW = 0,66kg** **TOTAL = +0,06 kg**
Écart de PRF et Invest	**REF**	[redacted]	**REF**	[redacted]	Châ[redacted]€
		BIW = sans impact		BIW = [redacted]	
Prestation Crash	☺	☹	☺	☺	☺
Prestation NVH	☹	☹	☹	☺	☺
Bourdonnement	☹	☺	☹	☺	☺
Bruit roulement	☹	☹	☹	☺	☺
Vibration plancher	☹	☹	☹	☹	☺

* dégradation Inertance en X dûe à modif de coquille inf --> suppression de cette modif.
* gain potentiel avec ep=3mm ald 2mm (3mm en X98)

Figure 29 - Synthesis of the alternatives proposed in the Front Subframe case

Data collection

The DA first read the 8 slides decision dossier and formulated questions to ask to DaPs. One out of the 6 authors of the decision dossier available within the 2 weeks. A 10 min discussion was sufficient to grasp the design issue, 20 min to clarify what the IRDS inputs are and how they relate to the information already available, 5 min to elicit the probabilities. The available alternative H1c was associated to the IRDS alternative “Incorporate” A, H2 to B and H3 to C. For NVH performances (rolling noise, floor vibration) Simulation Analysts know that the attributes they measure at their level of detail contribute significantly to the achievement of the requirements the more global level represented in the synthesis. They rely both on numerical simulation and on their experience. In case of failure, the Simulation Analyst reported that it is assumed that the solution that is considered as the most « safe » (although

more expensive) (H3) will be implemented. That also ultimately involves a per-unit manufacturing cost increase ($Ic_2{}' > Ic_2$).

The sensitivity analysis performed with standard variation ranges (cf. Section 5.4.1) showed a decision sensitivity to the inputs Ic_2^C, $P(OK|\overline{ITDC})^B$, $P(\overline{Fav}|\overline{OK})^{A,B,C}$, w^B, $P(OK|\overline{ITDC})^C$, $P(Fav|OK)^{A,B,C}$, and $P(OK|\overline{ITDC})^A$. The DA verified the accuracy on each input with the Simulation Analyst and concluded that the costs estimates are accurate (coming from cost analyses) and that it would be impossible to gain more accuracy about $P(\overline{Fav}|\overline{OK})^{A,B,C}$ and $P(Fav|OK)^{A,B,C}$ in the project time frames. The input w^B was considered as accurate but reducible through optimization. The first results suggested to select an alternative (Analyze B) that was different from the one chosen in reality by the project manager (Incorporate C). To better understand what assumptions or information the DA may have overlooked, another meeting has been organized with an expert recommended by the Simulation Analyst. The expert reported different beliefs about $P(OK|\overline{ITDC})^B$ for the moment the decision was considered. This did not change the decision prescribed by IRDS. He acknowledged that, after he had gained more knowledge about these types of technical solutions and material properties through physical tests within other projects, the prior estimate of $P(OK|\overline{ITDC})^B$ was too optimistic. He said that further analyses would have discarded B. In parallel, the DA chose to exchange with the Synthesis Architect who framed the decision dossier by email due to a 6h time difference. The latter explained objectives that was not expressed explicitly in the decision dossier but that mattered for the decision maker. These, once valued, fall into the VP_i input (added-value/penalty) that was actually not considered in the initial sensitivity analysis. This input data was computed with the cost of weight provided by the management control but did not include the valuation of the objective of making the vehicles of the segment lighter.

Decision prescribed

The decision prescribed by IRDS was “Analyze B”, closely followed by “Analyze B+C” in the sensitivity analysis. This can be explained by the fact that incorporating B potentially offer significant savings despite having a technical definition more heavy than C. If further analyses would be favorable to B, incorporating B would be recommended. Otherwise incorporating C would be recommended. If ignoring the process alternatives (Analyze, Analyze in parallel, Postpone), the decision prescribed would have been to incorporate C right away.

Decision made at the time

As mentioned above, the decision made by the project manager was to directly incorporate C. The physical tests performed during the manufacturing phase were favorable to this solution.

Comments

The difference in expected value – computed with IRDS decision model – between the decision prescribed and the decision made is 700 k€ in favor of the decision prescribed, with beliefs reported in the first place, and 15 k€ in favor of the decision prescribed after having updated the penalty due to weight. This case shows that despite decision dossiers contain useful information and DaPs can report their beliefs on the data that they are used to manipulate, implicit information considered by the DM need to be investigated.

5.5.5. Booming Noise case

Context

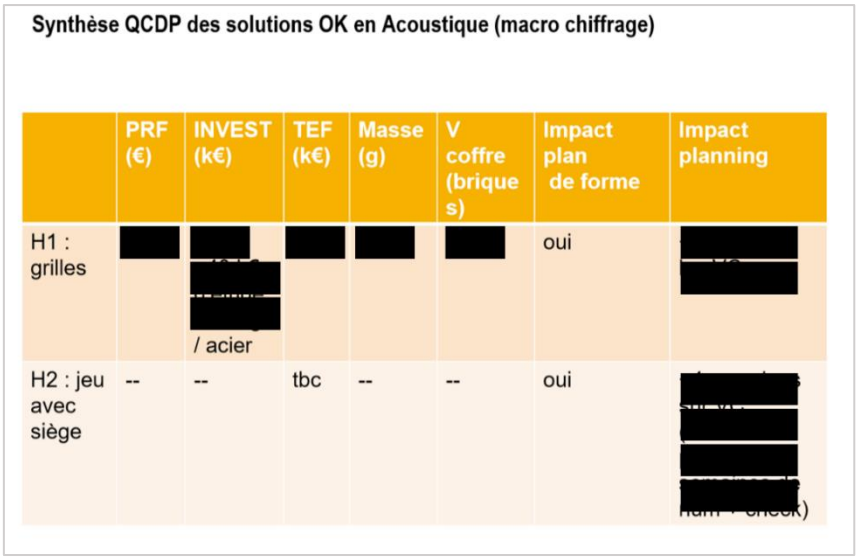
The design issue was presented 4 and 2 weeks prior to the "Tooling Go Ahead" (TGA) milestone – the milestone that completes the development phase and leads to the industrialization phase. Simulations results about booming noise performance for rear passengers did not reach the target. Several vehicle parts contributing to the problem were identified. Two technical solutions were presented in the decision dossier. H1, consisting in incorporating a grille to the vehicle, and H2, consisting in modifying the backlash between two parts.

