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THÈSE



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Léah RIFI

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ABSTRACT

With healthcare demand rising worldwide, hospital services are increasingly needed. Hospitals' performance is tightly linked to their surgical suite performance. Indeed, the surgical suite is an important revenue and expense center with over 40% of the hospital's budget dedicated to it (Macario et al. 1997) and 60% of the patient coming into the hospital for surgical intervention (Fugener et al. 2017). This makes it necessary for surgical suites to be efficient.

However, running a profitable surgical suite is quite hard and requires a methodological approach due to the complexity of its functioning: the diversity of patient pathways, the multiplicity of professions, the tight link with upstream and downstream wards, the synchronization of several resources and logistic flows (drug and medical devices), etc. On the other hand, durations variability and disruptions inherent in medical care like emergency cases are the main factors and events that degrade the scheduled execution and involve the staff making decisions frequently to preserve the surgical suite activity in an optimal way. Therefore, OR planning and scheduling activities are of increasing interest to the scientific community.

In this PhD thesis, we focus on offline operational and online operational levels (Hans and Vanberkel 2012). This leads us to the following research questions: (1) How can we assess the robustness and the resilience of the schedule before its execution (prospective way)? (2) How can we replay the schedule to have feedback and assess the decisions made during its execution (retrospective way)?

The contribution of this manuscript is threefold: (1) we propose a digital twin-based decision support system for the prospective and retrospective simulation and analysis of the operating room schedule execution, (2) we describe a standardized methodology to conceive, build and implement this tool in any surgical suite, (3) This methodology is applied to an operating room inspired by the Private Hospital of La Baie (Vivalto Santé group, France), in order to have a proof of concept allowing to simulate an operating program prospectively and retrospectively.

Keywords: Operating room, Digital twin, Operating room management, Decision support system, Modeling and simulation, Uncertainties.

RESUME

Avec l'augmentation de la demande de soins dans le monde, les services hospitaliers sont de plus en plus sollicités. Leur performance est étroitement liée à la performance de leur bloc opératoire. En effet, le bloc opératoire est un important centre de revenus et de dépenses puisqu'il représente 40% du budget de l'hôpital (Macario et al. 1997), et que 60% des patients viennent à l'hôpital pour une intervention chirurgicale (Fugener et al. 2017). Il est donc nécessaire que les blocs opératoires soient efficaces.

Cependant, cela est rendu difficile par la complexité de leur organisation due à la diversité des parcours patients, la multiplicité des métiers, les liens étroits avec les services amont et aval, la synchronisation de plusieurs ressources et flux logistiques (personnels, médicaments et dispositifs médicaux), etc. D'autre part, la variabilité des durées et les perturbations inhérentes à la pratique médicale, comme les cas d'urgence, sont les principaux facteurs et événements qui dégradent le programme opératoire et impliquent que le personnel prenne de fréquentes décisions pour maintenir l'activité du bloc opératoire de manière optimale. Par conséquent, les activités de planification et d'ordonnancement du bloc opératoire intéressent de plus en plus la communauté scientifique.

Dans cette thèse de doctorat, nous nous concentrons sur les niveaux opérationnels hors ligne et en ligne (Hans et Vanberkel 2012). Ceci nous amène aux questions de recherche suivantes : (1) Comment évaluer la robustesse et la résilience du programme opératoire avant son exécution (dimension prospective) ? (2) Comment rejouer le programme opératoire pour avoir un retour d'expérience et évaluer les décisions prises lors de son exécution (dimension rétrospective) ?

La contribution de ce manuscrit est triple : (1) Nous proposons un système d'aide à la décision basé sur un jumeau numérique pour la simulation et l'analyse prospective et rétrospective de l'exécution du programme opératoire. (2) Nous décrivons une méthodologie standardisée pour concevoir, construire et mettre en œuvre cet outil dans n'importe quel bloc opératoire. (3) Cette méthodologie est appliquée à un bloc opératoire inspiré de l'Hôpital Privé de La Baie (groupe Vivalto Santé), afin de disposer d'une preuve de concept permettant de simuler un programme opératoire de façon prospective et rétrospective.

Mots clés : Bloc opératoire, Jumeau numérique, Régulation, Outil d'aide à la décision, Modélisation et simulation, Incertitudes

RESUME LONG EN FRANÇAIS

Avec l'augmentation de la demande de soins dans le monde, les hôpitaux se doivent d'être plus performants. Cela est étroitement lié à la performance de leurs blocs opératoires. En effet, le bloc opératoire est centre de revenus et de dépenses important : 40 à 50 % du budget de l'hôpital lui est consacré, ce qui représente 30 % des coûts globaux des soins de santé (Macario et al., 1997 ; Kaye et al., 2020). Deux études mentionnent que le coût horaire d'un bloc opératoire en 2014 est compris entre 2 000 € et 2 500 € (Mercier et Naro 2014 ; Childers et Maggard-Gibbons, 2018). En France, le coût moyen du parcours d'un patient opéré varie de 1 316 € (chirurgie courte ou ambulatoire) à 16 653 € (chirurgie lourde). En ce qui concerne le flux de patients, en 2021, en France, pour les services de médecine, de chirurgie et d'obstétrique (MCO pour « Médecine, Chirurgie, Obstétrique »), 38 % des patients hospitalisés (12 millions) ont été admis pour une intervention chirurgicale (4,6 millions). 2,8 millions (61%) des patients opérés le sont en ambulatoire¹. Pour toutes ces raisons, il est nécessaire que les blocs opératoires soient efficaces et rentables.

Dans ce manuscrit, nous faisons la différence entre **le bloc opératoire** (BO), qui est l'ensemble du service hospitalier dédié à la chirurgie, et **la salle d'opération** (SO) ou salle de bloc, qui est une pièce à l'intérieur de du bloc opératoire où l'intervention chirurgicale est pratiquée. Par exemple, aux États-Unis, un bloc opératoire compte en moyenne 6 à 7 salles d'opération².

Tout au long de cette thèse, nous avons eu l'opportunité de travailler avec trois hôpitaux français différents : *l'Hôpital Privé de La Baie* (HPB, GIE Vivalto Santé, Avranches, France), *le Centre Hospitalier d'Albi* (CHA, Albi, France) et *le Centre Hospitalier Intercommunal de Créteil* (CHIC, Créteil, France). Afin de nous assurer que nos travaux de recherche répondent au besoin du système de soins et de ses acteurs, nous avons formé un comité d'experts avec des directeurs d'hôpitaux, des chirurgien.nnes, des anesthésistes et des ingénieurs. Grâce à eux, nous nous sommes assurés de la pertinence de notre question de recherche, et avons défini un périmètre d'étude en termes de KPI, d'incertitudes, et de décisions opérationnelles.

¹ https://www.atih.sante.fr/sites/default/files/public/content/4416/atih_chiffres_cles_h_2021_.pdf

² <https://www.definitivehc.com/resources/healthcare-insights/number-of-us-operating-rooms>

1. Partie 1 - Contexte et problématiques

Dans cette première partie, nous décrivons le contexte et les problématiques en lien avec notre projet de recherche, tant du point de vue métier, que du point de vue de la communauté scientifique.

1.1. Chapitre 1. Contexte de l'étude : le bloc opératoire et ses salles opératoires

Ce Chapitre est divisé en 5 sections. Tout d'abord, nous proposons un aperçu du fonctionnement d'un bloc opératoire (section 1). Puis, nous décrivons les différents types de parcours patient possibles pour un patient admis en chirurgie (section 2). Nous donnons ensuite une présentation approfondie des différentes ressources requises (section 3) et des indicateurs de performance utilisés (section 4) dans les blocs opératoires. Enfin, nous concluons ce chapitre par une discussion autour des problématiques sélectionnées pour cette thèse (section 5). Ci-dessous un court résumé de chacune des sections.

Veillez noter que dans ce premier chapitre, nous structurons et synthétisons les connaissances que nous avons recueillies sur le fonctionnement général des blocs opératoires de nos trois partenaires. Ces connaissances sont basées sur (1) des observations sur place, (2) des entretiens avec le personnel et (3) l'analyse de la base de données des logiciels du bloc opératoire. Les lecteurs experts de l'organisation des blocs opératoires peuvent ne pas lire ce chapitre.

Section 1. Le bloc opératoire est un environnement complexe qui interagit constamment avec les services internes ou externes de l'hôpital. D'une part, en interne, l'organisation du bloc opératoire s'articule autour de trois types de processus : les processus décisionnels (planifier et gérer l'activité), les processus opérationnels (prodiguer des soins aux patients) et les processus supports (permettre la bonne exécution du parcours patient). D'autre part, le bloc opératoire est fortement lié à des services externes. Ces services peuvent être (1) à l'intérieur ou à l'extérieur de l'hôpital, et (2) médicaux ou non médicaux. La performance du bloc opératoire dépend donc fortement de la façon dont le flux de patients, des informations et des services sont gérés. Dans notre étude nous nous concentrons sur les flux internes, c'est-à-dire sur les processus qui se déroulent entre l'arrivée et la sortie du patient au bloc opératoire.

Section 2. L'activité principale du bloc opératoire est de fournir des soins aux patients. Ce faisant, le service, qui accueille une variété de patients, propose plusieurs parcours différents. On distingue notamment le type d'admission (en ambulatoire ou hospitalisation), le type de programmation (électif ou non-électif) et le niveau d'urgence (non urgent, semi-urgent, urgent).

Les patients en ambulatoire sont admis, subissent une intervention chirurgicale et quittent l'hôpital le jour même, tandis que les patients hospitalisés restent au moins une nuit à l'hôpital. Les patients en ambulatoire et hospitalisés diffèrent en termes de type de chirurgie, de date d'admission, de nombre de nuits d'hospitalisation et de parcours du patient. Dans notre étude, nous prenons en compte à la fois les patients hospitalisés et les patients en ambulatoire ; nous les modélisons de la même manière car ils suivent les mêmes parcours patients et sont opérés dans les mêmes blocs opératoires.

La chirurgie des patients électifs n'est pas urgente : ils sont programmés des semaines ou des mois à l'avance. Les patients non-électifs arrivent à l'improviste et doivent être traités

immédiatement (patient urgent) ou dans les jours qui suivent (patient semi-urgent). Dans notre étude, nous considérons les patients électifs/non-électifs ainsi que les patients non urgents, semi-urgents et urgents. Nous les modélisons de différentes manières.

Section 3. Les ressources requises au bon fonctionnement du bloc opératoire peuvent être matérielles ou humaines. Les ressources matérielles peuvent être achetées ou louées. Elles englobent les moyens de transport, l'équipement de protection individuelle, les instruments chirurgicaux (réutilisable après stérilisation), les fournitures chirurgicales (non réutilisables), le matériel d'anesthésie, les médicaments, le matériel d'imagerie et de visualisation, les systèmes d'information et de communication et les ressources d'infrastructure.

Pour ce qui est des ressources humaines, le personnel est médical, paramédical, technique et administratif. Le personnel médical et paramédical prodigue des soins directs au patient, tandis que l'équipe administrative veille au bon déroulement de la planification et à l'exécution du planning opératoire. Le personnel technique, bien qu'il ne rentre généralement pas dans les salles opératoires, contribue au fonctionnement du service. Le bloc opératoire est un service multidisciplinaire où les individus travaillent ensemble vers le même objectif qui est de fournir des soins de qualité aux patients mais avec des organisations de travail différentes.

Section 4. La performance d'un bloc opératoire est définie à partir de trois critères : (1) le nombre d'heures supplémentaires (sa diminution reflète de meilleures conditions de travail pour le personnel), (2) les temps d'attente du patient (des temps d'attente plus courts satisferont les patients, et (3) le taux d'utilisation des salles d'opération (des taux d'utilisation élevés assurent une efficacité organisationnelle rentable). Les taux de débordement, d'enchaînement, de surutilisation, et de sous-utilisation sont des indicateurs qui viennent en complément du taux d'utilisation.

D'autre part, l'organisation d'un bloc opératoire est dite robuste si elle peut maintenir son niveau de performance sans s'adapter, malgré des perturbations aléatoires (exemple : les incertitudes sur les durées opératoires). L'organisation d'un bloc opératoire est résiliente si après qu'une perturbation aléatoire telle l'arrivée d'urgence lui ait faite baisser en performance, elle peut revenir au niveau de performance antérieur.

Section 5 – Synthèse. Le bon fonctionnement du bloc opératoire nécessite de synchroniser les ressources à l'intérieur *et* à l'extérieur du bloc avec l'exécution du parcours du patient. Par conséquent, l'organisation d'un bloc opératoire performant repose sur la communication et la coordination des ressources (1) en son sein, et (2) entre le bloc opératoire et le monde extérieur. Ce point est particulièrement complexe pour les raisons que nous présentons maintenant.

Tout d'abord, le personnel du bloc opératoire est composé de ressources humaines variées (personnel médical, personnel paramédical, personnel technique, personnel administratif) qui ont toutes besoin d'un accès rapide à des ressources matérielles adéquates (fournitures, locaux, stockages...). D'autre part, en raison des interactions requises entre le bloc opératoire et les unités extérieures, les dysfonctionnements apparaissant dans l'un ont un impact sur l'autre, et vice-versa. Tout retard, absence ou erreur peut entraîner une perturbation et entraver l'exécution du planning opératoire. En effet, si la bonne ressource n'est pas disponible au bon endroit et au bon moment, le parcours patient s'arrêtera. Cela vaut autant pour un.e chirurgien.nne.ne que

pour un.e infirmier.ère. Dans ce contexte, le personnel doit avoir une bonne communication, une bonne collaboration, une bonne coordination et le respect des processus établis.

1.2. Chapitre 2. Revue de littérature et travaux similaires

Ce Chapitre est divisé en 4 sections. Dans un premier temps, nous abordons le problème de planification et d'ordonnement des bloc opératoires (section 1). Ensuite, nous discutons des méthodes de management prédictive et réactive des perturbations au BO (section 2). Ensuite, nous proposons une courte bibliographie sur l'utilisation du jumeau numérique et de la simulation à évènement discrets dans le domaine de la santé – et plus particulièrement au bloc opératoire (section 3). Enfin, nous clôturons le chapitre avec une synthèse (section 4). Ci-dessous un court résumé de chacune des sections.

Section 1. Il existe quatre niveaux de décision en matière de planification et d'ordonnement au bloc opératoire. Premièrement, le niveau **stratégique** (long-terme) traite de la planification et de l'allocation de la capacité et des problèmes de combinaison de cas. Deuxièmement, le niveau **tactique** (moyen-terme) s'attaque au problème du calendrier de la chirurgie principale (MSSP). Troisièmement, le niveau opérationnel hors ligne à court terme lié au problème de planification de la chirurgie (qui peut être divisé en problèmes de planification avancée et d'allocation). Quatrièmement, le niveau opérationnel en ligne en temps réel consiste dans le problème d'exécution du calendrier.

Section 2. La gestion des perturbations au niveau opérationnel se divise en deux enjeux principaux : (1) la gestion prédictive des perturbations : les perturbations sont anticipées et traitées avant qu'elles se produisent ; (2) la gestion réactive des perturbations : les perturbations sont traitées après qu'elles se sont produites.

Section 3. La simulation à évènements discrets (SED) est une technique de modélisation qui permet de modéliser le comportement d'un système sous la forme d'une séquence d'événements dans le temps. Elle est notamment utilisée dans les blocs opératoires pour évaluer la performance de l'organisation, ou pour soutenir les processus de planification et de programmation. Même si la littérature scientifique regorge d'études sur le jumeau numérique (JN), il n'en existe toujours pas de définition unique. On retrouve cependant certaines caractéristiques communes d'une définition à l'autre : un JN doit (1) être la réplique virtuelle d'un jumeau physique désigné, (2) être capable de simuler le comportement du jumeau physique en temps réel ou presque, et (3) permettre une communication bidirectionnelle avec le jumeau physique. Bien que moins développés que dans l'industrie, les jumeaux numériques sont également utilisés dans les soins de santé. On retrouve des JN de personnes, d'organes et de parcours patient.

Section 4 – Synthèse. Après avoir étudié les problématiques du terrain et les problématiques scientifiques liées au bloc opératoire, nous avons décidé de focaliser notre étude sur la gestion des perturbations aléatoires au niveau opérationnel. Notre question de recherche générale est la suivante : « Comment améliorer et maintenir la performance d'un bloc opératoire soumis à des incertitudes ? ». Nous proposons 5 questions de recherche plus spécifiques :

Q1. Comment anticiper les déviations avant l'exécution du programme ?

Q2. Comment évaluer la qualité du management prédictif des déviations ?

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- Q3. Comment évaluer la qualité du management réactif des déviations ?
 - Q4. Comment identifier la cause racine des manques de performance ?
 - Q5. Comment entraîner les régulateurs au management des déviations ?

Dans le cadre de notre étude, nous étudions la performance du bloc opératoire via le taux d'utilisation et le taux de débordement des salles opératoires, ainsi que le temps d'attente des patients au bloc opératoire. Nous prenons en compte 3 types d'incertitudes : l'arrivée de patients non-électifs, la variabilité des durées d'activité et la disponibilité des ressources. Nous nous concentrons sur un type de décision : la programmation des arrivées de patients non électifs.

Sur la base de notre analyse documentaire et de nos observations sur le terrain, nous avons décidé de proposer un système d'aide à la décision hors ligne basé sur un jumeau numérique utilisant la simulation à événements discrets. Cette outil devrait nous permettre d'améliorer les décisions prises au niveau opérationnel en ligne via une analyse prospective et rétrospective du programme opératoire.

2. Partie 2 – Proposition d'une méthode et d'un outil

Dans la Partie 1, nous avons présenté le contexte et la problématique de notre recherche. Dans cette Partie 2, nous décrivons notre proposition de solution.

2.1. Chapitre 3. Proposition de solution

Ce Chapitre est divisé en 5 sections. Nous décrivons une méthodologie d'analyse prospective du programme opératoire prévisionnel (section 1), une méthodologie d'analyse rétrospective du programme effectivement réalisé (section 2), une méthodologie pour la formation du régulateur de BO à la gestion des perturbations (section 3), une méthode standardisée pour construire un jumeau numérique de BO (section 4). Nous concluons avec une synthèse (section 5). Ci-dessous (voici) un court résumé de chacune des sections.

Dans ce résumé de chapitre, nous utilisons les termes suivants :

- **programme prévisionnel** ou programme opératoire prévisionnel (POP) : programme théorique disponible la veille de la journée opératoire. Il contient des interventions non urgentes et semi-urgentes.
- **programme réalisé** ou programme effectivement réalisé (PER) : programme tel qu'il s'est vraiment déroulé lors de la journée opératoire. Il contient des interventions non urgentes, semi-urgentes et urgentes.