Data collection

We obtained the pdf version of the decision dossier that was presented during the last decision meeting. It contains 23 slides with explanations of the design issue and its root causes, a history of the tests and foreseen solutions, and a synthesis of the technical solutions proposed.

Figure 30 is a screenshot of this synthesis – confidential data have been concealed.

The IRDS inputs available are Ic_1, Ic_2, w and Ic_3 is announced "to be calculated" for H1 and H2. The impact on the volume of the trunk is estimated, as well as the impact on the planning. The latter corresponds to how incorporating the technical solution might delay the "Agreement to Build Vehicle Check" (ABVC) milestone. The phase between the TGA and ABVC corresponds to the manufacturing of the tool by the supplier, the parts are expected to be delivered with an excellent level of conformity at ABVC, so that the vehicle can be assembled and physically tested. What mostly differentiate H1 and H2 is the cost differences with the current technical definition (almost inexistent for H2) and the impact on the planning that are higher for H2.



Synthèse QCDP des solutions OK en Acoustique (macro chiffrage)

	PRF (€)	INVEST (k€)	TEF (k€)	Masse (g)	V coffre (briques)	Impact plan de forme	Impact planning
H1 : grilles	[redacted]	[redacted] / acier	[redacted]	[redacted]	[redacted]	oui	[redacted]
H2 : jeu avec siège	--	--	tbc	--	--	oui	[redacted]

Figure 30 - Synthesis of the alternatives proposed in the Booming Noise case decision dossier

Once discovering the available data, the DA requested a 1h interview with both the CAE Synthesis Engineer and the Customer Performance Leader who handled the decision dossier under consideration. The goal was to further understand the issue and the information presented in the decision dossier, and to reconstruct the prior beliefs based upon the data available. The sensitivity analysis showed that the expected values of alternatives related to H2 were mostly sensitive to the probabilities of success of H2, but no decision sensitivity (i.e. the decision prescribed remains the same even if the inputs vary significantly, cf. Section 2.8). An exchange of 1 hour with the CAE Synthesis Engineer allowed the DA to use IRDS and issue a recommendation.

Decision prescribed

The decision prescribed was to incorporate H2, with an expected value significantly superior to H1. The alternatives consisting in Analyzing the solutions H2 and H1 were equally the second preferred alternatives. As expected, the postpone alternative had a low expected value. Indeed, close to the TGA, the cost of delay is high compared to the valuable information that can be gained, and the whole vehicle technical definition has low chances to change.

Decision made at the time

The decisions made by the DM was H2. The impact on the planning of this solution was actually overestimated and no bad consequences happened later in the design process.

Comments

On paper, this decision may seem trivial, but the issue was presented to the project manager because of its level of criticality – level 1, i.e. show stopper if not solved. Moreover H2 was potentially conflicting with interior design, so a check with the project team and an agreement of the project manager was necessary. The sensitivity analysis used with IRDS showed that available data and one round of interview to ensure the understanding of the DA were sufficient to compute the decision problem and obtain a robust recommendation. This recommendation was consistent to the decision actually made at the time which did not have bad consequences.

5.6. Discussion

5.6.1. Time necessary for data collection

It is important to note that due to the nature of the case study – an historical case that is not a priority for actors of ongoing project – people were not immediately available to work with the decision analyst. We assume that in a situation where IRDS is implemented and associated with standard practices, the time between the elicitation meetings would be reduced, if not concurrent to the data production.

5.6.2. Elicitation and beliefs modeling

The data providers often spontaneously reported ranges of probabilities rather than single values, as illustrated in 5.5.1. This encourages the decision analyst to leverage sensitivity analysis in the phase of data collection.

Breaking down Dc into Dc_1 and Dc_2 is not relevant since these two activities are interdependent and are neither dissociated by the management control nor the data providers. Moreover, even if Dc can be calculated by tracking the full time equivalent employees activities in ongoing projects, it was not possible to obtain these data – with a reasonable effort – for our case studies.

For Ic_4 and Ic_5, it was difficult to obtain estimates from data providers. The general response was that in the case of failure during the manufacturing phase, a task force was set up with the roles concerned by the design issues, and people were working as fast as possible to solve the issue before the upcoming milestones. An estimate can be constructed with generic values, such as a generic number full time equivalent employees and a generic time.

5.6.3. Decision analysis results

In some problems (e.g. Booming Noise, Door Hinge, B Pillar cases) the differences of expected values of alternatives are important, whether it is to provide accurate data or rough estimates. Sensitivity analysis enables the decision analyst to identify which inputs have a decision sensitivity.

Some decision problems (e.g. B Pillar case) include alternatives with costs inputs differences so important that the probabilities of success variations have little influence on the decision. However, it should be noted that there is seldom situations where probabilities of success differences are very important between *new technical solutions*. Indeed, the technical solution that corresponds to the current technical definition generally is generally assigned a low probabilities of success (< 10%) – this is actually why a design issue was detected – and the new technical solutions proposed to solve the problem have generally purposefully higher probabilities of success (>60%, otherwise they are not considered as competitive).

5.7. Conclusion and future work

This chapter addressed the question of the difficulties associated with the uncertainty encountered when implementing IRDS. Based on an empirical study extended for the research presented in this chapter, we observed that 5% to 20% of IRDS inputs are already available in the current decision dossiers. The qualitative data also provided can support the belief modeling for probabilities of success of the technical solutions proposed. We proposed to elicit the data providers' beliefs by the free elicitation rule, considering the tradeoff between accuracy and time and effort that people are willing to commit. Some data are difficult to elicit, mostly the ones related to the scenario of failure and the time-related functions. Estimating these inputs requires to examine assumptions with the data providers and to solicit their experience, which may be uneven among individuals. However, this

exercise encourages critical thinking and prompts participants to step back from their usual frame of reference. In order to better allocate effort when collecting data for using IRDS, we proposed to perform sensitivity analyses on rough estimates. In this way, the decision analyst can identify the inputs that are decision sensitive and increase the accuracy sought by elicitation or further analyses immediately available. As we conducted our research we tackled the questions of incorporating various experts' beliefs that are sometimes contradicting each other. IRDS prompts the data providers to communicate their beliefs explicitly, and this enables the others to discuss them and contribute their knowledge to update prior beliefs.

Through 5 case studies, we observed how the decision analyst collected data practically for historical design issues, dealing with constraints related to the availability of people, their relative discomfort with quantifying their beliefs, contradictions, and biases. In most cases, the IRDS inputs available in decision dossiers enhanced with a 60 min elicitation meeting led to decisions consistent with the ones made by decision makers at the time. In one case, IRDS prescribed a different decision that consists in performing additional analyses to explore the opportunity of making important savings. In another case, a technical solution already implemented in other vehicles and presenting good performances was competing with a technical solution that would allow the company to save about 4 million euros (eventually more, if implemented on similar future projects). The latter solution was criticized by experts, despite favorable simulation results. Depending on the beliefs reported, IRDS prescribed either to gather more information or to pursue the opportunity to make important savings. This illustrated the fact that the decision analyst must confront information from different sources and seek an agreement, and that rational decision making does not prevent bad luck or error due to lack of expertise.

This research could be extended by exploring ways to facilitate the data collection process and communication between the three roles involved in the IRDS. Working on ongoing projects could benefit from the availability of people, as they would work in coherence with the activities for which they have been mandated. Considering an information system and practices supported by management would facilitate a more efficient use of IRDS.

6. Conclusion

In this chapter, we review the research questions that have framed the thesis and show how they were tackled.

The research objective we have pursued in this PhD was to support decision making for solving design issues in the development phase of a complex system. We conducted our research in a multinational automotive company.

We identified and addressed the two following research questions :

1) In practice, how does decision making unfold in a M&S environment?

2) To which extent can a method based on normative decision theory enhance the decision-making process supported by simulation?

To address these questions, we applied a methodology composed of 3 main phases: a descriptive phase, a prescriptive phase, and a descriptive-prescriptive phase. These phases correspond to 3 studies supported by a literature review on decision theory, decision analysis in engineering design, value of information, beliefs elicitation. uncertainty management and sensitivity analysis (Chapter 2). Hence, the first research question has been addressed by Chapters 3 , and the second one has been addressed by Chapters 4 and 5 from different perspectives, both prescriptive and descriptive.

Through a summary of the studies that we conducted, we show in Section 6.1 how addressing these research questions has contributed to the fulfillment of the overall research objective. We also discuss the limitations of our research in Section 6.2 and suggest potential directions for future work to carry out in Section 6.3.

6.1. Contributions

6.1.1. In practice, how does decision making unfold in a M&S environment?

The **empirical study** – presented in Chapter 3 – allowed us to understand the decision-making process implemented in the company, and its interaction with the modeling and simulation process. The study highlighted the cascade-escalation paradigm of design decisions. This means that decisions are trans-hierarchical, and that the level at which decisions are made depends on the control that the decision makers have on the technical and economic constraints and the availability of information in their scope. Hence, decisions to solve design issues are often escalated to upper hierarchical levels when the alternatives considered lack information and involve a risk of cost and time overruns. The study mapped out the issue resolution process and its interaction with simulation activity and decision making. We established the basis for understanding how a decision meeting is conducted at a project manager level, and what a decision dossier consists of. Also, we identified the challenges encountered by the participants of the decision-making process, both in terms of

subjective uncertainty and communication. The lack of conclusive information is the main reason for postponing an artifact decision. Although decision dossiers only propose artifact decisions, product project managers make process decisions; they choose between finalizing the issue resolution by selecting a technical solution and waiting and collecting information to finalize the issue resolution later. Considering the continuous evolution of the product specification the multiple interactions between decisions made at different levels and in different interrelated projects, defining the optimal moment and the valuable information to make a decision is challenging. We also observed that the lack of knowledge about modeling and simulation, and the lack of trust about the results, are likely to facilitate irrational behavior such as off-loading responsibilities and workload.

Through this study, we addressed the question of the interaction between decision-making process and M&S process in the company. It allowed us to identify room for improvement and to hypothesize that a framework grounded in rigorous mathematical principles and integrating industrial considerations would help decision makers make more rational and informed decisions.

6.1.2. To which extent can a method based on normative decision theory enhance the decision-making process supported by simulation?

The results of the empirical study led us to consider the question of the enhancement of the decision-making process through a method based on normative decision theory. To do so, we **proposed a decision support framework** to solve design problems in Chapter 4.

We designed the Issue Resolution Decision Support (IRDS) to integrate process related data in the Modeling and Simulation based vehicle development process. Experts contributed to the definition of the decision model so that it can reflect the possibilities and the constraints of the industrial process. IRDS allows for process-focused decision-making, incorporating the analysis of the consequences of actions such as information gathering and postponing the choice of artifact alternatives. We proposed a tailored tool to compute the decision problems and a definition of the roles involved in the decision-making process supported by IRDS: a decision analyst, a decision maker, and data providers.

While building and testing IRDS, we noted that the information sources were scattered among individual and entities, and gathering some data in this context could be challenging. That raised the questions of the difficulties encountered when deploying IRDS in the company. We investigated these issues in the Chapter 5, by **exploring the difficulties related to uncertainty** when implementing the decision support framework. We observed that 5% to 20% of IRDS inputs are already available in the current decision dossiers, amongst quantitative and qualitative data presented in different forms. Considering the tradeoff between accuracy and time and effort that data providers are willing to commit, we proposed to elicit their beliefs with the free elicitation rule. We observed that the inputs related to the scenario of failure as well as the time-related functions are difficult to obtain. For these risk and process-related aspects, people are not used to formulate their beliefs, quantify them, and back them up with explicit assumptions. Therefore, the data collection phase of IRDS prompts

the participants to step back from their usual frame of reference. As the accuracy of the beliefs reported could be questioned, the question of the need for accuracy or not was tackled. We proposed to perform sensitivity analyses on rough estimates, so that the decision analyst can identify the inputs that are decision sensitive and eventually seek more accuracy by retargeting elicitation or requesting further analyses that would be immediately available. This enables the IRDS user to better allocate effort when collecting data.

We observed how the decision analyst collected data in the real industrial environment through 5 case studies on historical design issues. In most cases, the IRDS inputs available in decision dossiers enhanced with a 60 min elicitation meeting led to decisions consistent with the ones made by decision makers at the time. In one case, IRDS prescribed to explore the opportunity of making important savings, which was a different alternative than the one selected by the decision maker at the time, but presenting a higher expected value. In another case, depending on the beliefs reported, IRDS prescribed either to gather more information or to pursue the opportunity to make important savings – decision consistent with the one made by the decision maker, but leading to an unfortunate outcome. This illustrated the fact that the decision analyst must confront information from different sources and seek an agreement, and that rational decision making does not prevent bad luck or error due to lack of expertise.