Le régulateur se sert du POP comme guide au court de la journée opératoire bien qu'il sache que le PER n'en sera pas identique ; les perturbations aléatoires (incertitudes sur les durées, arrivées d'urgences) creusent en effet un écart entre les deux programmes.

Section 1. La méthodologie d'**analyse prospective** du programme opératoire prévisionnel a pour objectifs d'anticiper les perturbations avant l'exécution du POP (Q1), et d'évaluer la qualité de la gestion prédictive des perturbations (Q2). Cette méthodologie correspond à notre contribution #1. Les étapes de l'analyse prospective sont les suivantes : évaluer pour le POP : (1) la faisabilité, (2) la performance, (3) la robustesse, (4) la résilience et (5) la meilleure stratégie de programmation des cas non-électifs.

Section 2. La méthodologie d'**analyse rétrospective** du planning effectivement réalisé a pour objectifs d'évaluer la qualité de la gestion réactive des perturbations (Q3), et d'identifier si le manque de performance provient de décisions hors ligne ou en ligne (Q4). Au cours de cette analyse, nous souhaitons notamment fournir un retour d'informations sur le déroulement du POP qui a conduit à l'obtention du PER. Cette méthodologie correspond à notre contribution #2. Les étapes de l'analyse rétrospective sont les suivantes : évaluer pour le PER : (1) la performance, (2) l'impact de la stratégie de programmation des cas non-électifs effectivement choisie, et (3) les causes racines des écarts à la performance.

Section 3. Dans le Chapitre II, nous avons décrit un outil d'aide à la décision capable de simuler l'exécution du programme opératoire dans un environnement stochastique (variabilité de la durée et arrivées supplémentaires de cas non-électifs) tout en suivant une stratégie de gestion des perturbations spécifiques. Nous proposons d'utiliser ce même environnement virtuel pour permettre au régulateur de tester ses propres stratégies afin de le former. Cela nous permet de

répondre à notre question de recherche « Comment former les régulateurs à la gestion des perturbations ? » (Q5). Cette méthodologie correspond à notre contribution #3.

Section 4. Une fois ces trois méthodologies présentées, nous proposons une méthode standardisée en 5 étapes pour construire le jumeau numérique d'un bloc opératoire à l'aide de la simulation d'événements discrets. Les étapes sont les suivantes : (1) recueillir les données, (2) traiter et analyser les données, (3) construire un modèle déterministe, (4) implémenter des incertitudes, (5) développer les fonctionnalités de l'outil d'aide à la décision. Cet outil modélise l'exécution d'un programme prévisionnel ou exécuté, dans un environnement déterministe ou stochastique, tout en respectant les ressources et les contraintes du patient, en appliquant des stratégies de programmation d'interventions non-électives, et en calculant des KPIs (section 4).

2.2. Chapitre 4. Modélisation et simulation du déroulement du programme opératoire

Dans ce Chapitre divisé en 3 sections, nous décrivons comment nous modélisons et simulons l'exécution du programme opératoire, qu'il soit prévisionnel ou réalisé. D'abord, nous proposons différentes manières de modéliser le bloc opératoire en fonction des données disponibles (section 1). Ensuite, nous proposons une application de cette méthode sur le cas d'un de nos hôpitaux partenaires (section 2). Nous concluons avec une synthèse (section 3). Ci-dessous voici un court résumé de chacune des sections.

Section 1. Les processus du bloc opératoire (PBO) sont complexes et nécessitent des ressources humaines et matérielles variées à différents moments et lieux. Puisqu'il est courant de ne pas avoir accès à tous les jalons temporels inclus dans le processus (exemples : heure d'arrivée et de départ du patient au bloc, heure d'entrée et de sortie de salle du patient, etc.), nous proposons de définir deux modèles de PBO : (1) un **modèle agrégé** basé sur les données horodatées disponibles dans le logiciel de bloc, et (2) un **modèle détaillé** basé sur les données horodatées disponibles dans le logiciel de bloc *et* sur nos observations sur site. Le modèle agrégé comprend naturellement moins de jalons et d'activité(s) que le modèle détaillé. **Nous modélisons l'exécution du programme prévisionnel à l'aide du processus détaillé et nous modélisons le programme réalisé à l'aide du processus agrégé.**

D'autre part, pour modéliser de manière exhaustive les processus du bloc opératoire, nous avons besoin d'informations sur les ressources utilisées : quelle ressource est nécessaire ? Quand ? Où ? Combien de temps ? Cependant, comme pour les horodatages, les informations relatives aux ressources ne sont pas toujours disponibles dans la base de données de la salle d'opération. Par conséquent, nous proposons de définir deux types de contraintes sur les ressources à respecter lors de la modélisation des PBO : (1) les **contraintes strictes** sont les contraintes (éventuellement incomplètes) imposées par les valeurs des jalons temporels de la base de données sur les ressources matérielles et humaines, et (2) les **contraintes flexibles** qui sont les contraintes imposées de la base de données sur les salles opératoires seulement. **Nous utilisons des contraintes flexibles pour modéliser le déroulement du programme réalisé, et des contraintes strictes pour modéliser l'exécution du prévisionnel.**

Section 2. Nous proposons une application concrète des modèles et contraintes théoriques proposés dans la section 1.

Section 3 - Synthèse. Nous modélisons l'exécution du programme prévisionnel à l'aide du processus détaillé et nous modélisons le programme réalisé à l'aide du processus agrégé. Nous utilisons des contraintes flexibles pour modéliser le déroulement du programme réalisé, et des contraintes strictes pour modéliser l'exécution du prévisionnel.

2.3. Chapitre 5. Calculer les durées

Ce Chapitre est divisé en 5 sections. Dans un premier temps nous proposons et appliquons une méthode pour corriger les données d'horodatage initialement disponibles dans la base de données (section 1). Ensuite, nous calculons les durées de chaque activité du parcours patient à partir des jalons corrigés (section 2). Puis, nous utilisons ces durées historiques afin de calculer un maximum de jalons initialement non relevés dans la base de données (section 3). Enfin, nous combinons toutes ces données temporelles du programme réalisé pour calculer les jalons et les durées du programme prévisionnel (section 4). Nous concluons avec une synthèse (section 5). Ci-dessous voici un court résumé de chacune des sections.

Pour information, les données d'horodatage (ou jalons temporels) initialement disponibles dans la base de données correspondent au programme réalisé. En effet, les jalons prévisionnels ne sont pas préservés dans le logiciel de bloc. Des exemple de jalons sont : heure d'arrivée du patient au bloc opératoire, heure d'incision, heure de suture, etc.

Section 1. Nous proposons et appliquons une méthode pour corriger deux types d'erreur dans les données d'horodatage initialement disponibles : les incohérences sur (1) les jalons au sein d'un même parcours patient (exemple : le patient se fait inciser avant d'entrer en salle), et (2) l'utilisation des salles opératoires (exemple : deux patients sont en salle au même moment).

Section 2. Nous utilisons les jalons restant dans la base données pour calculer les durées des activités du programme réalisé. Ces durées permettront : (1) de simuler l'exécution du programme réalisé dans notre DT-DSS, (2) de calculer les durées prévisionnelles discrètes, et (3) de calculer les durées prévisionnelles stochastiques.

Section 3. Nous combinons les jalons temporels corrigés (section 1) et les durées discrètes calculées (section 2) pour en déduire les jalons manquant de la base de données tout en respectant les contraintes sur l'utilisation des blocs opératoires et la cohérence des jalons d'un même parcours patient. Pour cela, nous implémentons les étapes suivantes :

- Corriger les jalons aux extrémités du parcours patient : entrée au bloc, sortie du bloc.
- Corriger chaque parcours patient de manière indépendante : incision, suture et entrée en salle de réveil.
- Corriger les parcours des patients en se basant sur l'utilisation des salles opératoires : entrée en salle, sortie de salle.

Les étapes sont toutes répétées jusqu'à ce que le nombre de jalons corrigés cesse d'augmenter. En effet, puisque les horodatages sont dépendants les uns des autres, en corriger un peut permettre d'en corriger un autre.

Section 4. Les sections précédentes nous ont permis de corriger, de compléter l'horodatage du programme réalisé. Nous allons maintenant utiliser ces données historiques pour déterminer

l'horodatage du programme prévisionnel (jalons et durées), ainsi que pour calculer des durées prévisionnelles stochastiques. Cette tâche est particulièrement complexe à cause de la non-standardisation des noms de chirurgie dans notre base de données. En effet, cette information est habituellement utilisée avec l'ID du/de la chirurgien.nne pour estimer les durées prévisionnelles. Nous proposons et appliquons différentes méthodes de calculs en fonction des données disponibles dans la base de données.

Section 5 – Synthèse. Dans cette section, nous avons proposé et illustré une méthodologie permettant de corriger et de compléter les horodatages et les valeurs de durée des plannings réalisés et prévisionnels extraits de la base de données réelles pour alimenter le jumeau numérique.

2.4. Chapitre 6. Modéliser et programmer les interventions non-électives

Ce Chapitre est divisé en 3 sections, Nous décrivons la modélisation des arrivées de cas non-électifs (section 1) et la modélisation de leur programmation (section 2). Nous concluons avec une synthèse (section 3). Ci-dessous voici un court résumé de chacune de ces sections.

Section 1. Nous souhaitons modéliser l'arrivée des cas non-électifs lors de la simulation de l'exécution du programme prévisionnel, et lors de la simulation du programme réalisé. Nous appelons « programme initial », le programme tel qu'il est avant le lancement de la simulation. Notez que :

- Un programme prévisionnel initial contient des interventions non-urgentes et *potentiellement* des interventions non-électives semi-urgentes.
- Un programme réalisé initial contient des interventions non-urgentes ainsi que *potentiellement* des interventions semi-urgentes et urgentes.

Premièrement, dans le cadre de l'analyse prospective, nous souhaitons modéliser l'arrivée des cas non-électifs au cours de l'exécution du programme prévisionnel à deux dates distinctes : (1) lors de la réunion de programmation : dans ce cas, le programme prévisionnel initial ne contient que des interventions non urgentes), et (2) la veille de la journée opératoire : dans ce cas, le programme prévisionnel initial contient des interventions non urgentes et potentiellement semi-urgentes.

Deuxièmement, afin de réaliser notre analyse rétrospective, nous souhaitons reproduire l'arrivée des cas-électifs telle qu'elle était dans la réalité. Il n'y a pas besoin de modéliser d'interventions non-électives additionnelles.

Enfin, pour l'outil d'entraînement des régulateurs, nous souhaitons proposer un environnement virtuel pour permette de (1) simuler un programme prévisionnel ou réalisé, (2) d'inclure ou pas des cas non-électifs du programme initial, et (3) de rajouter ou pas des cas non-électifs additionnels.

D'une part, nous modélisons les cas non-électifs additionnels par (1) une heure d'entrée dans la salle d'opération, (2) la liste des chirurgiens capables d'effectuer la chirurgie, (3) la liste des salles d'opération dans lesquelles le cas peut être programmé, (4) un type d'anesthésie, (5) le niveau d'urgence du cas et (6) la durée des activités du parcours (du) patient. Ainsi, avant d'être

programmée, une intervention non-élective additionnelle n'a pas de chirurgien, d'anesthésiste ou de salle d'opération attribués. D'autre part, nous modélisons les scénarios d'arrivées de cas non-électifs additionnels par (1) le niveau d'urgence des cas, (2) le nombre de cas entrants et (3) la fenêtre d'heures d'arrivée des cas au bloc opératoire.

Section 2. Nous proposons 6 stratégies de programmation pour les interventions non-électives : (1) maintenir la programmation initiale (si on simule un programme réalisé), (2) first in first out, (3) best fit, (4) worst fit, (5) programmation manuelle et (6) file d'attente.

Section 3 – Synthèse. Notre DT-DSS permet de modéliser et de programmer des interventions non-électives, qu'elles soient urgentes ou semi-urgentes.

3. Partie 3 – Preuve de concept

Dans la Partie 1, nous avons présenté le contexte et la problématique de notre recherche. Dans la Partie 2, nous avons décrit notre proposition de solution. Dans cette troisième et dernière partie, nous fournissons une preuve de concept basée sur un cas d'étude.

3.1. Chapitre 7. Présentation du cas d'étude

Le Chapitre 7 est divisé en 3 sections. Tout d'abord, nous décrivons les établissements de santé de nos partenaires (section 1). Ensuite, nous discutons des bases de données fournies par chacun d'eux, nous expliquons comment nous avons structuré et traité ces données, et nous présentons une méthode pour sélectionner un cas d'étude pertinent (section 2). Puis, nous mettons en œuvre cette méthode et présentons le cas d'étude que nous avons retenu pour notre recherche (section 3). Nous concluons avec une synthèse (section 4).

Section 1. Nous présentons nos trois partenaires hospitaliers : *l'Hôpital Privé de La Baie* (GIE Vivalto Santé, Avranches, France), *le Centre Hospitalier d'Albi* (Albi, France) et *le Centre Hospitalier Intercommunal de Créteil* (Créteil, France). La combinaison de ces trois sites nous permet d'avoir accès à des hôpitaux : des secteurs publics et privé, régionaux et universitaires, avec différents volumes d'activité, des services de chirurgie ambulatoire, une maternité, une unité de soins intensifs, des services d'urgence, différentes tailles de bloc opératoires, différentes populations de patients dans les services d'urgences.

Section 2. Nous proposons une méthode pour choisir un cas d'étude permettant de : (1) simuler le déroulement de programmes prévisionnels et réalisés pour une journée entière, (2) tester la robustesse d'un programme en simulant son exécution dans un environnement où les durées sont stochastiques, (3) tester la résilience d'un programme en simulant son exécution dans un environnement où il y a des arrivées stochastiques de cas non électifs, et (4) être représentatif d'une journée opératoire normale.

Section 3. Nous présentons pour le programme prévisionnel et le programme réalisé du cas d'étude : le planning des vacations, le diagramme de Gantt de l'activité des salles opératoires, la description des interventions non-electives, et le calcul des KPI.

Section 4 - Synthèse. Dans ce chapitre, nous avons extrait et présenté notre cas d'étude.

3.2. Chapitre 8. Application des analyses prospective et rétrospective.

Le Chapitre 8 est divisé en 4 sections. Dans un premier temps, nous présentons les expérimentations à réaliser pour appliquer les analyses prospective. (section 1). Ensuite, nous décrivons les résultats obtenus pour l'analyse prospective (section 2) et pour l'analyse rétrospective (section 3). Enfin, nous proposons une synthèse de chapitre qui fait le lien entre les deux analyses et qui explicite les actions concrètes qui pourraient être prise après l'application de notre démarche d'aide à la décision (section 4). Ci-dessous un court résumé de chacune des sections.

Section 1. Nous présentons les différentes expérimentations nécessaires à l'application des analyses prospective et rétrospective. Pour ce faire nous décrivons la configuration des paramètres du modèles.

Sections 2 et 3. Nous appliquons les étapes 1-5 de l'analyse prospective et l'étape 2 de l'analyse rétrospective sur notre cas d'étude.

Section 4 – Synthèse. Nous présentons des actions concrètes à appliquer après l'implémentation de nos deux analyses.

4. Conclusion

La conclusion est divisée en 4 sections. Dans un premier temps, nous rappelons la problématique adressée au cours de la thèse (section 1). Puis, nous mettons en évidence les contributions réalisées (section 2). Enfin, nous discutons des limites et des améliorations possibles (section 3), avant de terminer en évoquant de futures pistes de recherche (section 4). Ci-dessous voici un court résumé de chacune des sections.

Section 1. Comme nous l'avons démontré dans la partie 1 de cette thèse de doctorat, le bloc opératoire est un environnement intrinsèquement complexe et soumis à des incertitudes. Cela est dû aux nombreux moyens humains et techniques impliqués et devant être synchronisés pour chaque cas d'opération. Cette complexité implique de maîtriser la problématique de planification et d'ordonnancement des cas chirurgicaux. Le problème de planification et d'ordonnancement est divisé en 4 niveaux de décision : (1) stratégique (problème de planification de la capacité), (2) tactique (problème de planification de la chirurgie principale), (3) opérationnel hors ligne (problème de planification de la chirurgie) et (4) opérationnel en ligne (problème de gestion de l'exécution du programme opératoire). Dans le Chapitre II, nous montrons qu'il existe peu de travaux de recherche pour traiter les problèmes survenant au niveau opérationnel par rapport à l'ensemble des contributions aux 2 niveaux supérieurs. En effet, des observations et des entretiens dans 5 blocs opératoires hospitaliers nous ont permis de mettre en évidence qu'il n'existe pas d'outil d'aide à la décision aidant le personnel du bloc opératoire à chaque fois qu'une perturbation survient. C'est le point de départ de cette thèse qui se concentre sur le niveau opérationnel.

À la fin du niveau opérationnel hors ligne, un planning prévisionnel est créé. Ce planning est utilisé par le responsable de la salle d'opération comme guide lors du niveau opérationnel en ligne (exécution du planning), bien que l'on sache dès le début de la journée qu'il ne sera pas entièrement respecté. En effet, une partie de la complexité du bloc opératoire réside dans le caractère stochastique de son activité. Nous nous concentrons sur deux types d'incertitudes : (1) la variabilité des durées et (2) les arrivées non électives. Ces incertitudes peuvent perturber l'exécution du planning. Par conséquent, les niveaux opérationnels sont fortement liés à la problématique de (la) gestion des perturbations.

Dans le chapitre II, nous montrons que la *gestion prédictive des perturbations* peut avoir lieu à la fois au niveau hors ligne et en ligne ; son objectif est d'anticiper et de prendre en compte les perturbations avant même qu'elles ne se produisent. D'autre part, la *gestion réactive des perturbations* est liée uniquement au niveau en ligne, au cours duquel le responsable de la salle d'opération ne fournit un remède à une perturbation qu'après qu'elle se soit produite. La gestion des perturbations vise à maintenir, voire à améliorer, la performance du programme prévisionnel tout au long de son exécution. Dans ce travail, nous évaluons la performance de la salle d'opération en fonction de trois indicateurs clés : (1) l'utilisation de la salle d'opération, (2) les heures supplémentaires du personnel et (3) le temps d'attente moyen des patients.

Cela nous amène à notre question générale de recherche : « Comment favoriser et maintenir la performance de l'organisation d'un bloc opératoire dans des conditions d'incertitude ? ». Nous nous concentrons sur la question de la gestion des perturbations au niveau opérationnel.