These three studies covered different aspects of the decision-making process *as-is* and *to be* in the company – from considering the reasons why some artifact decisions are postponed many times, sometimes suboptimal, to how they are framed and informed, to how the decision-making process could be supported by a mathematical and organizational framework.

6.2. Limitations

While conducting this research, we identified and faced several limitations. These are related to the methodological challenge to demonstrate that IRDS lead to *better* decisions, the biases to working with historical material, the possible biases related to the use and interpretation of IRDS results, and the difficulty to value the contributions of the framework to the company beyond the decision problems under consideration that can improve the overall decision making.

Collecting empirical evidence that support the assumption that IRDS enables to make *better* decisions is difficult. It is challenging to compare situations with and without IRDS, knowing that outcomes on single experiment do not inform about the quality of the decision.

Ideally, a comparative study should have been performed on a large number of parallel identical universes. In this theoretic study, each universe should have been be isolated, so that an action in one universe would not affect the course of action of other universes. Such conditions are obviously unrealistic. Such an experiment could have been possible in numerical simulation, but creating models realistic enough to embrace the variety of interactions happening in projects is challenging, and would have consume too much of the

time allocated for the PhD. Time constraints also made impossible to track decisions and consequences on ongoing projects in the real-world.

We therefore chose to focus on historical cases. This approach also has its own limitations. This choice imposed us to deal uncomplete information and participants memories potentially biases. Moreover, the participants had to dedicate time besides the missions for which they were evaluated. So they were not immediately available to work with the decision analyst, and imposed time restrictions when available. This prevented us to examine more into detail some cases.

We also acknowledged that framing the decision problem and the actions upfront can discourage the decision maker to think broader than the frame presented. Moreover, IRDS may not include all the alternatives that are actually available – e.g. technical solutions not documented or unusual actions. Another bias is related to data gathering by beliefs elicitation and modeling: if the beliefs are inaccurate, the computation can provide results that are mathematically correct but do not conform to the actual state of reality. IRDS decision problem model is the results of assumptions and modeling choices we have made. Consequently, the functional relationships that we impose through our model can also introduce biases as these assumptions may not reflect the beliefs of the people using IRDS.

Finally, using the IRDS requires time and efforts in terms of data gathering and beliefs modeling. In the case where IRDS would lead to the same decision as to the current practice, the use of IRDS would have involved unnecessary expenses – or expenses would have been involved to increase the confidence. In such case, by investigating decision alternatives, the organization can gain insights that can be useful for other purposes. However, this gain is difficult to quantify.

6.3. Perspectives

Since we have highlighted the limitations of the research presented in this dissertation, we suggest further studies to collect empirical evidence that better decisions are made on ongoing projects with IRDS. Moreover, studies would provide interesting insights by measuring the value of the decision support framework in the company from a broader perspective than the decision problems considered individually. The research on the implementation of the framework in company settings should be continued by exploring ways to facilitate the data collection process and communication between the three roles involved in IRDS. Devising practices that integrate IRDS requirements alongside the digital transformation of the company would allow for better management of information exchanges and accelerate the decision-making process. Concurrently, considering an information system that takes advantage of knowledge capitalization would enhance the use of IRDS.

The prospect of being able to identify the best moment to postpone a resources allocation serves as a continuous incentive for future research. Moreover, solving problems and making decisions in a dynamic and uncertain environment is not limited to the automotive industry, and we believe that this work on a decision support framework could serve as a basis for further developments in other sectors.

7. References

[1] Forsberg, K., and Mooz, H., 1991, "The Relationship of System Engineering to the Project Cycle," INCOSE Int. Symp., **1**(1), pp. 57–65.

[2] Boehm, B., 2000, "Spiral Development : Experience , Principles , and Refinements," Spiral Dev. Work. Febr. 9, 2000, (July), p. 49.

[3] Cooper, R. G., 1990, "Stage-Gate Systems: A New Tool for Managing New Products," Bus. Horiz., **33**(3), pp. 44–54.

[4] Yassine, A., and Braha, D., 2003, "Complex Concurrent Engineering and the Design Structure Matrix Method," Concurr. Eng., **11**(3), pp. 165–176.

[5] Meier, C., Browning, T. R., Yassine, A. A., and Walter, U., 2015, "The Cost of Speed: Work Policies for Crashing and Overlapping in Product Development Projects," IEEE Trans. Eng. Manag., **62**(2), pp. 237–255.

[6] Qian, Y., Xie, M., Goh, T. N., and Lin, J., 2010, "Optimal Testing Strategies in Overlapped Design Process," Eur. J. Oper. Res., **206**(1), pp. 131–143.

[7] Weber, J., 2009, *Automotive Development Processes*, Springer Berlin Heidelberg, Berlin, Heidelberg.

[8] Bullinger, H.-J., and Warschat, J., eds., 1996, *Concurrent Simultaneous Engineering Systems*, Springer London, London.

[9] Becker, M. C., Salvatore, P., and Zirpoli, F., 2005, "The Impact of Virtual Simulation Tools on Problem-Solving and New Product Development Organization," Res. Policy, **34**(9), pp. 1305–1321.

[10] Thomke, S. H., 1998, "Simulation, Learning and R&D Performance: Evidence from Automotive Development," Res. Policy, **27**(1), pp. 55–74.

[11] Tan, C. L., and Vonderembse, M. A., 2006, "Mediating Effects of Computer-Aided Design Usage: From Concurrent Engineering to Product Development Performance," J. Oper. Manag., **24**(5), pp. 494–510.

[12] Yassine, A., Kim, K.-C., Roemer, T., and Holweg, M., 2004, "Investigating the Role of IT in Customized Product Design," Prod. Plan. Control, **15**(4), pp. 422–434.

[13] West, J., and Iansiti, M., 2003, "Experience, Experimentation, and the Accumulation of Knowledge: The Evolution of R&D in the Semiconductor Industry," Res. Policy, **32**(5), pp. 809–825.

[14] Thomke, S. H., 1998, "Managing Experimentation in the Design of New Products," Manage. Sci., **44**(6), pp. 743–762.

[15] Thomke, S., 2000, "The Effect of 'Front-Loading' Problem-Solving on Product Development Performance," J. Prod. Innov. Manag., **17**(2), pp. 128–142.

[16] Renzi, C., Leali, F., and Di Angelo, L., 2017, "A Review on Decision-Making Methods in Engineering Design for the Automotive Industry," J. Eng. Des., **28**(2), pp. 118–143.