Section 2. Dans cette section, nous revenons sur toutes les contributions que ce manuscrit apporte, à savoir :

- (1) Une méthodologie prospective pour évaluer la qualité de la gestion prévisionnelle des perturbations.
- (2) Une méthodologie rétrospective pour évaluer la qualité de la gestion réactive.
- (3) Une méthodologie pour former le régulateur à la gestion des perturbations dans un environnement virtuel.
- (4) Une méthodologie pour concevoir et construire un système d'aide à la décision d'un bloc opératoire basé sur un jumeau numérique.
- (5) Une proposition de solution pour modéliser l'exécution du programme prévisionnel et du programme réalisé
- (6) Une méthodologie pour nettoyer et compléter les horodatages du parcours du patient dans une base de données de bloc opératoire du monde réel.
- (7) Un prototype d'un système d'aide à la décision basé sur un jumeau numérique appliqué à une étude de cas réelle.

Section 3. Dans cette section, nous établissons un parallèle entre les limites de notre étude et les améliorations possibles que nous pourrions mettre en œuvre dans les recherches futures. Premièrement, il aurait été intéressant d'avoir accès une **base de données** plus riche et plus fiable. Deuxièmement, la **modélisation du bloc opératoire** pourrait être améliorée en termes de ressources (humaines et matérielles), d'incertitudes, et de périmètre spatial (étendre l'étude au-delà du bloc opératoire afin d'englober des départements voisins qui ont un impact sur le BO). Troisièmement, des développements intéressants pour **l'outil d'aide à la décision** pourraient inclure le rajout (1) d'indicateurs de performance d'utilisation de ressources, (2) de stratégies de gestion des perturbations *au cours* de l'exécution du programme, (3) de stratégies de gestion de perturbation *avant* l'exécution du programme, et (4) de la prise en compte du point de vue d'experts terrain testant notre OAD. Enfin, une dernière piste d'amélioration pourrait porter sur **les cas d'étude**. D'une part, il serait intéressant d'avoir un panel de différents plannings d'une journée pour avoir une vision plus exhaustive des informations que notre DT-DSS peut fournir en fonction de la situation. D'autre part, nous utilisons un cas d'étude d'une journée. Or, les gestionnaires de salle d'opération doivent en réalité prendre des décisions en matière de planification et de rééchelonnement ne se limitant pas à l'horizon d'une journée. Par exemple, un cas électif peut être reporté au lendemain ou à la semaine suivante. Il en va de même pour les cas semi-urgents. Une amélioration importante serait d'examiner des cas d'étude de plusieurs jours (par exemple, un cas d'étude d'une semaine) et d'élaborer des décisions telles que la programmation ou le report d'un cas sur un horizon d'une semaine.

Section 4. Au cours de ce projet de recherche, nous avons développé un jumeau numérique de bloc opératoire basé sur la simulation d'événements discrets et nous l'avons utilisé comme système d'aide à la décision hors ligne pour améliorer la gestion prédictive et réactive des perturbations. Dans cette section, nous discutons des perspectives de recherches futures : la génération automatique de jumeau numérique de bloc opératoire et le passage en mode « en ligne » de notre outil.

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LIST OF ABBREVIATIONS

KPI	Key Performance Indicator
OR	Operating Room
DT	Digital Twin
DES	Discrete Event Simulation
LRA	Locoregional Anesthesia
OIP	Ophthalmologic Induction Preparation
PACU	Post Anesthesia Care Unit
MSSP	Master Surgery Scheduling Problem
SSP	Surgery Scheduling Problem
DT-DSS	Digital Twin Decision Support System

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INTRODUCTION

With healthcare demand rising worldwide, medical services are increasingly needed. Hospitals' performance is tightly linked to their surgical suite's performance. Indeed, the surgical suite is an important revenue and expense center with 40%-50% of the hospital's budget dedicated to it, which amounts to 30% of overall healthcare costs (Macario et al. 1997; Kaye et al. 2020). Two studies mention a surgical suite hourly cost in 2014 between 2,000€ and 2,500€ (Mercier and Naro 2014; Childers and Maggard-Gibbons 2018). In France, the average cost of a surgical patient pathway ranges from 1,316€ (short or ambulatory surgery) to 16,653€ (heavy surgery). Concerning patient flow, in 2021, in France, for medicine, surgery and obstetric services (French acronym: MCO for "Médecine, Chirurgie, Obstétrique"), 38% of hospitalized patients (12 million) were admitted for a surgery (4.6 million). 2,8 million (61%) of surgery patients are outpatients³. For all these reasons, it is necessary for surgical suites to be efficient and profitable.

In this manuscript, we make the difference between **the surgical suite** (suite), which is the entire hospital service dedicated to surgery, and **the operating room** (OR), which is a room within the surgical suite where the surgery is performed. For example, in the US, a surgical suite has an average of 6 to 7 ORs⁴.

In Figure 1, we illustrate a patient pathway for a surgery (blue boxes) and the surgical suite within the hospital as well as its interactions with external services. We represent intra-hospital non-clinical units (green boxes), intra-hospital diagnostic units that can delay patient access to the surgical suite (orange boxes), and units outside hospitals (grey boxes). The full arrows represent the usual patient pathway: the patient is admitted in the hospital, goes to the ward, enters the surgical suite, and comes back to the ward before being discharged. The dashed arrows represent a similar process, with the only difference being that the patient stops by the intensive care unit after the surgical suite. This research work focuses on the surgical suite.

³ https://www.atih.sante.fr/sites/default/files/public/content/4416/atih_chiffres_cles_h_2021_.pdf

⁴ <https://www.definitivehc.com/resources/healthcare-insights/number-of-us-operating-rooms>

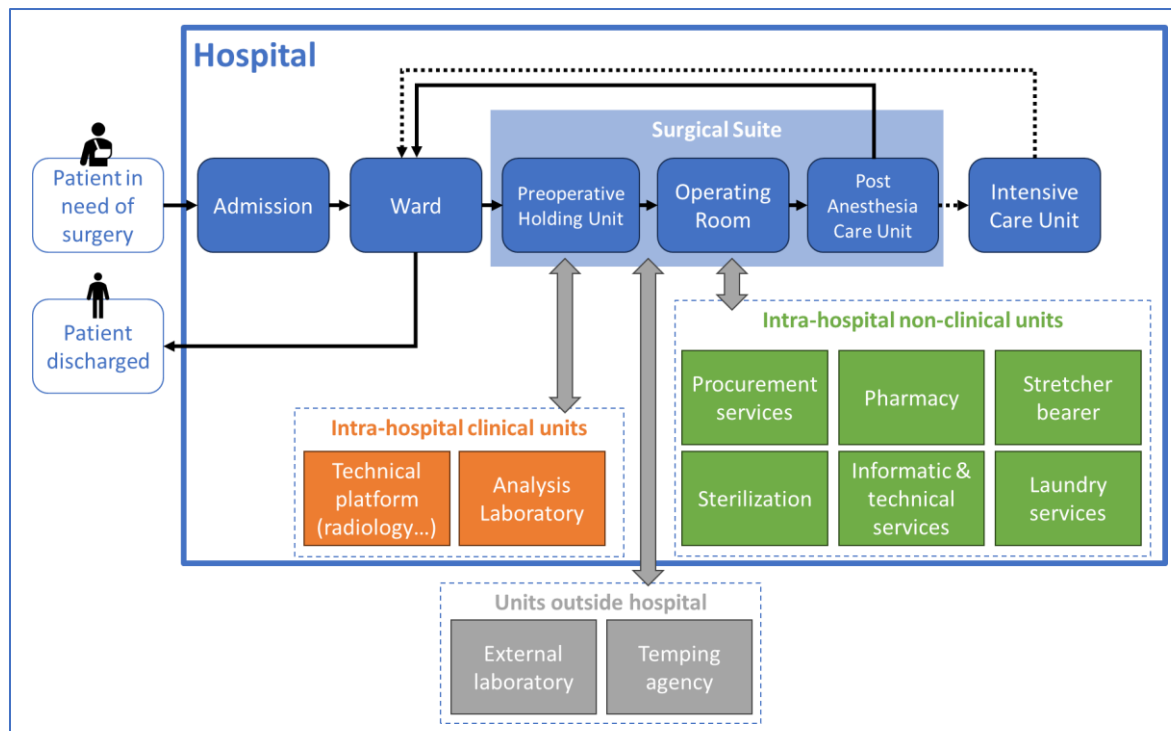


Figure 1 –Interactions between the surgical suite and the other services.

Running a surgical suite is quite complex. First, patient pathways change depending on the **patient admission type**: some patients come and go during the same day (outpatients, ambulatory care), while others stay at least one-night (inpatients, conventional care). Second, patient pathway can also differ based on the **patient emergency level**: patients either need immediate and acute care (non-elective) or can wait for up to several months before their surgery (elective). Third, the surgical suite is the workplace of a **multiplicity of medical and paramedical professions** such as surgeons, anesthesiologists, and registered nurses. Although they all aim at providing care to the patient, they can have different – sometimes even conflicting – work organization. Fourth and finally, as displayed in Figure 1, the surgical suite must maintain a close relationship with **upstream wards** that supply patients (inpatient units, outpatient units, emergency services, intense care unit), **downstream wards** that retrieve patients (inpatient units, outpatient units, intense care unit), **intra-hospital non-clinical units** that directly affect the efficiency of the surgical suite (pharmacy, sterilization, procurement services, informatics services, technical services, stretcher-bearers, laundry services...), **intra-hospital diagnostic units** that can delay patient access to the surgical suite (technical platform, analysis laboratory...), and companies outside the hospital (external laboratory, temping agency...) (S. Zhu et al. 2019). In Chapter I of this thesis, we will discuss in more details the relationship between the surgical suite and outside units because it can affect the organization and the scheduling of the surgeries.

The complexity of the surgical suite's organization is worsened by the uncertainties inherent to medical practice that degrade the activity. They both impact and come from the patient, human resources, and material resources. They can lead to **duration variability** such as cases lasting longer or shorter than expected, or they can lead to **unexpected events** such as no-shows, cancellations, postponements, and emergency arrivals.

Within this context, the objective of this research work is to promote a **performant, robust** and **resilient** surgical suite organization - we define these key words in Table 1 and review them in more depth in Chapter I and Chapter II. This goal contributes directly to surgical suite efficiency and profitability, and indirectly to high quality medical care and patient safety.

Table 1 – Proposed definitions

Key words	Proposed definitions
Performant	We define performance based on three key performance indicators (KPIs): <ol style="list-style-type: none"> 1. staff working conditions (overtime), 2. patient satisfaction (patient waiting time), 3. organization efficiency (OR utilization). We consider these KPIs both together and independently.
Robust	A surgical suite's organization is robust if it can maintain the same level of performance, being able to resist variability of surgery durations or patient arrivals, without a need to adapt.
Resilient	A resilient surgical suite's organization can maintain the same level of performance despite strong disruptions such as emergency arrivals or cancellations.

To reach our objective, we rely on the **operating schedule**, which is the ranked sequence of surgical cases to be performed in each operating room of the surgical suite. For instance, Figure 2 represents a provisional operating schedule for a 4-OR surgical suite with 18 patients. We represented in blue the time during which surgeries can be performed: all 4 rooms open at 8am, OR#1 and OR#2 close at 6pm and OR#3 and OR#4 close at 4pm. In this specific case, ORs are dedicated to a specialty and different surgeons can perform surgeries in the same room.

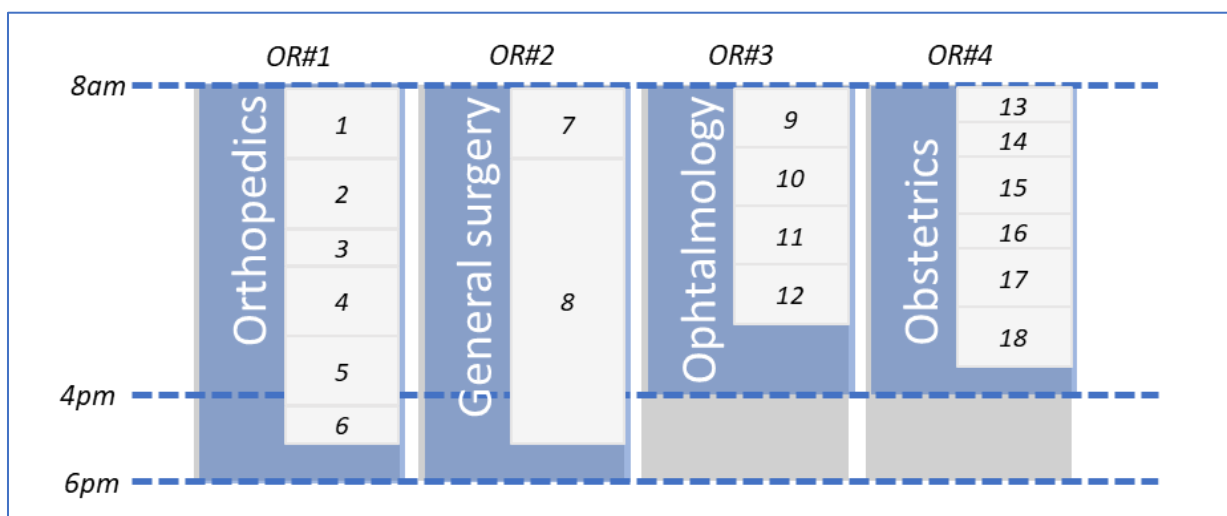


Figure 2 - Example of a provisional operating schedule for a 4-OR surgical suite.

As we will see in Chapter II, the construction of the operating schedule is referred to in the scientific literature as the **OR planning and scheduling problem**. Its activities comprise decisions from four hierarchical levels: strategic, tactical, offline operational, distributing and online operational (Figure 3):

- At the **strategic level** (long-term, up to 10 years), hospital management aligns the available surgical suite’s resources with the forecasted patient demand. This level includes identifying what are the required resources (capacity planning problem) and distribute them between the different surgical specialties (capacity allocation problem).
- The **tactical level** (medium-term, between 6 and 12 months) considers the master surgical scheduling problem (MSSP). It consists in building a cyclic schedule that describes the different shifts available for surgeons to operate on patients. This schedule is usually decided every 6 or 12 months and it spreads over 1 or 2 weeks.
- The **offline operational level** (short term, weekly) tackles the surgery scheduling problem (SSP) and is divided into advanced scheduling and allocation scheduling. It consists in assigning a date, a start time, and resources to each surgery of the following week. When the SSP is resolved in a stochastic environment, it can also be called predictive disruption management (Kamran, Karimi, and Dellaert 2020).
- At the **online operational level** (real-time), the OR manager coordinates the resources, handles disruptions, and makes real-time decisions to smooth the OR schedule execution (Hans and Vanberkel, 2012). These decisions include (1) scheduling new non-elective cases in the current schedule, (2) deciding whether to keep or postpone a case that might go overtime, and (3) re-organizing the schedule when patients don’t show or when surgeries are canceled. The online operational level can be found in the literature under different names such as “OR management operational decision-making on the day of surgery” (Franklin Dexter et al. 2004) or “reactive management” (Kamran, Karimi, and Dellaert 2020).

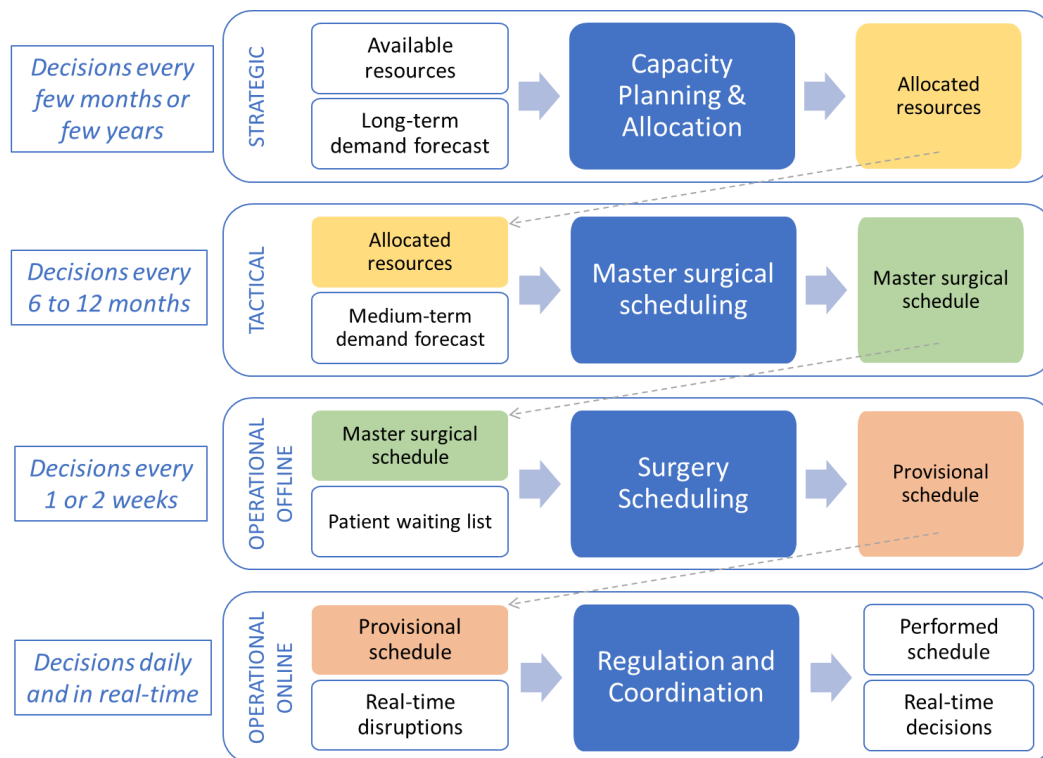


Figure 3 – The 4 decision levels of planning and scheduling activity

The scientific community has shown an increasing interest in planning and scheduling in the operating room. The literature is abundant on strategical, tactical, and offline operational planning of ORs; it focuses mostly on offline decisions. However, in an environment as uncertain as the surgical suite, multiple important gaps can appear between the provisional and the performed schedule. To the best of our knowledge, there are few studies on disruption management at the online operational level. Indeed, as mentioned in (Guerriero and Guido 2011), "Few papers consider on-line scheduling, aimed at modifying an existing schedule since urgent and emergency arrivals".

Several reasons could explain this fact. First, **higher decision levels impact and condition the lower ones**. Thus, if the strategic, tactical, and offline operational levels are not mastered, the benefits of improving the online level are greatly reduced. Second, **working at the operational level requires to make decisions quickly**. Therefore, optimization methods with little or no requirement in terms of reaction time (such as the ones used for higher decision levels) may not be suitable. Third, making decisions at the operational level brings the difficult task of **finding (or developing) mathematical models that consider both the complexity and the stochasticity of the real world**. This is all the more true for online operational decisions. Fourth and finally, the lack of research work on the operational level may be the consequence of the **strong involvement of human resources in the surgical suite organization**. Indeed, since decisions are not all based on explicit rules, teams are left to choose their own. The current *modus operandi* is to tackle organizational issues on the spot during schedule execution: the staff finds empirical solutions to each disruption before moving on to the next one. At the end of the day, except for serious incidents that need the involvement of the hierarchy or outside services, the staff does not revisit past problems.

All these reasons leave us room to improve the disruption management strategies. This is why, in this research work, we wish to build on the existing academic work and further improve the online aspects of the operational level activity management. We make the three following hypothesis: (1) the allocated resources are fixed, (2) the master surgical schedule is fixed, (3) the provisional schedule is fixed.

Within this context, we propose the following general research question: “How can we promote and maintain the performance of a surgical suite’s organization under uncertainties?”

To answer this question, we propose: (1) A methodology for a prospective analysis of the provisional schedule, (2) A methodology for a retrospective analysis of the performed schedule, and (3) A methodology for real-time decision-making virtual training destined to OR managers.

We illustrate the positioning of these 3 methodologies using Figure 4. Based on our literature review and on-site observations, we have decided to propose an **offline digital twin-based decision support system (DT-DSS) to improve the decisions made at the online operational level**. This means that this DT-DSS **directly** supports the prospective analysis of the provisional schedule and of the retrospective analysis of the performed schedule. This DT-DSS could be used by the OR manager to indirectly prepares the schedule execution and provides feedback on it. We detail and justify this choice in Chapter III.

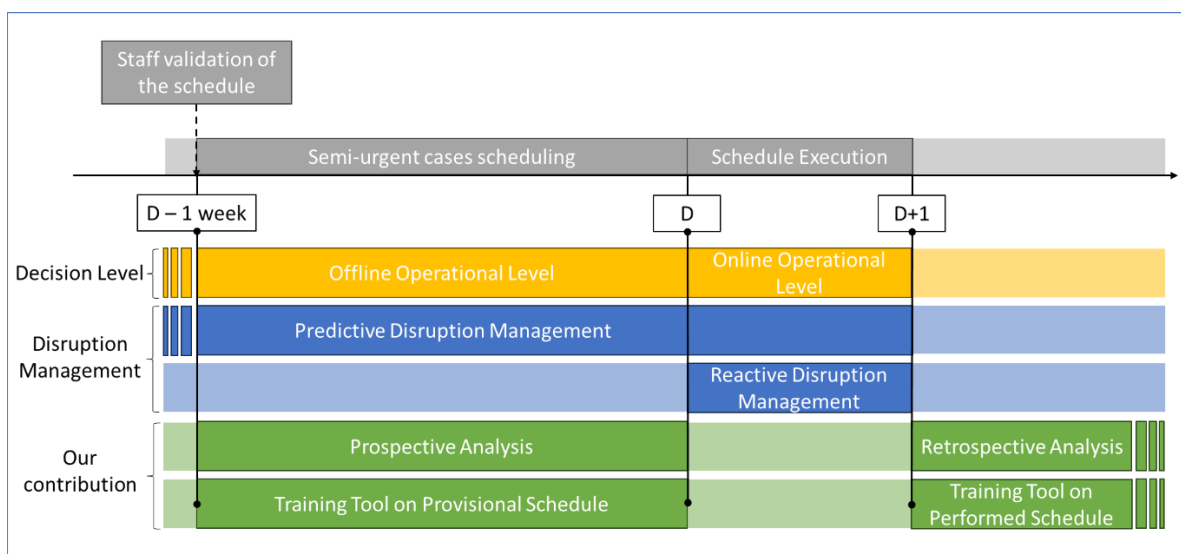


Figure 4 – Research Positioning

We discuss the green boxes’ problematics of Figure 4 in Table 2, and we use a PDCA structure (plan, do, check, act) (Sokovic, Pavletic, and Pipan 2010) to decompose our research question into 5 sub-questions. We discuss this methodology in more details in Chapter III. Since we only focus on offline decisions, we exclude step #2 of the research scope.

As a **proof of concept**, we propose a study case in which we apply these three methodologies to a surgical suite inspired by the *Hôpital Privé de La Baie* (GIE Vivalto Santé, France). To do so, (1) we develop a **digital twin-based decision support system** for the prospective and retrospective simulation and analysis of the operating room schedule execution, and (2) we infer from this prototype a standardized methodology to conceive and build such a tool in any surgical suite.

Table 2 – Proposed methodology

#	Step	When?	Objective	Research Questions	Proposition
1	Plan	Before schedule execution	Plan schedule execution	<p>Q1. How can we anticipate disruption before schedule execution?</p> <p>Q2. How can we assess the quality of the predictive disruption management?</p>	Prospective analysis
2	Do	During schedule execution	Execute the provisional schedule while managing uncertainties	/	/
3	Check	After schedule execution	Provide feedback on the schedule execution	<p>Q3. How can we assess the quality of the reactive disruptions management?</p> <p>Q4. How can we identify whether performance lack stems from offline or online decisions?</p>	Retrospective analysis
4	Act	After schedule execution	Take measures to normalize or improve the process	Q5. How can we train OR managers to disruption management?	Virtual Training

These led us to propose several scientific and technical contributions; we list them in Table 3.

Table 3 - Suggested contributions

#	Domain	Contribution	Q1	Q2	Q3	Q4	Q5	Chapter(s)
1	Methodology	Prospective methodology to assess the quality of the predictive disruption management.	X	X				Chapter III + Chapter VIII
2	Methodology	Retrospective methodology to assess the quality of the reactive management.			X	X		Chapter III + Chapter VIII
3	Methodology	Methodology to train the OR manager on disruption management in a virtual environment.					X	Chapter III
4	Methodology	Methodology to conceive and build a digital twin-based decision support system of a surgical suite.	X	X	X	X	X	Chapter III
5	Model	Proposition of process models for provisional schedule execution and performed schedule execution.	X	X	X	X	X	Chapter IV
6	Data	Methodology to clean and complete the patient pathway timestamps of a real-world surgical suite database.	X	X	X	X	X	Chapter V
7	Result	Prototype of a digital twin-based decision support system applied to a real-world case study.	X	X	X	X	X	Part II + Part III

After this introduction, the remainder of this manuscript is divided into 3 parts that are themselves divided into 9 Chapters.

In Part 1, we present the context of our research and the problematics we focus on. First, based on our on-site observations, staff interviews and database analysis, we present the general functioning of a surgical suite (Chapter I). Second, we provide a background and related works on the planning and scheduling problem, on the disruption management problem, and on digital twin and simulation tools (Chapter II).

In Part 2, we discuss our proposed methodologies and our digital twin-based decision support system (DT-DSS). In Chapter III, we present our three methodologies and justify why our DT-DSS is fit to perform them (contributions #3, #4 and #5). The rest of Part 2 is dedicated to conceiving and building a DT-DSS for our specific study case (contributions #6 and #7). To begin with, we discuss how we model and simulate schedule execution in a determinist environment (Chapter IV). Then, we explain how we model duration variability using historical data (Chapter V). Finally, in Chapter VI, we discuss how we model and simulate non-elective cases arrivals and scheduling during schedule execution (contribution #1).

In Part 3, we apply our methodology on a one-day operating schedule. In Chapter VII, we describe the study case we use, which is an operating day inspired from the database of the *Hôpital Privé de La Baie* (contribution #2). Using our previously developed DT-DSS, we describe each step and analyze the obtained results for: the prospective analysis and the retrospective analysis (Chapter VIII).

Finally, we conclude by summarizing our work, the contributions provided, and presenting future research perspectives.

PART 1 - CONTEXT AND PROBLEMATICS

CHAPTER I. THE CONTEXT OF THE SURGICAL SUITE / OPERATING ROOM

For this applied research project, we worked with three different French hospitals: *Hôpital Privé de La Baie* (HPB, GIE Vivalto Santé, Avranches, France), *Centre Hospitalier d'Albi* (CHA, Albi, France) and *Centre Hospitalier Intercommunal de Créteil* (CHIC, Créteil, France). HPB is a private hospital while CHA and CHIC are public. In France, it is common to use the term “hospital” (*hôpital*) to refer to both public hospitals and private non-profit hospital facilities. The term “clinic” (*clinique*) refers to private for-profit hospital facilities. Since there is no need to systematically make a difference in this research, we will use the term hospital indifferently for any of these structures.

At the beginning of this PhD project, an expert committee was created with directors, surgeons, anesthesiologists, and engineers from these three hospitals. Together, we ensured the relevance of our research question, and defined the study perimeter (KPI, uncertainty, operational decisions to focus on). This helped us shape our research work so that it could be beneficial for the healthcare community.

In this first Chapter, we structure and synthesize the knowledge we gathered on the general working of the surgical suites of our three partners. This knowledge is based on (1) on-site observations, (2) staff interviews, and (3) OR software database analysis. **Expert readers of the surgical suite organization can skip this Chapter and only read the synthesis section 5 at the end.**

First, we propose an overview of the working of a surgical suite. Second, we describe the different types of pathways for patients admitted to surgery. Third, we give an in-depth presentation of the different resources required in a surgical suite. Fourth, we make a short review on performance indicators in the OR, and we conclude this Chapter 1 with a synthesis of the problems we raise.

1. Overview of the working of a surgical suite

The surgical suite is a complex environment that is constantly interacting with services that are internal or external to the hospital. In this section, we describe the inner workings of the surgical suite (1.1), and we present their relationship with outside services (1.2).

1.1. The inner workings of a surgical suite

In this subsection, we present an overview of the internal functioning of a surgical suite, and we propose a high-level process map in Figure 5. We designed it based on our on-site observations, staff interviews and literature review; it is applicable in each of our partners' suites. Although, deliberately not exhaustive, this map allows for a clear overview of the service's complex internal affairs.

The proposed process map is based on the process-oriented approach defined by the ISO 9001 standard⁵. Thus, it displays three types of processes; from top to bottom: **decision-making processes, operational processes** and **supporting processes**. Each blue box represents a macro-process that could be divided into several steps. The processes have inputs (left column) and produce outputs (right column).

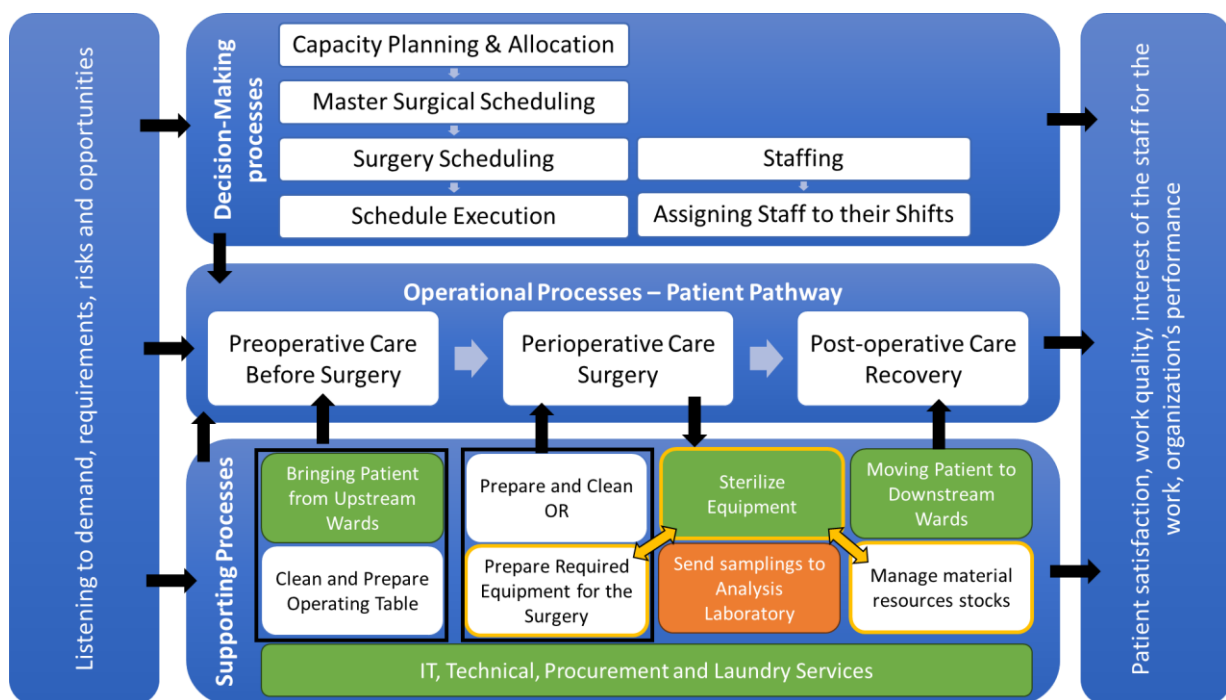


Figure 5 - High level process mapping for the surgical suite

Decision-making processes (first row) ensure the smooth execution of the operational processes by planning and managing the activity. In the surgical suite, these processes focus on aligning patient demand for care with the surgical suite resources while respecting the constraints imposed by external services. We represented decision-making processes leading to the building of the

⁵ <https://www.iso.org/iso-9001-quality-management.html>

operating schedule (ordered list of surgeries to be realized during a specific day) and the staff schedule. We propose a more in-depth description of decision-making processes in Chapter II; our focus is on disruption management that occurs in both surgery scheduling and schedule execution.

Operational processes (second row) include the processes through which the suite provides added value. As the suite's core activity is to provide care to the patient, they integrate the entire patient pathway. They are divided into three phases: the pre-operative phase (before surgery), the peri-operative phase (during surgery), and the post-operative phase (after surgery, or recovery). We describe the different patient pathways taking place in the suite in section 2; our study perimeter encompasses these three phases.

Supporting processes (third row) do not themselves contribute to an added value. However, even if they do not provide care to the patients, they are required for the proper execution of the operational processes. We represent processes related to intra-hospital non-clinical units (green boxes), to intra-hospital clinical units (orange boxes), and to equipment management (yellow outline). Processes in white boxes are operated by the suite's staff. These supporting processes can degrade the everyday schedule execution if they are not properly synchronized with the operating processes. For instance, a patient brought too early in the surgical suite will have to wait before being received for preoperative care (hence decreasing patient satisfaction), but a patient arriving too late will make the surgical team wait for them and keep an operating room idle (hence risking the decrease of OR utilization and increase of staff overtime). In this research, we consider the operating room cleanup.

The surgical suite's organization revolves around three types of processes: Decision-making processes (plan and manage the activity), operational processes (provide care to patients), and supporting processes (allow the proper execution of the patient pathway).

Our objective is to improve the performance of operational processes by working on the disruption management occurring during the surgery scheduling and the schedule execution processes. We consider the three phases of the patient pathway and include the supporting process that is the operating room cleanup.

In this section, we presented an overview of the working of a surgical suite and highlighted the processes on which our work is focused. In the following section (1.2), we focus on the relationships of the surgical suite with its outside environment.

1.2. The relationship between the surgical suite and outside units

In Figure 6, we propose a representation of the relationship established between the surgical suite and external services to provide care to patients. This includes the operational and supporting processes described in Figure 5. Each box represents one or several services: intra-hospital non-clinical units (green boxes), outside hospital units (grey boxes), intra-hospital clinical units (orange boxes), patients ward (blue boxes), surgical suite (white boxes). Arrows represent flows of patient, information, material resources or service.

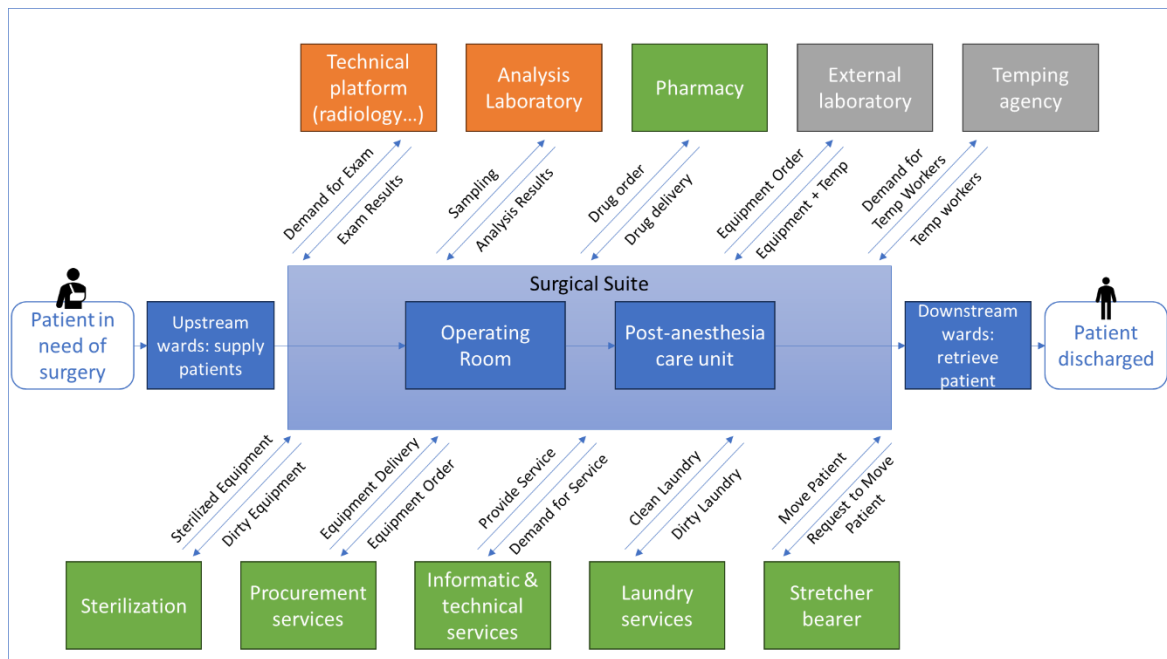


Figure 6 – Interactions between the surgical suite and external services

The surgical suite is strongly tied to external services. First, the surgical suite receives patients from upstream wards (the inpatient unit, the outpatient unit, and the emergency ward). It supplies patients to the same service, plus the intensive care unit (ICU). Second, patients can have delayed access to the surgical suite because of intra-hospital diagnosis units such as the radiology or the laboratory. Third, the surgical suite relies on resources from outside the hospital to complete its capacity (equipment provided by laboratories, temporary workers...). Fourth, the efficiency of the surgical suite is directly affected by intra-hospital non-clinical units such as: IT department, technical services (procurement), cleaning services, sterilization unit, pharmacy (drugs), and stretcher bearers.

The surgical suite is strongly tied to external units. These units can be either inside or outside the hospital, and either clinical or non-clinical. The performance of the suite's organization is dependent on how well the patients flow, information flow, and service flow with these units are managed.

Now that we have a better understanding of the inner functioning of the surgical suite (1.1) and of its relation with other units (1.2), we will provide a detailed description of the patient pathways going through the surgical suite (this includes the operational processes described in Figure 5).

2. Patient pathways involving the surgical suite

The surgical suite's core activity is to provide care to patients. Doing so, the service welcomes a variety of patients, and thus, a variety of patient pathways are possible.