[17] Chen, W., Hoyle, C., and Wassenaar, H. J., 2013, *Decision-Based Design*, Springer London, London.

[18] Martins, J. R. R. A., and Hwang, J. T., 2013, "Review and Unification of Methods for

Computing Derivatives of Multidisciplinary Computational Models," AIAA J., **51**(11), pp. 2582–2599.

[19] de Weck, O., Agte, J., Sobieszczanski-Sobieski, J., Arendsen, P., Morris, A., and Spieck, M., 2007, "State-of-the-Art and Future Trends in Multidisciplinary Design Optimization," *48th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, American Institute of Aeronautics and Astronautics, Reston, Virigina.

[20] Tahera, K., Earl, C., and Eckert, C., 2017, "A Method for Improving Overlapping of Testing and Design," IEEE Trans. Eng. Manag., **64**(2), pp. 179–192.

[21] Mocko, G., Malak, R., Paredis, C., and Peak, R., 2004, "A Knowledge Repository for Behavioral Models in Engineering Design," *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, American Society of Mechanical Engineers.

[22] Alter, S., 1994, "Why Persist with DSS When the Real Issue Is Improving Decision Making," IEEJ Trans. Electron. Inf. Syst., **114**(3), pp. 310–315.

[23] Power, D. J., 2002, *Decision Support Systems: Concepts and Resources for Managers*, Greenwood/Quorum Books, Westport, CT.

[24] Hayen, R. L., 2006, "Investigating Decision Support Systems Frameworks," Issues Inf. Syst., **VII**(2), pp. 9–13.

[25] Renault, C. D., 2016, *Atlas Renault 2015*.

[26] Blessing, L. T. M., and Chakrabarti, A., 2009, *DRM, a Design Research Methodology*, Springer London, London.

[27] Dictionary, M.-W., "Decision" [Online]. Available: https://www.merriam-webster.com/dictionary/decision. [Accessed: 01-Oct-2019].

[28] Howard, R., 1966, "Decision Analysis: Applied Decision Theory," Proc. Fourth Int. Conf. Oper. Res., pp. 55–71.

[29] Klein, G., Associates, K., and Ara, D., 2008, "Naturalistic Decision Making," **50**(3), pp. 456–460.

[30] Adams, E., and Simon, H. A., 1962, "Models of Man, Social and Rational: Mathematical Essays on Rational Human Behavior in a Social Setting.," J. Philos., **59**(7), p. 177.

[31] Bell, D. E., Raiffa, H., and Tversky, A., 1988, "Descriptive, Normative, and Prescriptives Interactions in Decision-Making," *Decision Making*, D.E. Bell, H. Raiffa, and A. Tversky, eds., Cambridge University Press, Cambridge, pp. 9–30.

[32] Belton, V., and Stewart, T. J., 2002, *Multiple Criteria Decision Analysis*, Springer US, Boston, MA.

[33] Altshuller, G., 1999, *The Innovation Algorithm:TRIZ, Systematic Innovation and Technical Creativity*, Technical Innovation Center, Inc., Worcester.

[34] Saaty, R. W., 1987, "The Analytic Hierarchy Process—What It Is and How It Is Used," Math. Model., **9**(3–5), pp. 161–176.

[35] Zahedi, F., 1986, "The Analytic Hierarchy Process: A Survey of the Method and Its Applications," Interfaces (Providence)., **16**(4), pp. 96–108.

[36] Malak, R. J., Aughenbaugh, J. M., and Paredis, C. J. J., 2009, "Multi-Attribute Utility Analysis in Set-Based Conceptual Design," Comput. Des., **41**(3), pp. 214–227.

[37] Earl, C., Johnson, J., and Eckert, C., 2005, "Complexity," *Design Process Improvement: A Review of Current Practice*, J. Clarkson, and C. Eckert, eds., Springer, London, pp. 174–197.

[38] Bernoulli, D., 1738, "Exposition of a New Theory on the Measurement of Risk," Econometrica, **22**(1), p. 23.

[39] von Neumann, J., and Morgenstern, O., 2007, *Theory of Games and Economic Behavior (60th Anniversary Commemorative Edition)*, Princeton University Press, Princeton.

[40] Clemen, R. T., 1997, *Making Hard Decisions, an Introduction to Decision Analysis*, Duxbury.

[41] Edwards, W., Miles, R. F. J., and von Winterfeldt, D., 2007, *Advances in Decision Analysis*, Cambridge University Press, Cambridge.

[42] Raiffa, H., 1968, *Decision Analysis*, Longman Higher Education Division.

[43] Schlaifer, R., 1969, *Analysis of Decisions Under Uncertainty*, McGraw-Hill, New York.

[44] Tribus, M., 1969, *Rational Descriptions, Decisions, and Designs*, Pergamon Press, New York.

[45] Winkler, R. L., 1972, *Introduction to Bayesian Inference and Decision*, Holt, Rinehart & Winston, New York.

[46] Brown, R. U., Kahr, A. S., and Peterson, C., 1974, *Decision Analysis for the Manager*, Holt, Rinehart & Winston, New York.

[47] Keeney, R. L., and Raiffa, H., 1976, *Decisions with Multiple Objectives*, Wiley, New York.

[48] Moore, P. G., and Thomas, H., 1976, *The Anatomy of Decisions*, Penguin Books, New York.

[49] Kaufman, G. J., and Thomas, H., 1977, *Modern Decision Analysis*, Penguin Books, New York.

[50] LaValle, I. H., 1978, *Fundamentals of Decision Analysis*, Holt, Rinehart & Winston, New York.

[51] Holloway, C. A., 1979, *Decision Making under Uncertainty*, Prentice-Hall, Englewoods Cliffs, NJ.

[52] Howard, R., and Abbas, A., 2015, *Foundations of Decision Analysis*, Prentice Hall, New-York.

[53] Shupe, J., Allen, J., Muster, D., and Mistree, F., 1988, "Decision-Based Design: Some Concepts and Research Issues," *Expert Systems*, A. Kusiak, ed.

[54] Hazelrigg, G. A., 1998, "A Framework for Decision-Based Engineering Design," J. Mech. Des., **120**(4), p. 653.

[55] Howard, R., 1966, "Information Value Theory," IEEE Trans. Syst. Sci. Cybern., **2**(1), pp. 22–26.