2.1. Patient features that influence the patient pathway

To begin with, we present three distinctive patient features that impact the patient pathway: the admission type, the emergency level and the anesthesia type. Then, we present the steps followed by patients before entering the suite within the suite, and after exiting the suite 2.5, based on these features. Finally, we will address the uncertainties linked to patients during their passage at the hospital, and more specifically, in the surgical suite. Patient features that influence the patient pathway.

2.1.1. Patient type with respect to admission type: outpatients and inpatients

Patients receiving surgery are either outpatients or inpatients. **Outpatients** are admitted, undergo surgery, and leave the hospital on the same day, while **inpatients** stay at least one night in the hospital (S. Zhu et al. 2019). In other words, outpatients correspond to ambulatory surgery, while inpatients correspond to conventional surgery. We describe below the other main differences between inpatients and outpatients: admission date and transportation. We display a synthesis in Table 4.

Admission date. Inpatients are usually admitted one or more days before the day of the surgery, whereas outpatients are admitted on the day of the surgery. Thus, inpatients can be classified as stand-by while outpatients can cancel, be no-show or arrive late (Duma and Aringhieri 2015; Guinet and Chaabane 2003). It is interesting to note that, in some hospitals, inpatients have the option to arrive on the day of their surgery like outpatients (but are hospitalized afterwards).

Transportation. Outpatients usually receive light surgeries and can thus enter the suite walking, on wheelchair or on a stretcher. Inpatients, with heavier surgeries, mostly come in lying down on a stretcher. Thus, patient admission type impacts the patient transportation process. Indeed, stretcher-bearers (the staff in charge of transporting patients), stretchers, and wheelchairs are limited resources of which the unavailability can hinder the schedule execution.

Table 4 - Main differences between inpatients and outpatients

#	Characteristics	Inpatients	Outpatients
1	Type of surgery	Ambulatory	Conventional
2	Admission date	Before surgery date	On surgery date
3	Number of hospitalized nights	At least one	None
4	Where do patients start and end their day?	Inpatient wards	Home
5	Usual transportation mode	Lying down	Walking, sitting, lying down

Outpatients are admitted, undergo surgery, and leave the hospital on the same day, while inpatients stay at least one night in the hospital. Outpatients and inpatients differ in terms of type of surgery, admission date, number of hospitalized nights and patient pathway.

In our study, we consider both inpatients and outpatients; we model them in the same way: they follow the same patient pathways and receive surgery in the same operating rooms.

2.1.2. Patient type with respect to emergency level: elective and non-elective patients

Patients receiving surgery can either be elective or non-elective patients. **Elective patients** can wait before their surgery. They are scheduled weeks or months ahead of time (S. Zhu et al. 2019). Non-elective patients arrive unexpectedly and need to be treated right away.

That being said, non-elective patients are not all prioritized equally: a patient with a peritonitis⁶ (an acute inflammation of the peritoneum) will have a priority over a patient with a closed ankle fracture (i.e. bone does not break through the skin). However, as displayed in Table 5 (Van Riet and Demeulemeester 2015), the criteria to categorize non-elective patients are not standardized in the scientific literature. References can be found in the article. The *Category* column specifies the name given to the non-elective type studied, and the *Target* column specifies the ideal maximum delay duration between the hospital admission and the surgery times. For instance, depending on the article, the term “emergent” may refer to patients needing to undergo surgery within 30 minutes, 1 hour, 2 hours, 6 hours, or 24 hours.

⁶ <https://www.elsan.care/fr/pathologie-et-traitement/maladie-digestive/peritonite-definition-causes-traitements>

Table 5 – Examples of categorization of non-elective patients found in the scientific literature. Taken from (Van Riet and Demeulemeester 2015))

Category	Target
Trauma	Now
Emergent	<30 min, <1 h, <2 h, <6 h, <24 h
Urgent	<4 h, < 24h
Semi-urgent	<8 h, <1/2 w
Add-on	<24 h
Add(-on) elective	No target: fill up free capacity
Non-urgent	<24 h
Work-in	[24 h – 1 w]
Priority levels (P)	P1–P3 (emergent): <1 h, <4 h, <12 h P1–P3: <8 h, <8–24 h, <24–48 h P1–P3: <6 h, <24 h, <78 h P1–P5 (emergent): <45 min, 2 h, 4 h, 8 h, 24 h

The non-elective category definition disparity makes it crucial to specify it for this study. Consequently, we adapt Table 5 definitions and propose in Table 6 three categories of patients that differ based on their target.

Table 6 - Proposition of categories based on target for our study.

#	Category	Target
1	Semi-Urgent Non-Elective (SUNE)	Surgery is maximum three days after the first admission.
2	Urgent Non-Elective (UNE)	Surgery is on the same day as the first admission.

Elective patients can wait before their surgery. They are scheduled weeks or months ahead of time. Non-elective patients arrive unexpectedly and need to be treated right away.

In our study we consider both types of patients and model them in different ways. We consider elective patients, semi-urgent patients and urgent patients.

To conclude this part dedicated to patient type, we add that:

- Inpatients, outpatients, elective patients, and non-elective patients follow the same pathway and/or use the same facilities, or not. This depends on the surgical suite's organization and can change from one site to another. For instance, a hospital with two surgical suites can: (1) have one suite dedicated to outpatients and one suite dedicated to inpatients, (2) have ORs dedicated to outpatients and ORs dedicated to inpatient within the same surgical suite, (3) mix outpatients and inpatients in the same OR.
- The admission type and the emergency level features are independent: elective patients and non-elective patients can be either outpatients or inpatients (and inversely). However, most outpatients are also elective patients. This can be explained by the fact that the non-elective patients usually require heavier surgeries and thus need more after-surgery care.

2.1.3. The four main types of anesthesia

The type of anesthesia the patient receives during surgery can change the patient pathway within the surgical suite. We describe here the four main types of anesthesia: general anesthesia, sedation or monitored anesthesia care, local-regional anesthesia, and local anesthesia⁷⁻⁸.

General anesthesia (GA). For a GA, the anesthesiologist and/or the nurse anesthetist put the patient in a sleeping state where they have no awareness, nor sensations. The anesthesia can be provided in a dedicated anesthesia room, or in the operating room itself – although its mostly performed in the OR.

Loco-regional anesthesia (LRA). During an LRA, the patient stays awake while the anesthesiologist (most of the time assisted by a nurse anesthetist), uses numbing medication on a specific area of the body in order to prevent the patient from feeling pain. Common types of LRA include spinal anesthesia, epidural anesthesia, and nerve blocks. Spinal and epidural anesthesia can be used for childbirth or for heavy orthopedic surgeries below the waist such as total knee and total hip replacements. On the other hand, nerve blocks are used for smaller areas such as an arm or a leg (e.g. femoral nerve block or brachial plexus block). GA and MAC (see below) can be coupled with LRA in order to reduce patient pain during recovery.

Sedation or Monitored anesthesia care (MAC)⁹. Sedation is provided by the anesthesiologist and/or the nurse anesthetist; it makes the patient feel drowsy and relaxed without necessarily losing consciousness. Mild sedation is often used for eye surgery (e.g. cataract surgery) and allows the

⁷ <https://www.uclahealth.org/medical-services/anesthesiology/types-anesthesia>

⁸ <https://www.chuv.ch/fr/anesthesiologie/alg-home/patients-et-familles/types-danesthesie>

⁹ <https://sfar.org/sedation-salle-de-surveillance-post-interventionnelle-sspi/>

patient to answer questions and follow instructions. Moderate sedation may let the patient doze off, although they would be able to wake up easily. With deep sedation, patients fall asleep but are still able to breathe on their own – contrary to GA. It is notably used for endoscopy or colonoscopy.

Local anesthesia (LA). LA can be provided without the supervision of an anesthesiologist or a nurse anesthetist. Staff may inject medication (such as lidocaine) or apply a numbing cream on a specific small area. LA is usually used to relieve pain during short procedures (e.g. sewing a deep cut) and is often coupled with MAC during minor outpatient surgery.

Some anesthesia types are provided in the operating room, others are provided in the PACU. Some require anesthesia team members, others do not. From now on, we will discuss anesthesia not based on their type but based on where they are provided, and by whom. We provide a synthesis of the anesthesia type in Table 7.

Table 7 - Brief description of the four main types of anesthesia provided in the surgical suite.

Anesthesia type	Patient State	Anesthesia team?	Induction Location
General anesthesia (GA)	The patient is deeply asleep.	Yes	OR
Local-regional anesthesia (LRA)	A specific area of the patient's body is completely numbed using injected medication. The most common types of LRA are spinal, epidural and block.	Yes	Spinal and epidural: OR Block: PACU
Sedation or monitored anesthesia care (MAC)	Depending on the sedation intensity, the patient is either deeply asleep (deep), dozing off (moderate), or able to follow instructions and answer questions (mild).	Yes	PACU
Local anesthesia (LA)	The patient is injected medication or is applied cream in order to relieve them from pain.	No	OR

Now that we have defined these patient features, we present the different patient pathways that pass by the surgical suite and explain how these features impact them. We describe the patient pathway as a multi-step process.

2.2. From taking a surgeon appointment to being ready for hospital admission

We present the patient pathway as a multi-step process. In this section, we focus on the period from when the patient requires a surgeon consultation to the moment where the patient is ready for hospital admission. We describe this process for elective patients (i.e. who can wait before undergoing surgery), whether they are outpatient or inpatient. Indeed, for these specific steps,

inpatient and outpatient pathways barely differ. Note that there can be up to several months between the surgery consultation and the surgery day.

The process consists in 5 main phases: (1) taking an appointment with the surgeon, (2) surgeon consultation, (3) anesthesiologist consultation, (4) patient pre-admission, and *for outpatient only*: (5) nurse calls before the surgery day. We visually display the pathway in Figure 7.

We describe slightly more each step:

- First, the patient **takes an appointment for a surgery consultation** at the surgery secretariat. This can be made in person, over the phone, or on the internet. See Figure 7.1.
- Second, on the day of the **surgery consultation**, the patient meets with the surgeon. They discuss whether there is a need for surgery or not, and if it's the case, whether it will require conventional or ambulatory surgery. The surgeon also explains whether anesthesia will be needed, and if yes, what type. The surgeon can also order more exams before making any decision. Then, the patient **schedules the date of the surgery** with the surgeon or with its secretariat. They also **schedule the anesthesia consultation** (if needed) as well as a **preoperative consultation** (or pre-admission) with a nurse. See Figure 7.2.
- Third, **during the anesthesia consultation** (2 to 3 weeks before the surgery), the anesthesiologist decides whether the patient can be administered the required anesthesia. If not, the surgery is postponed. See Figure 7.3.
- Fourth, on the day of the **pre-admission**, a nurse from the surgery service explains and organizes: (1) the admission, (2) the hospital's exit and (3) the post-operative follow-up with the patient. Other members of the medical and/or paramedical team can be present if needed. Note that pre-admission is usually on the same day as the anesthesiologist consultation. See Figure 7.4.
- Fifth, the patient waits for their admission day. In case of an ambulatory surgery (outpatient case), a member of the suite staff will call the patient the day before the admission to give them the hours at which they will be expected at the ambulatory service. Apart from that, the inpatient and outpatient pathways are very similar. See Figure 7.5.

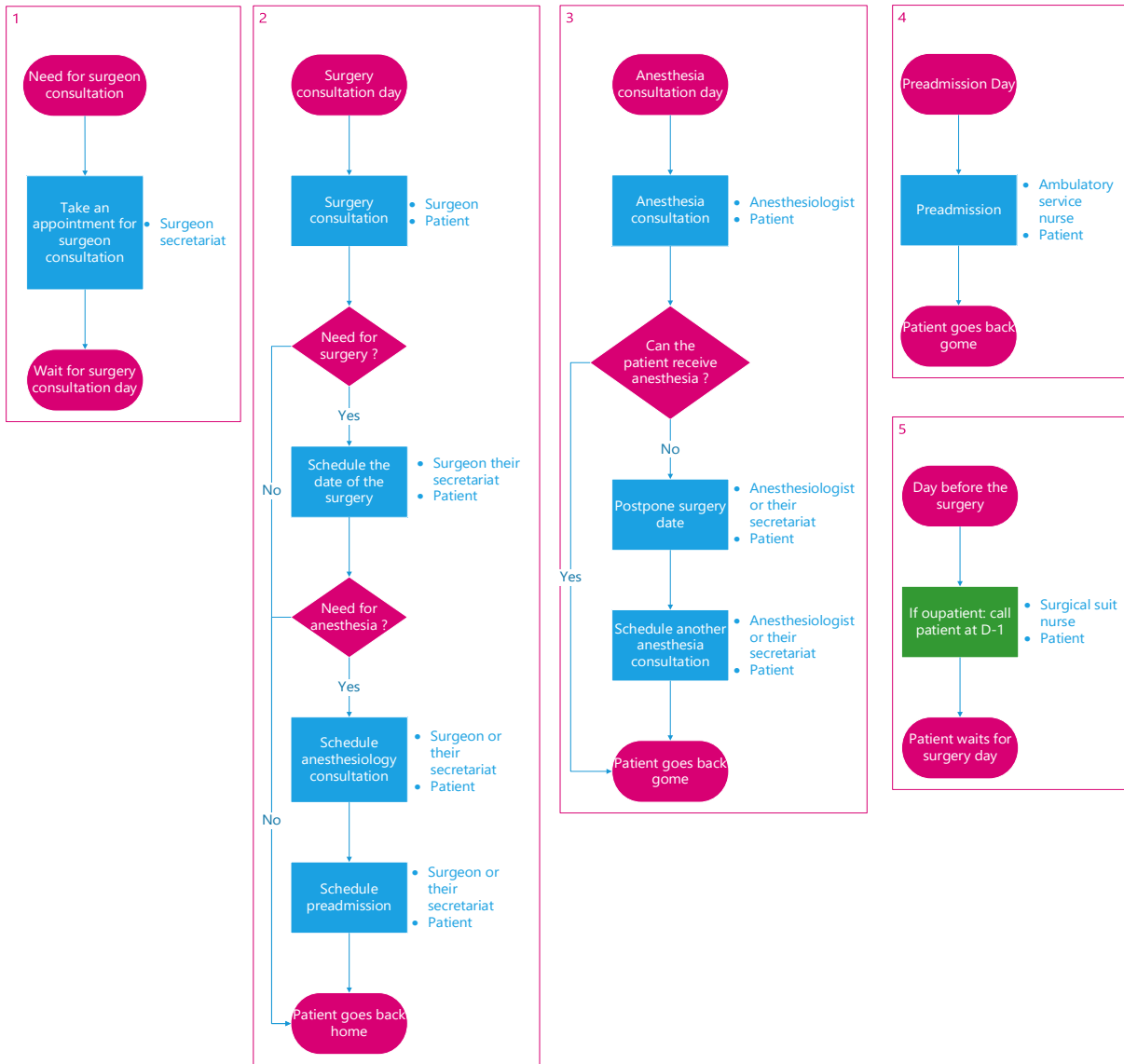


Figure 7 – Patient pathway from surgeon consultation to being ready for the hospital admission for elective inpatients and outpatients.

For elective patients (whether they are inpatient or outpatient), the steps from needing a surgeon consultation to being ready for hospital admission are (1) taking an appointment for a surgeon consultation, (2) surgeon consultation, (3) anesthesiologist consultation, (4) preadmission, and (5) if outpatient: wait for OR nurse call on the day before surgery. In our study, we focus on the surgery day; we consider these steps to have already been performed.

2.3. From the hospital admission to entering the surgical suite.

The hospital admission steps change depending on the admission type and the emergency level of the patient. We first present the steps for an inpatient elective case, then for an outpatient elective case, and then finally for a non-elective case (Figure 8).

Inpatient elective case. On the admission day, inpatients present themselves to the hospital for administrative admission. They are moved to their bedroom in their specific ward where they will

sleep during their stay. A nurse recovers their latest exams and reminds them how their stay is going to unwind. The patient also meets the surgeon and the anesthesiologist for a last check-up before the surgery. On the surgery day (usually the next day), a nurse informs the inpatient of their departure for the surgical suite and prepares them for surgery. Once the patient is ready, one or two stretcher-bearers bring them to the surgical suite.

Outpatient elective case. The steps are quite similar for outpatients except that: (1) the admission and the surgery are the same day, (2) the patient does not spend the night at the hospital, (3) the patient does not meet the surgeon and anesthesiologist before entering the suite, (4) the patient is admitted to the ambulatory ward instead of the surgery service, (5) outpatients are more likely to go to the suite sitting on a wheel chair or walking, although they will still be accompanied by stretcher-bearers.

Non elective patients. The process for **non-elective patients** is quite different^{10,11}. A non-elective patient can be either outpatient or inpatient depending on the severity of the surgery and on the waiting time between the date of the patient arrival at the hospital and the patient surgery date. First, the patient can either enter the emergency department through the pedestrian entry (if they came by their own mean of transportation) or lying down on a stretcher (if they were brought in by an ambulance). In both cases, they undergo administrative reception and triage in the emergency department. During the triage, a specialized nurse assesses the emergency level of the patient. Mildly severe patients are moved to the waiting area while severe cases are immediately moved to the treatment area. In the treatment area, patients are examined by doctors and nurses and prescribed further exams if needed. Between exams, patients are moved back to the waiting area. Once the examination is completed, the doctor decides where to send the patient next: (a) their home, (b) a hospitalization bed, (c) the surgical suite, (d) another care facility.