[56] Matheson, J., 1968, "The Economic Value of Analysis and Computation," IEEE Trans. Syst. Sci. Cybern., **4**(3), pp. 325–332.

[57] Bradley, S. R., and Agogino, A. M., 1994, "An Intelligent Real Time Design Methodology for Component Selection: An Approach to Managing Uncertainty," J. Mech. Des., **116**(4), p. 980.

[58] Ling, J. M., Aughenbaugh, J. M., and Paredis, C. J. J., 2006, "Managing the Collection of Information Under Uncertainty Using Information Economics," J. Mech. Des., **128**(4), p. 980.

[59] Thompson, S. C., and Paredis, C. J. J., 2010, "An Investigation Into the Decision Analysis of Design Process Decisions," J. Mech. Des., **132**(12), p. 121009.

[60] Radhakrishnan, R., and McAdams, D. A., 2005, "A Methodology for Model Selection in Engineering Design," J. Mech. Des., **127**(3), p. 378.

[61] Panchal, J. H., Paredis, C. J. J., Allen, J. K., and Mistree, F., 2008, "A Value-of-Information Based Approach to Simulation Model Refinement," Eng. Optim., **40**(3), pp. 223–251.

[62] Bayes, M., and Price, M., 1763, "An Essay towards Solving a Problem in the Doctrine of Chances. By the Late Rev. Mr. Bayes, F. R. S. Communicated by Mr. Price, in a Letter to John Canton, A. M. F. R. S.," Philos. Trans. R. Soc. London, **53**, pp. 370–418.

[63] Lee, P. M., 2012, *Bayesian Statistics: An Introduction*, Wiley.

[64] Dubois, D., and Prade, H., 2010, "Panorama Des Nouvelles Méthodes de Traitement de l'incertitude et de l'imprécision."

[65] Wang, Q., Lee, B. D., Augenbroe, G., and Paredis, C. J. J., 2017, "An Application of Normative Decision Theory to the Valuation of Energy Efficiency Investments under Uncertainty," Autom. Constr., **73**, pp. 78–87.

[66] Thiry, M., 2002, "Combining Value and Project Management into an Effective Programme Management Model," Int. J. Proj. Manag., **20**(3), pp. 221–227.

[67] Head, G. L., 1967, "An Alternative to Defining Risk as Uncertainty," J. Risk Insur., **34**(2), pp. 205–214.

[68] Knight, F. H., 1921, *Risk, Uncertainty and Profit*, Houghton Mifflin Harcourt Publishing Company, Boston.

[69] Ayyub, B. M., and Chao, R.-J., 1997, "Uncertainty Modeling in Civil Engineering with Structural and Reliability Applications," *Uncertainty Modeling and Analysis in Civil Engineering*, CRC Press, New York, pp. 3–32.

[70] Klir, G. J., and Yuan, B., 1995, *Fuzzy Sets and Fuzzy Logic: Theory and Applications*, Prentice Hall, Upper Saddle River, NJ.

[71] Oberkampf, W., DeLand, S., Rutherford, B., Diegert, K., and Alvin, K., 1999, "A New Methodology for the Estimation of Total Uncertainty in Computational Simulation," *40th Structures, Structural Dynamics, and Materials Conference and Exhibit*, American Institute of Aeronautics and Astronautics, Reston, Virigina.

[72] Haukaas, T., 2003, "Types of Uncertainties, Elementary Data Analysis, Set Theory, Reliability and Structural Safety."

[73] Isukapalli, S. S., Roy, A., and Georgopoulos, P. G., 1998, "Stochastic Response Surface Methods (SRSMs) for Uncertainty Propagation: Application to Environmental and Biological Systems," Risk Anal., **18**(3), pp. 351–363.

[74] Kiureghian, A. Der, 1989, "Measures of Structural Safety Under Imperfect States of Knowledge," J. Struct. Eng., **115**(5), pp. 1119–1140.

[75] Hassanzadeh, S., 2012, "Analysis of the Causes of Delay in Collaborative Decision-Making under Uncertainty in Pharmaceutical R and D Projects," Toulouse, INPT.

[76] Galbraith, J. R., 1973, *Designing Complex Organizations*, Addison-Wesley Pub. Co.

[77] Klir, G. J., 2005, "Uncertainty and Information: Foundations of Generalized Information Theory," *Uncertainty and Information: Foundations of Generalized Information Theory*, Wiley-IEEE Press.

[78] Zadeh, L. A., 2006, "Generalized Theory of Uncertainty (GTU)—Principal Concepts and Ideas," Comput. Stat. Data Anal., **51**(1), pp. 15–46.

[79] Lipshitz, R., and Strauss, O., 1997, "Coping with Uncertainty: A Naturalistic Decision-Making Analysis," Organ. Behav. Hum. Decis. Process., **69**(2), pp. 149–163.

[80] Milliken, F. J., 1987, "Three Types of Perceived Uncertainty about the Environment: State, Effect, and Response Uncertainty," Acad. Manag. Rev., **12**(1), p. 133.

[81] Thompson, J. D., 1967, *Organizations in Action: Social Science Bases of Administrative Theory*, McGraw-Hill Book Company.

[82] De Finetti, B., 1937, "La Prévision: Ses Lois Logiques, Ses Sources Subjectives," Ann. l'Institut Henri Poincaré.

[83] Ramsey, F. P., 1931, "Truth and Probability," *The Foundations of Mathematics and Other Logical Essays*, R.& R.B. Braithwaite, ed., London, pp. 156–198.

[84] Savage, L. J., 1954, *Foundations of Statistics*, Wiley, New-York.

[85] Thunnissen, D. P., 2003, "Uncertainty Classification for the Design and Development of Complex Systems," 3rd Annu. Predict. Methods Conf., p. 16.

[86] Walker, W. E., Harremoës, P., Rotmans, J., van der Sluijs, J. P., van Asselt, M. B. A., Janssen, P., and Krayer von Krauss, M. P., 2003, "Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support," Integr. Assess., **4**(1), pp. 5–17.

[87] Jones, M. C., Cline, M., and Ryan, S., 2006, "Exploring Knowledge Sharing in ERP Implementation: An Organizational Culture Framework," Decis. Support Syst., **41**(2), pp. 411–434.

[88] Matt, C., Hess, T., and Benlian, A., 2015, "Digital Transformation Strategies," Bus. Inf. Syst. Eng., **57**(5), pp. 339–343.