¹⁰ <https://www.hopital-saint-joseph.fr/a/3041/le-parcours-patient-aux-urgences-adultes/>

¹¹ <https://www.ch-morlaix.fr/actualite/affiche-parcours-patient>

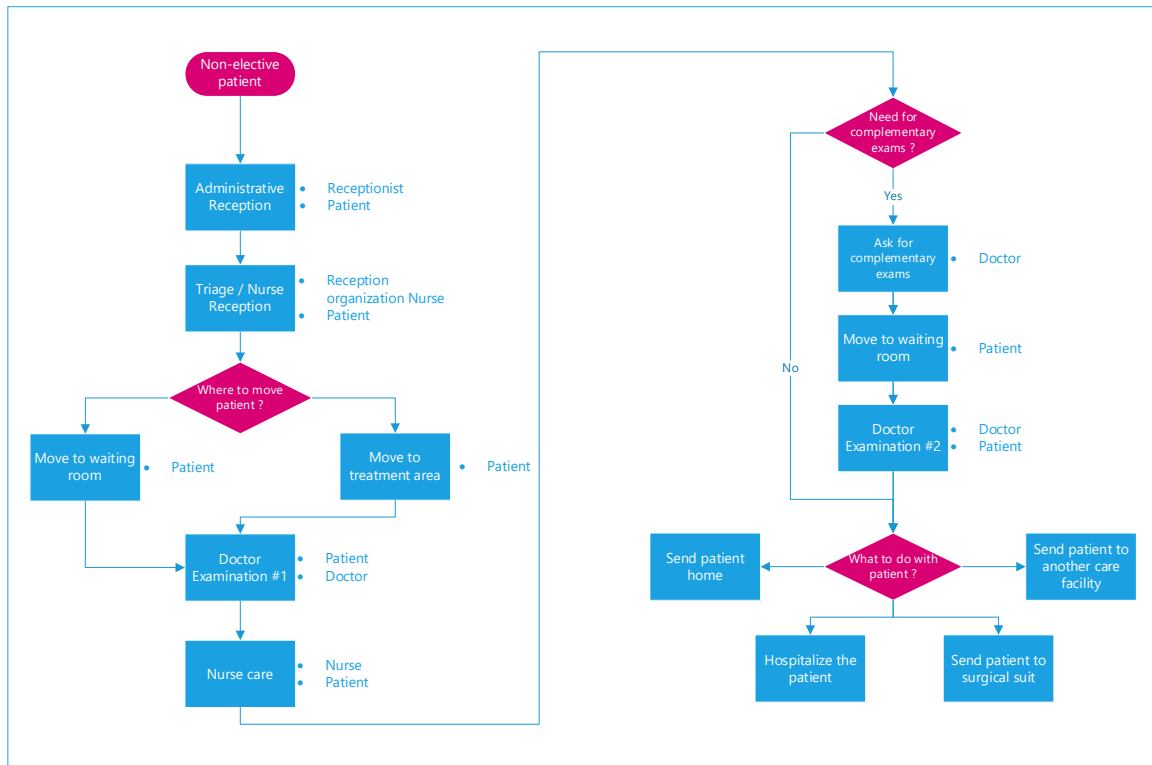


Figure 8 - Non-elective patient pathway in the emergency wards.

We have detailed the patient pathway's steps: (1) for elective patients, from requiring a surgery to being transported to the surgical suite, and (2) for non-elective patients, from being admitted to the emergency wards to being sent to the surgical suite. We now describe the patient pathway within the surgical suite.

2.4. From entering to exiting the surgical suite: the patient pathway in the surgical suite

In the preceding subsections, we described the patient pathway before entering the surgical suite (2.2 and 2.3). In this subsection we discuss the process as the core of our study. We present the 3 main types of patient pathways within the surgical suite that we observed on-site:

- a) Surgery with an induction in the OR (GA, spinal anesthesia, epidural anesthesia)
- b) Surgery with an induction in the PACU (block, sedation)
- c) Surgery without the need of the anesthesia team (local anesthesia)

To begin with, we describe in depth the patient pathway requiring induction in the OR (a). Then we explain what changes between this pathway and the two other cases (b and c).

a - Surgery with induction in the OR. To better understand the patient pathway in the surgical suite, we illustrate it with an example *inspired* by a patient pathway in HPB's surgical suite. The layout shown in Figure 9 is extracted from the complete surgical suite layout of HPB that is later shown in Figure 13. The arrows represent the path followed by the patient in the suite and the associated number the sequence of their steps. The example we present here is the one of an elective inpatient coming for a hip replacement under general anesthesia.

We highlighted:

- the **transfer area** (white): the area between the surgical suite and the rest of the hospital.
- the **patient waiting area** (blue): the area where the patient waits before the surgery.
- the **operating rooms** (green): the rooms in which surgeries take place.
- the **post-anesthesia care unit** or **PACU** (yellow): the area where patients are transferred to for recovery after their surgery.

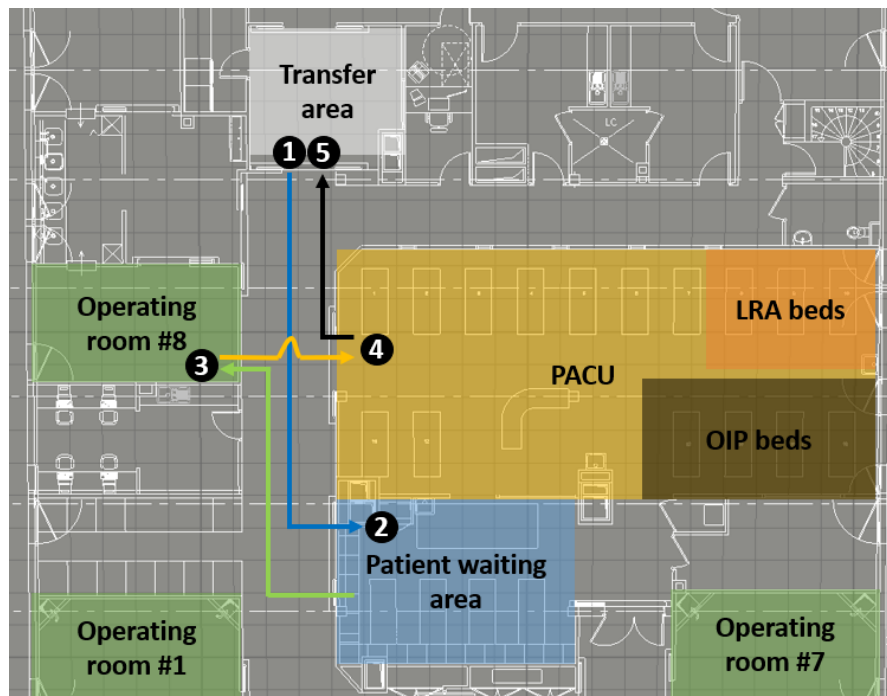


Figure 9 – Illustration of a patient pathway in the surgical suite.

Preoperative phase. The preoperative phase starts with a stretcher bearer transporting the patient from their inpatient wards (outside the surgical suite) to the **transfer area (1)**. The patient is welcomed in the suite by a nursing assistant that records the patient suite entry time, checks their identity, and installs them on an operating table. Since general anesthesia does not require passing by the PACU, the nursing assistant brings the patient directly to the **patient waiting area (2)**. If a PACU nurse is available, they come to put the patient on a drip. If not, the patient waits until the nurses from the surgical team (2 OR nurses and one anesthesiologist nurse) do the checklist and bring them to the **operating room (3)**. This is the end of the preoperative phase and the start of the peri-operative phase.

Peri-operative phase. In the operating room, the patient undergoes the following steps: setup, induction, procedure, and reversal. During the setup, the staff finishes preparing the material and installs the patient for the induction and/or the procedure. During **induction**, the anesthesiologist (and/or the anesthesia nurse) provide anesthesia to the patient and install them for the procedure. During the **procedure** (from incision to the suture), the surgeon and the OR nurses operate on the patients while the anesthesia team makes sure the patient stays asleep. During the **reversal**, the nurses close the patient's wound and prepare them to leave the OR and enter the PACU.

The surgeon and the anesthesiologist can stay during the entire peri-operative phase. However, usually the surgeon only stays for the procedure (incision to suture) and the anesthesiologist only stays for the induction (induction start to induction end). The nurses stay with the patient the entire time they are in the OR. Once the reversal is over, the nurses move the patient to an available PACU bed. This is the end of the peri-operative phase and the start of the post-operative one.

Post-operative phase. One nurse stays in the OR for the clean-up. The other one transports the patient to a PACU bed (4) and prepares the OR for the next case. The patient is then under the responsibility of the PACU nurses. Once the patient's vitals have been stabilized, the nurses call the stretcher bearer to transport the patient to the outpatient ward or to the patient's hospitalization ward (5). This marks the end of the surgical suite patient pathway.

In Figure 10, we represented all the steps of this patient pathway as well as the human resources required for each one.

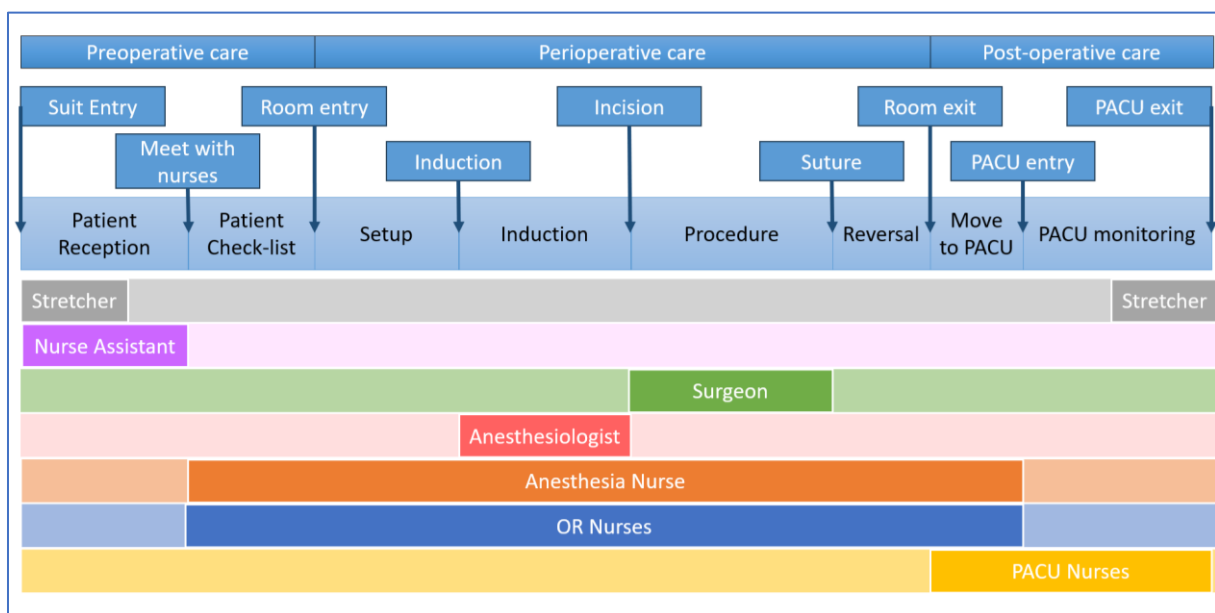


Figure 10 – Surgical suite patient pathway with in-OR induction.

b - Surgery with induction in the PACU. The main difference between this pathway and the previous one is that the induction is neither realized at the same location and nor at the same moment. To illustrate this, we represented the preoperative phase options in Figure 11's flowchart:

- Each box is a patient pathway step.
- The diamond marks an intersection based on the type of anesthesia required: patients go straight to the OR after their checklist (option 1), or receive anesthesia preparation, induction and monitoring for either block LRA or sedation.
- The required resources are listed on the right of the boxes.
- RN stands for “registered nurse”. Nurses, even if not specialized, can be trained to (1) help the anesthesiologist for LRA preparation and induction, and (2) perform sedation preparation, induction and monitoring alone.

Once in the OR, the patients who received their induction in the PACU follow the following process: setup, procedure, and reversal (no induction).

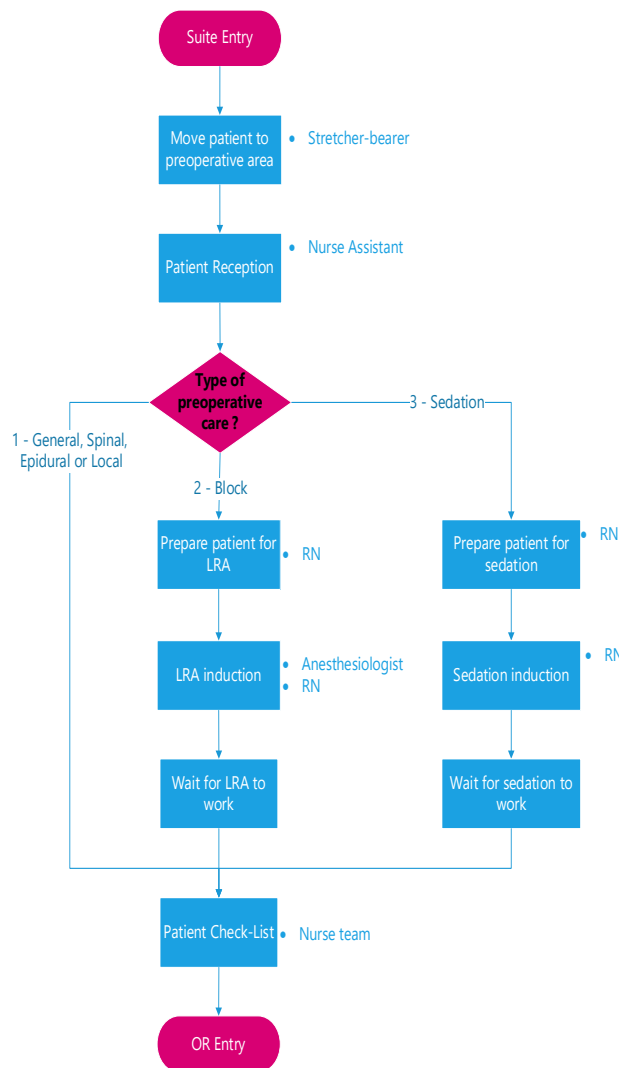


Figure 11 – Preoperative care patient pathway options.

c - Surgery without the need of the anesthesia team. This pathway is similar to the one with an anesthesia inside the OR (a). The two differences are: (1) there is no induction at all, (2) neither the anesthesiologist nor the anesthesia nurse are present throughout the entire patient pathway.

In this subsection, we have described how the anesthesia type required for the surgery could influence the patient pathway. As a side note:

- The emergency level can influence the patient pathway in the following way: in case of a vital emergency, the patient can be directly moved to an OR without having the preoperative phase.
- The admission type can influence the patient pathway in the following ways: (1) outpatients need to pass by the outpatient wards before exiting the hospital, thus, they need to leave the surgical suite soon enough so that the outpatient wards is still open for enough time to do so, (2) outpatients are mostly operated under anesthesia that do not put them in a deep sleep so that their recovery in the PACU is faster (typically: no general anesthesia).

We will now move on to the description of the final leg of a patient pathway passing by the surgical suite.

2.5. After the surgical suite: from exiting the surgical suite to leaving the hospital

Once the reversal of a surgery is over, the patient can either: (1) be moved to the ICU if they require close monitoring, or (2) be transported to the PACU for recovery.

In the first case, they stay in the ICU until their state is stabilized. They are then moved again to an inpatient service until they are free to return home.

In the second case (after passing by the PACU), stretcher-bearers bring patients to their bedroom; inpatients return to their surgical service, and outpatients return to the ambulatory service. Non-elective patients follow either the inpatient or the outpatient pathway.

Inpatients are welcomed by a nurse who checks their vitals and manages their pain. In the evening the patient has a medical check-up with both the surgeon and the anesthesiologist (not necessarily at the same time): they discuss the outcome of the surgery and inform the patient on the treatment follow-up. The inpatient will then have daily meetings with the surgeon, the anesthesiologist, the nurses, and other staff members until the end of their stay to (1) manage the pain, and (2) ensure a safe and quick recovery. More exams (blood test, radio, etc.) can be ordered if needed. Upon the agreement of the medical team, the inpatient will be authorized to leave the hospital.

On the other hand, outpatients are monitored until the RN judge they are stable enough to leave. A nurse calls them back a few days after the surgery to check-up on them one last time.

3. Surgical suite resources

In the previous sections, we presented an overview of how the surgical suite works (1.1), how it interacts with outside services (1.2), as well as detailed the patient pathways involving the surgical suite (2). Throughout these descriptions, we regularly referred to material resources (e.g. operating rooms or PACU beds) and human resources (e.g. surgeon or anesthetist nurse). We will now give a more in-depth description of these resources and the issues linked to their management.

3.1. Material resources

Material resources can be bought or rented. They refer to **transportation means** (stretchers or wheelchairs), **personal protective equipment**, **surgical instruments** (which are sterilized and reused), **surgical supplies** (which are thrown after being used once), **anesthesia equipment**, **drugs**, **imaging and visualization equipment** (e.g., X-ray machines, endoscopes or laparoscopes, cameras), **surgical support equipment** (surgical lights, surgical tables and positioning devices), **information and communication systems** (operating room information system, phones, emails...) and **infrastructure resources** (premises and storages). In Figure 12, we represented all these material resources, and colored in green the ones related to the medical domain.

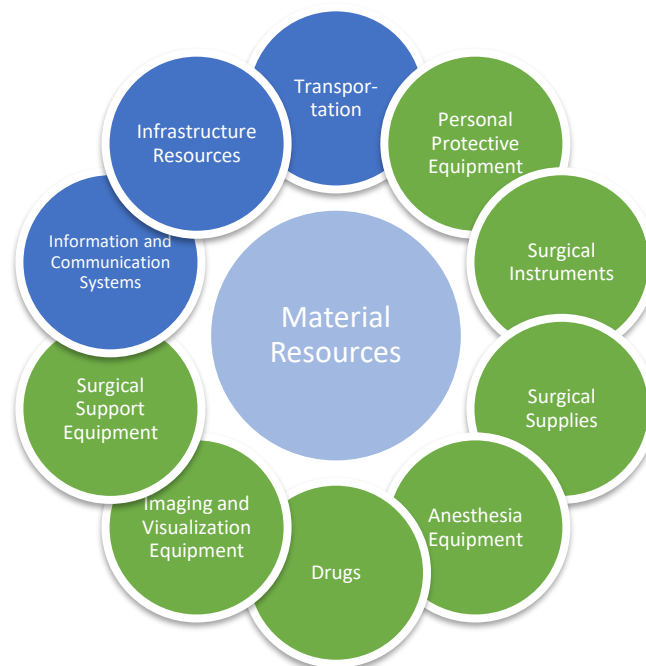


Figure 12 - The different types of material resources required in a surgical suite.

To illustrate this, we present an example of a real-world surgical suite infrastructure using the suite layout of our partner HPB (Figure 13). We use colors to highlight the different areas of the service. Some areas are dedicated to patients while other are for staff usage only. The zones used by the patients are:

- the **transfer area** through which patients enter and exit the surgical suite (white)
- the **preoperative patient waiting area** (blue)
- the **operating rooms** in which the patients undergo surgery (OR, green). Operating rooms can be of different types as they are not necessarily suited for all types of surgery.
- the **post-anesthesia-care unit** (PACU, yellow). This specific PACU has beds dedicated to preoperative care: beds for **locoregional anesthesia** (LRA, orange) and beds for **ophthalmic induction preparation** (OIP, brown). Note that although it is common to find the LRA beds in the PACU, the OIP beds are a specificity of HPB due to their important ophthalmology activity.

There are also areas that are only authorized for the staff:

- **staff office, toilets, and break room** (dark blue),
- **sterile arsenal storages** (SAS, black)
- **surgery preparation room** (Prep, red)
- **clean airlock area** (purple)
- **dirty airlock area** (pink)
- **waste area** (yellow).