[89] Aladwani, A. M., 2001, "Change Management Strategies for Successful ERP Implementation," Bus. Process Manag. J., **7**(3), pp. 266–275.

[90] Otto, K. N., 1995, "Measurement Methods for Product Evaluation," Res. Eng. Des., **7**(2), pp. 86–101.

[91] Antonsson, E. K., and Otto, K. N., 1995, "Imprecision in Engineering Design," J. Mech. Des., **117**(B), pp. 25–32.

[92] Schlosser, J., and Paredis, C. J. J., 2010, "Managing Multiple Sources of Epistemic Uncertainty in Engineering Decision Making," SAE Tech. Pap. Ser., **1**(April 2007).

[93] Helton, J. C., Johnson, J. D., and Oberkampf, W. L., 2004, "An Exploration of Alternative Approaches to the Representation of Uncertainty in Model Predictions," Reliab. Eng. Syst. Saf., **85**(1–3), pp. 39–71.

[94] Klir, G. J., 2004, "Generalized Information Theory: Aims, Results, and Open Problems," Reliab. Eng. Syst. Saf., **85**(1–3), pp. 21–38.

[95] Yager, R. R., 2004, "Uncertainty Modeling and Decision Support," Reliab. Eng. Syst. Saf.,

85(1–3), pp. 341–354.

[96] Shafer, G., 1976, *A Mathematical Theory of Evidence*, Princeton University Press.

[97] Pearl, J., 1988, "On Probability Intervals," Int. J. Approx. Reason., **2**(3), pp. 211–216.

[98] Pearl, J., 1990, "Reasoning with Belief Functions: An Analysis of Compatibility," Int. J. Approx. Reason., **4**(5–6), pp. 363–389.

[99] Dubois, D., and Prade, H., 1998, "Possibility Theory: Qualitative and Quantitative Aspects," *Quantified Representation of Uncertainty and Imprecision*, P. Smets, ed., Springer Netherlands, Dordrecht, pp. 169–226.

[100] Zadeh, L. ., 1978, "Fuzzy Sets as a Basis for a Theory of Possibility," Fuzzy Sets Syst., **1**(1), pp. 3–28.

[101] Walley, P., 1991, *Statistical Reasoning with Imprecise Probabilities*, Chapman and Hall, London.

[102] Zadeh, L. A., 1965, "Fuzzy Sets," Inf. Control, **8**(3), pp. 338–353.

[103] Moore, R. E., 1966, *Interval Analysis*, Prentice-Hall, Englewoods Cliffs, NJ.

[104] Alefeld, G., and Mayer, G., 2000, "Interval Analysis: Theory and Applications," J. Comput. Appl. Math., **121**(1–2), pp. 421–464.

[105] Neumaier, A., 1991, *Interval Methods for Systems of Equations*, Cambridge University Press, Cambridge.

[106] Kearfott, R. B., and Kreinovich, V., eds., 1996, *Applications of Interval Computations*, Springer US, Boston, MA.

[107] Sissoko, T. M., Jankovic, M., Paredis, C. J. J., and Landel, E., 2018, "An Empirical Study of a Decision-Making Process Supported by Simulation in the Automotive Industry," *Proceedings of the ASME 2018 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference*.

[108] Sissoko, T. M., Jankovic, M., Paredis, C. J. J., and Landel, E., 2019, "A Proposal for a Decision Support Framework to Solve Design Problems in the Automotive Industry," *Proceedings of the ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference IDETC/CIE2019 August 18-21, 2019, Anaheim, CA, USA*, pp. 1–10.

[109] Cooke, E., 1906, "Forecasts and Verifications in Western Australia," Mon. Weather Rev.

[110] Brown, B., 1968, *Delphi Process: A Methodology Used for the Elicitation of Opinions of Experts*, Document No P3925, Santa Monica, CA.

[111] Sackman, H., 1975, *Delphi Critique : Expert Opinion, Forecasting and Group Process*, Lexington Books, Lexington, MA.

[112] Woudenberg, F., 1991, "An Evaluation of Delphi," Technol. Forecast. Soc. Change, **40**(2), pp. 131–150.

[113] Morris, P. A. ., 1977, "Combining Expert Judgments : A Bayesian Approach," Manage. Sci., **23**(7), pp. 679–693.

[114] Morris, P. A., 1974, "Decision Analysis Expert Use," Manage. Sci., **20**(9), pp. 1233–1241.

[115] Albert, I., Donnet, S., Guihenneuc-Jouyaux, C., Low-Choy, S., Mengersen, K., and Rousseau, J., 2012, "Combining Expert Opinions in Prior Elicitation," Bayesian Anal.,

7(3), pp. 503–532.

[116] Colson, A. R., and Cooke, R. M., 2018, "Expert Elicitation: Using the Classical Model to Validate Experts' Judgments," Rev. Environ. Econ. Policy, **12**(1), pp. 113–132.

[117] Grigore, B., Peters, J., Hyde, C., and Stein, K., 2016, "A Comparison of Two Methods for Expert Elicitation in Health Technology Assessments," BMC Med. Res. Methodol., **16**(1), p. 85.

[118] Dallow, N., Best, N., and Montague, T. H., 2018, "Better Decision Making in Drug Development through Adoption of Formal Prior Elicitation," Pharm. Stat., **17**(4), pp. 301–316.

[119] Al-Awadhi, S. A., and Garthwaite, P. H., 2006, "Quantifying Expert Opinion for Modelling Fauna Habitat Distributions," Comput. Stat., **21**(1), pp. 121–140.

[120] Janssen, J. A. E. B., Krol, M. S., Schielen, R. M. J., and Hoekstra, A. Y., 2010, "The Effect of Modelling Expert Knowledge and Uncertainty on Multicriteria Decision Making: A River Management Case Study," Environ. Sci. Policy, **13**(3), pp. 229–238.

[121] Arrow, K. J., 1951, "Alternative Approaches to the Theory of Choice in Risk-Taking Situations," Econometrica, **19**(4), p. 404.

[122] Holt, C. A., and Smith, A. M., 2016, "Belief Elicitation with a Synchronized Lottery Choice Menu That Is Invariant to Risk Attitudes," Am. Econ. J. Microeconomics, **8**(1), pp. 110–139.

[123] Brier, G. W., 1950, "Verification of Forecasts Expressed in Terms of Probability," Mon. Weather Rev., **78**(1), pp. 1–3.

[124] McKelvey, R. D., and Page, T., 1990, "Public and Private Information: An Experimental Study of Information Pooling," Econometrica, **58**(6), p. 1321.

[125] Offerman, T., Sonnemans, J., and Schram, A., 1996, "Value Orientations, Expectations and Voluntary Contributions in Public Goods," Econ. J., **106**(437), p. 817.

[126] Nyarko, Y., and Schotter, A., 2002, "An Experimental Study of Belief Learning Using Elicited Beliefs," Econometrica, **70**(3), pp. 971–1005.

[127] Kadane, J. B., and Winkler, R. L., 1988, "Separating Probability Elicitation from Utilities," J. Am. Stat. Assoc., **83**(402), pp. 357–363.

[128] Kothiyal, A., Spinu, V., and Wakker, P. P., 2010, "Comonotonic Proper Scoring Rules to Measure Ambiguity and Subjective Beliefs," J. Multi-Criteria Decis. Anal., **17**(3–4), pp. 101–113.

[129] Andersen, S., Fountain, J., Harrison, G. W., and Rutström, E. E., 2009, *Estimating Subjective Probabilities*.

[130] Hollard, G., Massoni, S., and Subjective, J. V., 2010, "Subjective Beliefs Formation and Elicitation Rules : Experimental Evidence HAL Id : Halshs-00543828 Centre d ' Economie de La Sorbonne Documents de Travail Du Subjective Beliefs Formation and Elicitation Rules :"

[131] Merkhofer, M. W., 1987, "Quantifying Judgmental Uncertainty: Methodology, Experiences, and Insights," IEEE Trans. Syst. Man. Cybern., **17**(5), pp. 741–752.

[132] Shephard, G. G., and Kirkwood, C. W., 1994, "Managing the Judgmental Probability Elicitation Process: A Case Study of Analysmanager Interaction," **41**(4).

[133] Laskey, K. B., 1995, "Sensitivity Analysis for Probability Assessments in Bayesian Networks," IEEE Trans. Syst. Man. Cybern., **25**(6), pp. 901–909.

[134] Leurent, B., Gomes, M., Faria, R., Morris, S., Grieve, R., and Carpenter, J. R., 2018, "Sensitivity Analysis for Not-at-Random Missing Data in Trial-Based Cost-Effectiveness Analysis: A Tutorial," Pharmacoeconomics, **36**(8), pp. 889–901.

[135] Saltelli, A., Chan, K., and Scott, E. M., 2009, *Sensitivity Analysis*, Wiley.

[136] Cacuci, D. G., 2003, *Sensitivity & Uncertainty Analysis, Volume 1: Theory*, Chapman and Hall/CRC.

[137] Rocquigny, E. de, Devictor, N., and Tarantola, S., 2008, *Uncertainty in Industrial Practice: A Guide to Quantitative Uncertainty Management*, Wiley & Sons, Ltd.

[138] Iooss, B., and Lemaître, P., 2015, "A Review on Global Sensitivity Analysis Methods," *Uncertainty Management in Simulation-Optimization of Complex Systems*, D. G., and M. C., eds., Springer Boston, Boston, MA, pp. 101–122.

[139] Felli, J. C., and Hazen, G. B., 1998, "Sensitivity Analysis and the Expected Value of Perfect Information," Med. Decis. Mak., **18**(1), pp. 95–109.

[140] Simon, H. A., 1996, *The Sciences of the Artificial*, MIT Press, Cambridge, MA.

[141] Hazelrigg, G., 1996, *Systems Engineering: An Approach to Information-Based Design*, Prentice-Hall, Upper Saddle River, NJ.

[142] Broy, M., Kirstan, S., Krcmar, H., and Schätz, B., 2014, "What Is the Benefit of a Model-Based Design of Embedded Software Systems in the Car Industry?," *Software Design and Development*, IGI Global, pp. 310–334.

[143] Miles, M., Huberman, M., and Saldaña, J., *Qualitative Data Analysis*, SAGE Publications Inc.

[144] Longhurst, R., 2009, "Interviews: In-Depth, Semi-Structured," *International Encyclopedia of Human Geography*, Elsevier, pp. 580–584.

[145] Broom, A., 2005, "Using Qualitative Interviews in CAM Research: A Guide to Study Design, Data Collection and Data Analysis," Complement. Ther. Med., **13**(1), pp. 65–73.

[146] Almefelt, L., Berglund, F., Nilsson, P., and Malmqvist, J., 2006, "Requirements Management in Practice: Findings from an Empirical Study in the Automotive Industry," Res. Eng. Des., **17**(3), pp. 113–134.

[147] Robson, C., and McCartan, K., 2016, *Real World Research : A Resource for Users of Social Research Methods in Applied Settings*, John Wiley & Sons, Chichester, UK.

[148] Hofstede, G., 2001, *Culture's Consequences – Second Edition: Comparing Values, Behaviors, Institutions and Organizations Across Nations*, SAGE Publications, Inc, London.

[149] Gautam, V., and Blessing, L., 2009, "How Cultural Characteristics Influence Design Processes: An Empirical Study," *Volume 8: 14th Design for Manufacturing and the Life Cycle Conference; 6th Symposium on International Design and Design Education; 21st International Conference on Design Theory and Methodology, Parts A and B*, ASME, pp. 937–943.

[150] Lee, B. D., and Paredis, C. J. J., 2014, "A Conceptual Framework for Value-Driven Design and Systems Engineering," Procedia CIRP, **21**, pp. 10–17.

[151] Terwiesch, C., Loch, C. H., and Meyer, A. De, 2002, "Exchanging Preliminary Information in Concurrent Engineering: Alternative Coordination Strategies," Organ. Sci., **13**(4), pp. 402–419.

[152] Clark, K., and Fujimoto, T., 1987, "Overlapping Problem Solving in Product Development."

[153] Yassine, A. A., Chelst, K. R., and Falkenburg, D. R., 1999, "A Decision Analytic Framework for Evaluating Concurrent Engineering," IEEE Trans. Eng. Manag., **46**(2), pp. 144–157.

[154] NASA, 2016, *Standards for Models and Simulation - NASA-STD7009A*.

[155] Reich, Y., 2010, "My Method Is Better!," Res. Eng. Des., **21**(3), pp. 137–142.

[156] Jetter, A., "Elicitation — Extracting Knowledge from Experts," *Knowledge Integration*, Physica-Verlag, Heidelberg, pp. 65–76.

[157] Palisade, 2018, "Products & Services" [Online]. Available: https://www.palisade.com/products.asp.