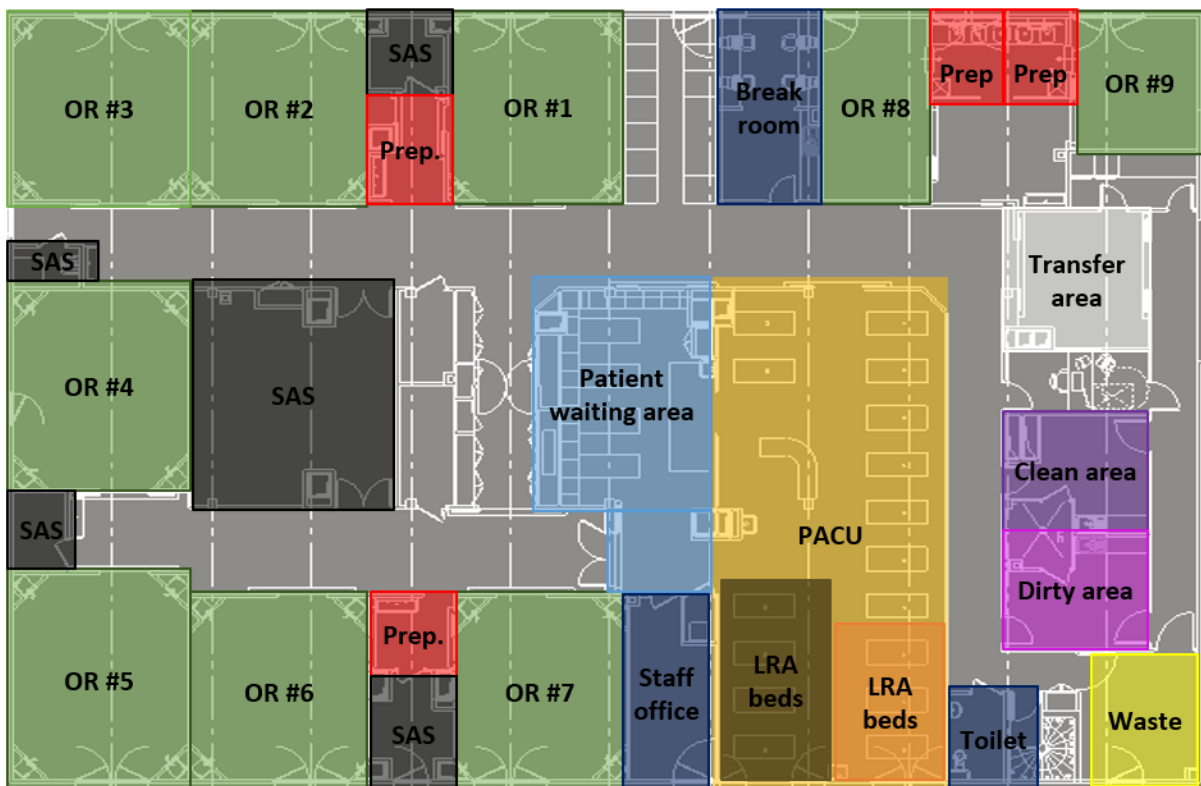


Figure 13 – Commented layout of a real-world surgical suite

Now that we have described the material resources required by surgical suites, we will discuss the human resources they need.

3.2. Human resources

3.2.1. Introduction

In the surgical suite, the medical staff and the paramedical staff provide direct care to the patient, while the management team ensures the smooth planning and execution of the operating schedule. The technical staff, although mostly not a part of the suite staff, contributes to the running of the service. The surgical suite is thus a multidisciplinary service where individuals work together towards the same goal - providing qualitative and safe care to the patients - but with different work organizations.

In Figure 14, we detail the four staff categories found in the surgical suite (medical, paramedical, management and technical); we color in green the members of the surgical team, meaning the staff allowed to enter the OR with the patient.

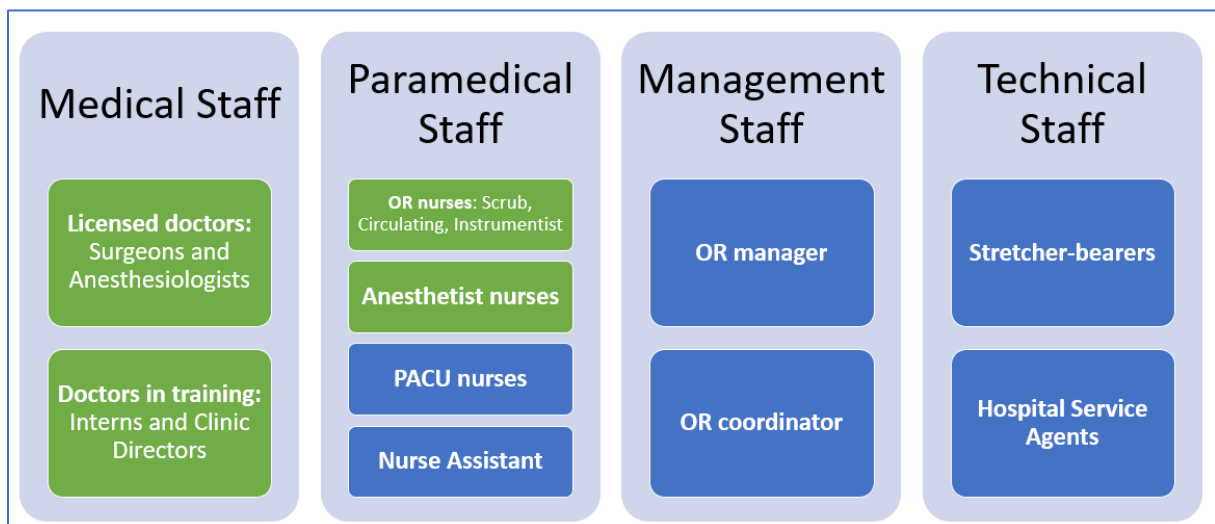


Figure 14 – Surgical suite staff categories and the different occupations they consist of.

In the remaining of this subsection, we describe the different roles and missions of the staff without extensively listing their tasks – especially not the medical ones¹²⁻¹³⁻¹⁴⁻¹⁵. Indeed, we only aim at giving the reader an overview of everyone’s role and an understanding of how coordinated human resources must be for the schedule to be smoothly executed.

¹² <https://www.urmc.rochester.edu/encyclopedia/content.aspx?contenttypeid=85&contentid=P01413>

¹³ <https://www.hopitalprivesevigne.com/la-piqure-article-3/>

¹⁴ <https://www.rnpeadia.com/nursing-notes/medical-surgical-nursing-notes/operating-room-team/>

¹⁵ <https://www.sciencemuseum.org.uk/objects-and-stories/medicine/surgeons-and-surgical-spaces>

As a side note:

- Human resources can be (1) external to the hospital, (2) internal to the surgical suite, or (3) external to the surgical suite but internal to the hospital.
- Individuals working in private hospitals can be private practitioners and are not strictly speaking “staff”. We will not make the difference between employees and liberals.¹⁶⁻¹⁷

3.2.2. Medical staff

The suite **medical staff** is composed of licensed doctors (surgeons, anesthesiologists) and of doctors in training such as interns and clinic directors. We discuss their missions and display them in Figure 15.

The **surgeon** first meets the patient during a consultation to establish whether there is a need for surgery. During the day of the surgery, they perform the surgical procedure and check the patient’s state after they exited the PACU. Surgeons can either stay during the entire intervention or from the incision to the suture (that they both perform). The surgeon can be assisted by another surgeon, a surgeon in training or an operating room nurse (see 3.2.3)

The **anesthesiologist** first meets the patient during a consultation to establish whether they meet the requirements to receive anesthesia. During the day of the surgery, they usually administer the anesthesia to the patient and monitor their vital signs during the surgical procedure. The anesthesiologist can be assisted by an anesthesiologist in training or an anesthetist nurse (see 3.2.3). The anesthesiologist is responsible for the proper anesthesia of the patient but is not required to provide the anesthesia themselves: it is possible for an anesthetist nurse to provide the anesthesia, even if the anesthesiologist is not in the room. Thus, the anesthesiologist can stay during the entire time the patient is in the operating room, only during the induction or the setup phase, or not at all.

Surgeon	Anesthesiologist
<ul style="list-style-type: none"> • Hosts surgery consultation • Realizes the surgical procedure (incision to suture) • Does follow-up after surgery • May be assisted by: another surgeon, a surgeon in training, OR nurses 	<ul style="list-style-type: none"> • Hosts anesthesiology consultation • Provides and maintains the anesthesia (OR entry to OR exit) • May be assisted by: anesthesiologist in training, anesthetist nurse

Figure 15 – Brief description of the missions of the suite medical staff.

3.2.3. Paramedical staff

The suite **paramedical staff** consists in non-medical staff that provide direct care to the patient, such as registered nurses, nurse assistants, and radio operators. Registered nurses can pass additional certifications to specialize themselves and become either operating room nurses or

¹⁶ <https://www.dictionnaire-medical.fr/definitions/383-paramedical/>

¹⁷ <https://www.dictionnaire-medical.fr/definitions/622-praticien>

anesthetist nurses. The PACU is managed by PACU registered nurse. This position does not require an additional diploma. First, we discuss the types of nurses in the surgical suite (Figure 16), then describe the different types of OR nurses (Figure 17), before finishing with the missions of the nurse assistants.

OR nurses are responsible for the smooth execution of the surgical procedure, the respect of hygiene and safety rules, as well as the traceability of the products, equipment and surgical acts provided during the intervention. OR nurses can fulfill three different roles in the OR. They can be a **circulating nurse**, a **scrub nurse** or an **instrumentist nurse**. Usually the scrub nurse and the instrumentist nurse are the same person.

Anesthetist nurses assist the anesthesiologist. Since the anesthesiologist is only responsible for the quality of care provided to the patient and is not required to be present in the OR, the anesthetist nurse role can go from assisting the anesthesiologist to providing and maintaining the anesthesia on their own.

PACU nurses ensure the safe care of patients in the PACU. During the preoperative step, they prepare patients requiring an LRA and assist the anesthesiologist providing it. They also welcome the patient once they exit the OR and ensure that they are safely recovering from the surgery, before sending them to their bedroom.

OR Nurse	Anesthetist Nurse	PACU Nurse
<ul style="list-style-type: none"> •Ensures execution of surgical procedure •Ensures respect of hygiene and safety rules •Ensures traceability of resources 	<ul style="list-style-type: none"> •Assists the anesthesiologist •Provides anesthesia (induction) •Maintains anesthesia 	<ul style="list-style-type: none"> •Participates in patient preparation for LRA •Ensures the patient's safety in the PACU

Figure 16 - Brief description of the missions of the suite paramedical staff (1/2).

During a surgical procedure, each OR nurse adopts a specific role: circulating, scrub and/or instrumentist. The **circulating nurse** is the OR conductor and ensures the communication between the sterile surgical team and the rest of the suite. They ensure the timely preparation, documentation, and delivery of the surgical supplies to the OR medical team, manage the documentation related to the patient, and record the in-room timestamps in the information system. OR nurses stay in-room during the entire intervention, except the circulating nurse that, when needed, can go fetch additional supplies or ensure communication with the rest of the suite.

The **scrub nurse and the instrumentist nurse** have overlapping missions: (1) before the surgery, they help prepare the OR, the surgical supplies, and the patient, and (2) after the surgery they suture incisions if the surgeon did not do it and perform the reversal. However, their focus is different. During the surgery, the **scrub nurse** directly assists the surgeon by holding open incisions, halting bleeding, cutting wires, and ensuring the surgeon has a clear vision of the surgical site. On the other hand, the **instrumentist nurse** hands the instruments to the surgeon and is responsible for surgical instrumentation and management of the sterile field.

OR Nurse Circulating	OR Nurse Scrub	OR Nurse Instrumentist
<ul style="list-style-type: none"> •Ensures communication between the OR team and the rest of the suite •Prepares surgical supplies •Enters data in the OR software 	<ul style="list-style-type: none"> •Prepares OR, surgical supplies and patient • Sutures incisions after surgery •Directly assists the surgeon with the surgery 	<ul style="list-style-type: none"> •Prepares OR, surgical supplies and patient •Sutures incisions after surgery •Hands the instruments to the surgeon

Figure 17 - Brief description of the missions of the suite paramedical staff (2/2).

Finally, the missions of a **nurse assistant**¹⁸ are related to patients (welcoming the patient, performing the identity check, helping to move the patient within the surgical suite), surgery (dressing the doctors, preparing the surgical supplies that need to be sterilized), equipment supply, maintenance, and premises cleaning. These missions can change from one site to another: some hospitals do not authorize nurse assistant to enter the room while the patient is inside, other only employ janitors for the cleaning.

3.2.4. Management staff

The surgical suite is also the workplace of the **management team**, which is made of the OR manager and the OR coordinator. Our research focuses on helping the OR manager.

An **OR manager** is an experienced nurse (preferably a former OR nurse). They are the intermediary between the medical staff and the paramedical staff, as well as between the surgical suite staff and the board of directors (or more globally, the administrative services). The OR manager ensures that the staff respects the surgical suite's charter and adheres to the service project.

The OR manager and the OR coordinator are two different positions with two different sets of missions; the OR manager takes care of the administrative tasks while the OR coordinator ideally only focuses on the day-to-day smooth execution of the operating schedule and the handling of disruptions. However, in some surgical suites, the OR manager is also in charge of ensuring the proper execution of the operating schedule. It is interesting to note that we noticed an increasing number of OR coordinators during the last decade. We describe the missions of an **OR coordinator** in Chapter II. where we also discuss the processes and decisions linked to the schedule execution.

3.2.5. Technical staff

Some **supporting staff** that are neither part of the medical, the paramedical nor the management team, work in the suite or in close contact with it. Namely: stretcher-bearers, and hospital service agents. **Stretcher-bearers'** organization change from one site to the other: some suites are assigned

¹⁸ <https://choisirleservicepublic.gouv.fr/offre-emploi/aide-soignant-de-bloc-operatoire-hf---pole-des-blocs-operatoires-et-ambulatoire--reference-2021-748246/>

dedicated stretchers while others are not. **Hospital service agents** can replace nurse assistants for the cleaning activities.

3.2.6. The surgical team

During a surgical case, there are several professionals in the OR with the patient: the surgeon, the anesthesiologist, an anesthetist nurse, and one to three OR registered nurses. The OR surgical team is divided into the sterile (surgeon, scrub nurse, instrumentist nurse) and unsterile team members (anesthesiologist, anesthetist nurse, circulating nurse). Additional members can include: a second surgeon, a medical student, or a resident (a physician undergoing a specialization), a medical device company representative or a radio operator. Depending on the surgical suite, there can be an important number of individuals present at the same time in the operating room: it is extremely important that they all know each other's work so that they can properly collaborate. An illustration is provided in Figure 18.

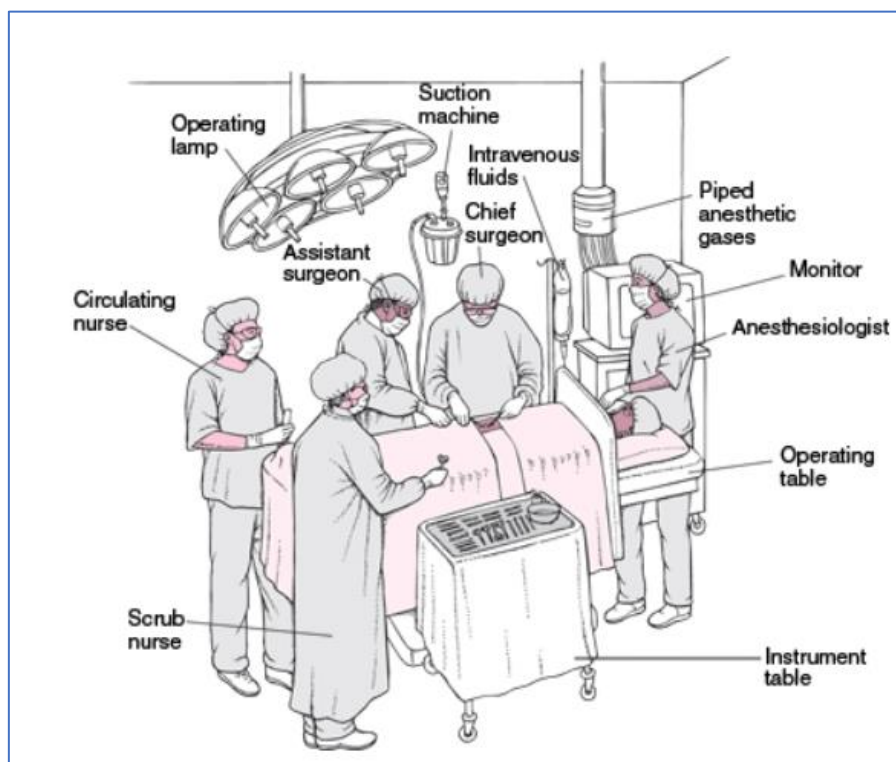


Figure 18 – Representation of the surgical team members during a surgery. ¹⁹

¹⁹ <https://www.rnpedia.com/nursing-notes/medical-surgical-nursing-notes/operating-room-team/>

4. Performance evaluation in the OR

In this section and the remaining of the manuscript, we talk about schedule performance, schedule robustness and schedule resilience through misuse of language. For instance, by “schedule performance”, we mean the performance of the organization (the surgical suite) which followed this specific schedule.

4.1. Brief review on performance in the OR

(Cima et al. 2011) presents the use of the industrial engineering and manufacturing oriented Lean and 6 sigma techniques within a medical journal to improve OR efficiency. The authors point out that efficiency improvement projects often focus on a limited number of ORs or on cases. However, there are rarely studies on the surgical suite. In this article, they present a Value Stream Mapping (VSM) of the entire suite, *from* the decision to operate *to* the patient's discharge from the hospital (patient pathway in the OR), carried out by a multidisciplinary team. Each activity is analyzed according to 3 domains: personnel, information, and time, with several value improvement objectives: reducing volume variability, streamlining the preoperative process, reducing non-operative time, eliminating redundant information, and promoting staff engagement. Results show significant improvements in adherence to start times, and a reduction in overtimes. The article concludes that "Process mapping, leadership support, staff engagement, and sharing performance metrics are keys to enhancing OR efficiency".

(Marjamaa, Vakkuri, and Kirvelä 2008) describes the operating room management in terms of who runs the operating room operationally.

(Michael Samudra et al. 2016) presents a classification of publications on the "OR planning and scheduling" problem according to patient type, performance measures used, decision support, services upstream and downstream of the OR, uncertainty, research methodology, and the test phase. It highlights 3 pitfalls that explain why these methods are not applied: (1) the lack of a clear choice of authors on whether to target researchers (contributing advanced methods) or practitioners (providing managerial insights), (2) the use of ill-fitted performance measures in models, and (3) the failure to understandably report on the hospital setting and method-related assumptions.

(Heydari and Soudi 2016) addresses the predictive and reactive disruption management problem. It provides a definition to the terms "schedule robustness" and "schedule stability": "A primary schedule is called robust if in confronting disruption, its performance does not exacerbate much. Similarly, it is stable if the schedule produced after the disruption does not deviate much from the primary schedule".

4.2. KPI used to assess schedule performance, robustness and resilience

When it comes to assessing schedule **performance**, **robustness**, and **resilience**, it is important to clearly define what a performant, robust and resilient schedule is. **Performance** is defined based on three key performance indicators (KPIs): (1) **overtime**, where lower overtime instances would reflect better working conditions for the staff, (2) **patience waiting times**, where lower waiting times would indicate an increased patient satisfaction, and (3) **OR utilization**, where higher

utilization rates ensure a profitable organizational efficiency. **OR overtime**, **OR idle time**, **OR overutilization** and **OR underutilization** are indicators that come naturally when it comes to studying OR usage. Figure 19 illustrates the different usage states of the OR. The represented OR shift starts at 8am and ends at 6pm; 4 cases are scheduled throughout the day. We use the following color code: (1) green: OR is supposed to be available, (2) orange: the OR is supposed to be closed but is opened for overtime, (3) yellow: the OR is open but empty, (4) light blue: a patient in undergoing surgery in the OR, and (5) deep blue: the staff is cleaning the OR between surgeries.

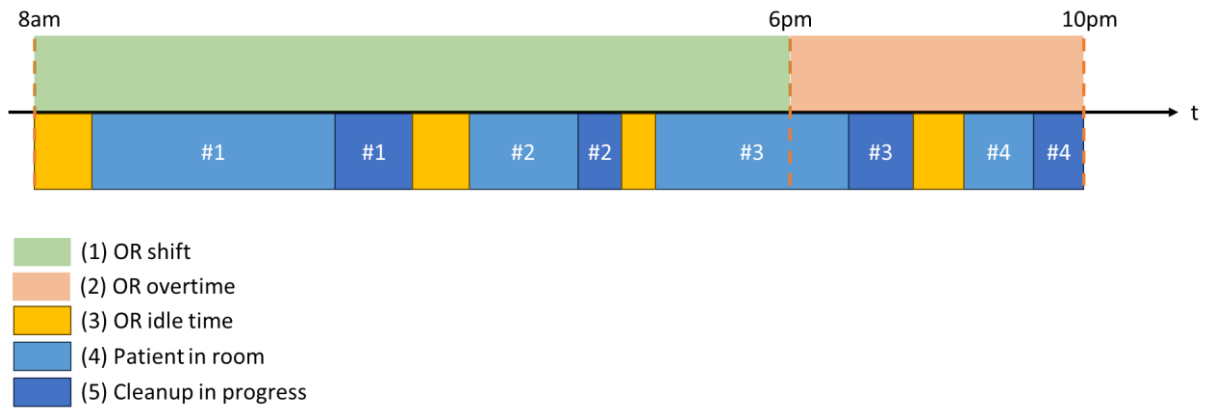


Figure 19 – Description of our OR usage related KPIs.

Below we describe how we compute each of our KPIs. Note that these are the duration side of the KPIs. Divided by the OR shift length, it becomes a rate.

$$OR_{utilization} = (1 \cap 4) + (1 \cap 5)$$

$$OR_{idle\ time} = (1 \cap 3)$$

$$OR_{overtime} = (2 \cap 4) + (2 \cap 5)$$

$$OR_{underutilization\ Maximum} (0, OR_{shift} - (OR_{utilization} + OR_{overtime}))$$

$$OR_{underutilization\ Maximum} (0, OR_{utilization} + OR_{overtime} - OR_{shift})$$

A surgical suite's organization is said to be **robust** if it manages to maintain the same level of performance despite system input variability such as stochastic surgery without the need to adapt. A surgical suite's organization is said to be **resilient** if it manages to maintain the same level of performance despite strong disruptions such as emergency arrivals or cancellations. Robustness and resilience are defined based on the schedule performance gap between the discrete and stochastic environments. We use the ANAP targets for surgical suite KPIs as performance targets²⁰.

²⁰ <https://anap.fr/s/>

5. Chapter synthesis: selected on-site problematics

Properly running the surgical suite requires to synchronize the resources inside *and* outside the suite with the patient pathway execution. Hence, a performant surgical suite's organization relies on resources communication, and coordination within the surgical suite, as well as between the surgical suite and the outside world. This is complex because both the interactions with external services and the suite resources are numerous.

First, the surgical suite staff is composed of a variety of human resources (medical staff, paramedical staff, technical staff, administrative staff) which all require timely access to adequate material resources (supplies, premises, storages...). **Any lateness, absence, or error can lead to a disruption and hinder the operating schedule execution. Indeed, if the right resource is not available at the right place and at the right time, the patient pathway will stop. This goes as much for a surgeon as for a registered nurse.**

Second, due to the required interactions between the suite and outside units, dysfunctions appearing in the suite impact outside units, and vice-versa. This is especially an issue as the default staff behavior - whether it is within the suite or not - is to focus on their own tasks without taking into consideration the global working of the hospital, thus neglecting the impact their actions can have on the overall process. This is all the more true when the surgical suite can be seen as an isolated environment, due to its strong hygiene and safety rules; the suite staff has few and constrained contacts with the outside world. One example of what should be clearly communicated is the ongoing state of the operating schedule and its related patient pathways. We give examples in Table 8.

Table 8 – Example of dysfunctions coming from a lack of communication.

Service	Why should they know about the operating schedule?	Example of dysfunction
Stretchers	They should know the patient service so that they can move back and forth between the patient service and the surgical suite	The stretcher bearers do not know where the patient is. The operating schedule falls behind.
Suite Staff	They should know what the schedule is so that they can prepare the adequate material. The schedule must be made knowing the material resources' limits (sterilization time for boxes or endoscopes in case of necessity at the same time, limited number of cameras, etc.).	The OR nurses do not know what equipment to prepare for the next surgery. The operating schedule falls behind.

Consequently, the staff must maintain a high level of communication on each patient pathway advancement - overall the operating schedule execution - so that they can act as a synchronized

team as well as prevent and deal with disruptions. Consequently, it is necessary to establish strong communication and collaboration, both within the surgical suite, and between the surgical suite and outside services. This requires understanding the surgical suite organization in its globality. The staff needs to pay attention to the processes they impact, the processes they depend on, and the processes they are responsible for. Resource coordination must be ensured at both the offline and the online operational steps. In this context, the staff needs to have great communication, collaboration, coordination, and adherence to established processes.

CHAPTER II. BACKGROUND AND RELATED WORKS.

In Chapter I, we have highlighted the complexity of the surgical suite. The smooth running of surgical operations requires perfect synchronization of the human and technical resources involved. The human factor is omnipresent and constantly thwarts synchronization, making the operating room a place of uncertainty. In such a context, the planning and scheduling of interventions in each room is a major challenge.

In Chapter II, we present works related to the operating room planning and scheduling problem from different levels and horizons. We progressively refocus our literature review on the operational level, with the management of disturbances, both predictively (before program execution) and reactively (during execution). Throughout our research, we have observed a cruel lack of methods and tools for managing disruptions at the operational level. Today, disruptions are managed empirically, based on the experience of teams, by making decisions without any guarantee of their effects. However, the scientific literature presents several very interesting contributions on mathematical approaches to solving the planning and scheduling of operating programs subject to random disturbances. Even if they prove to be effective in theory, we can only observe that these approaches are not deployed or integrated into the various OR management software packages we have seen in practice. This was confirmed in an exchange with international OR expert F. Dexter (MD, PhD, Professor, Department of Anesthesia, University of Iowa). It is for this reason that we assume that a digital twin of the operating room, capable of offering end-users a realistic and faithful visualization and simulation of the surgical program, taking disturbances into account, could undoubtedly be better accepted. We therefore conclude this chapter with a state-of-the-art review of digital doubles and simulations used in the field of hospital processes and patient pathways.

1. Planning and scheduling problem

In this section, we provide a state of the art on papers tackling the planning and scheduling problem in the surgical suite. This subject has been extensively studied within the literature and many review papers exist (Przasnyski 1986; Franklin Dexter et al. 2004; Cardoen, Demeulemeester, and Beliën 2010; Guerriero and Guido 2011; May et al. 2011; M. Samudra, Demeulemeester, and Cardoen 2013; Demeulemeester et al. 2013; Abdelrasol, Harraz, and Eltawil 2014; Michael Samudra et al. 2016; S. Zhu et al. 2019; L. Wang et al. 2021; Zonderland and Boucherie 2021; Rahimi and Gandomi 2021; Harris and Claudio 2022; Van Riet and Demeulemeester 2015).

(Zonderland and Boucherie 2021) provide “a classification of literature reviews on patient planning and scheduling decisions in healthcare” based on three dimensions: the service providing care (ambulatory, emergency, surgical, inpatient, home), the level at which the decision is made (strategical, tactical, offline operational, online operational), and the planning complexity (single activity planning, multidisciplinary planning, care pathway planning). (L. Wang et al. 2021) provide “the first literature review on comparing outpatient surgery scheduling with inpatient surgery scheduling”. Their analysis is based on three dimensions: “the uncertainty incorporation, the research methodology, and a scheduling performance comparison between both settings”.

The planning and scheduling problem is often divided into four hierarchical decision levels: long-term strategic, medium-term tactical, short-term offline operational and real-time online operational. The scientific community has shown a strong interest in the strategic, tactical, and offline operational levels, and thus focused less on the online operational level. We proceed to describe the strategic level, the tactical level, the offline operational level, and the online operational level.

1.1. Strategic level

The strategic level deals with a long planning horizon as well as aggregated and forecasted information. At this level, decisions are made to optimize the distribution of resources among the different surgical specialties of the suite. The focus is notably on the number and the specialty of potential future surgeries, the number of resources required, etc. The strategic level problem is usually divided into the capacity planning problem, the capacity allocation problem, and the case-mix problem (CPM):

- The **capacity planning problem** consists in determining the resources required to meet patient demand in a cost-effective manner (Roshanaei et al. 2017b; Fügenger, Schiffels, and Kolisch 2017; Koppka et al. 2018).
- The **capacity allocation problem** consists in assigning the previously identified OR capacity to each surgical specialty. (Koppka et al. 2018; Roshanaei et al. 2017b; Vancroonenburg, Smet, and Vanden Berghe 2015).
- The **case-mix problem** refers to forecasting the number and type of surgeries that will be performed in the suite. (Koppka et al. 2018; Liang, Guo, and Fung 2015; Castro and Marques 2015).

(Choi and Wilhelm 2014) propose a prototypical non-linear stochastic programming model to allocate each surgical specialty to a certain number of OR days, with the objective of minimizing total expected costs due to penalties related to not accommodated patients, OR undertime and OR overtime.

1.2. Tactical level: master surgery scheduling problem

The **master surgical schedule (MSS)** is a weekly cyclical schedule which describes the OR shifts for each day. The master surgical scheduling is a tactical process. Every 6 to 12 months, the board of directors meet with the representatives of the surgical suite staff: the OR manager, the OR coordinator, at least one surgeon per surgical specialty, and at least one anesthesiologist. Together, they study the past period surgical suite activity, the next period patient demand forecast, the future human and material resources evolutions, and the potential surgical activity development opportunities. They update the current master surgical schedule by adding, deleting, and modifying OR shifts from the schedule.

(Bovim et al. 2020) proposes an optimization-simulation method to build a MSS made of dedicated time slots for elective patients and flexible slots for handling potential non-elective patients. They assess the impact on uncertainties related to surgery duration and patient length of stay in the hospital using DES. (Makboul et al. 2022) discusses a robust optimization approach for tackling both MSSP and the scheduling case assignment problem (SCAP). They do it for elective outpatients on a one-week horizon while considering OR restrictions, surgery priority, resource availability (OR, surgeon, ICU and PACU beds, etc.), and uncertainties (surgery duration and ICU bed availability). They assess their solutions using the number of scheduled surgeries and the suite utilization rate. (Chaabane et al. 2006) and (Kharraja, Albert, and Chaabane 2006) compare two OR block scheduling strategies for elective cases: the first one considers individual surgeons, and the second consider groups of surgeons. More papers on MSS can be found in (Koppka et al. 2018; Vancroonenburg, Smet, and Vanden Berghe 2015).

There are three main scheduling strategies:

- **Block scheduling** (Koppka et al. 2018; Guido and Conforti 2017).
- **Open scheduling** (Hashemi Doulabi, Rousseau, and Pesant 2016; Vancroonenburg, Smet, and Vanden Berghe 2015; W. Xiang, Yin, and Lim 2015b).
- **Modified block scheduling** (Vancroonenburg, Smet, and Vanden Berghe 2015; Molina-Pariente, Fernandez-Viagas, and Framinan 2015; Van Huele and Vanhoucke 2015).

The **block scheduling strategy** consist in pre-allocating OR capacity to different individual surgeons, groups of surgeons or surgical specialty. This is the most common strategy followed in real-world surgical suites. For instance, in a MSS build using the block scheduling strategy, every Monday the OR#1 could be available for surgeon A from 8am to 1pm and to surgeon B from 1pm to 6pm. The **open scheduling strategy** is a more flexible solution that does not consider pre-allocating OR shifts to surgeons or surgical specialties. Consequently, in a surgery schedule following an open scheduling strategy two cases from two different surgeons, or even from two different specialties can be scheduled in the same OR. The **modified block scheduling strategy** is a mix between the two first strategies. In a modified strategy, the MSS is initially built

according to a block strategy. As the execution day approaches, the dedicated block can then be opened to other specialties if underutilization is most likely to happen in the OR. For instance, pediatrics has access to OR#2 every Monday from 8am to 6pm. If on Thursday OR#2 shift has a utilization rate of 30%, the OR manager might take the decision to open the shift to other specialties that are struggling to fit all their cases in their own shifts.

Commonly used non-elective scheduling strategies exist. We refer the reader to (Vancroonenburg, Smet, and Vanden Berghe 2015) for more information on it.

1.3. Offline operational level: the surgery scheduling problem

The surgery scheduling (“*programmation*”) depends on offline operational decisions. It is divided into three main phases:

- **Advance scheduling:** setting a date and a room for each case (Roshanaei et al. 2017b; Turhan and Bilgen 2017).
- **Allocation scheduling:** sequencing cases within each ORs. (Kroer et al. 2018; Roshanaei et al. 2017a),
- **Integration of advance scheduling and allocation scheduling**

In real life surgical suites, the offline operational level is divided into different steps. First, during the **surgery consultation**, the surgeon sets the admission type (outpatient/inpatient) and the provisional duration of the surgery. They also indicate if the surgery will require supplementary equipment or staff. The surgeon chooses the surgery date based on their own schedule (shifts, patient waiting list, already scheduled patients).

Second, during the **anesthesia consultation**, the anesthesiologist accepts, postpones, or rejects the surgery. They choose the anesthesia type and specify whether the case needs additional supply.

Finally, during the **weekly scheduling meeting** (*cellule de programmation*), the attendees (1) check that the required resources (staff, operating room, surgical supplies) will be available, (2) identify and tackle the potential disruptions linked to the schedule execution, (3) fix the sequence and the starting time of the provisional surgeries, (4) freeze the agreed-upon provisional schedule – meaning that staff cannot add patients for the following week without directly passing by the OR manager, (5) send the schedule to each surgical specialty staff, and (6) send the patients’ provisional suite entry times to the hospitalization services.

The scheduling meeting attendees ideally include the OR manager, the OR coordinator as well as a representative for each surgical specialty (a surgeon and/or a secretary), and for the anesthesiologists. The meeting can also include a representative for the pharmacy, the sterilization service, the ambulatory service, and the surgical suite nurses. At worst, only the OR coordinator and a representative of the doctors (usually an anesthesiologist) meet. The scheduling meeting usually takes place on Thursday morning. During the meeting, the attendees discuss the schedule of the following week (sometimes of the two following weeks).

(Guinet and Chaabane 2003) propose to solve the surgery schedule problem over a one to two weeks horizon in two phases: (1) assign an OR to each patient, and (2) assign a rank to each patient.

The article focuses on the first step and solve it using an “assignment model with resource capacity and time-window additive constraints”.

(Perdomo, Augusto, and Xie 2006) propose a Lagrangian relaxation approach to solve the surgery scheduling problem while considering both the operating rooms and the post-operative beds. (Augusto, Xie, and Perdomo 2008) does the same but also considers stretchers. (Lamiri et al. 2008) propose to use column generation as a decomposition approach to tackle the surgery scheduling problem while considering the same three types of resources (stretchers, operating rooms and PACU beds) and while minimizing a patient completion time-based criterion. (Augusto, Xie, and Perdomo 2010) use a Lagrangian relaxation-based method to study the possibility of using operating rooms for patient recovery after surgery when the PACU is full. They consider the same resources and assess their results based on several patients’ completion times indicators.

1.4. Online operating level: the schedule execution problem

We have previously discussed the strategic, tactical, and offline operational decision levels of the scheduling problem. These levels allow to build a provisional schedule that shall be executed on surgery day. In this section, we discuss the online operational level which consist in managing the schedule execution.

On the day of the surgery, the OR coordinator is responsible for the smooth execution of the provisional schedule. Since it is known in advance that this initial schedule will be disrupted by uncertainties, the goal of the OR coordinator is *not* to obtain a performed schedule identical to the provisional schedule. Instead, they use the provisional schedule as a guide to take the real-time (online) decisions that will allow them to manage the daily disruptions *and* reach the performance targets set for the service.

The **performed schedule** describes how the schedule unraveled during a past day. It is often different from the provisional schedule, as uncertainties create deviations between the two schedules. It comprises elective cases, old non-elective, and new non-elective cases. Usually, the ongoing schedule execution is represented as in Figure 9: one operating room per row.

The OR coordinator ensures the smooth execution of the schedule. They coordinate the staff and the equipment so that the patient is provided adequate care, and they take real-time decisions to deal with uncertainties inherent to the surgical suite functioning. These decisions are only organizational – never medical. They use the provisional schedule but know in advance that they are going to deviate from it as disruptions are an inherent part of the surgical suite activity. Below is a list of decisions to be taken in real-time:

We can note several things about these real-time decisions. First, they can vary from one coordinator to the other. Indeed, coordination strategy depends on the coordinator personality. For instance, some are more risk-averse than others. Second, real-time decisions are taken on the spot, usually based on both the medical and the organization related expertise of the coordinator – who most of the time is a former and experienced operating room registered nurse. There is no generally used tool for the coordinator, except maybe their phone and the timeline of the ongoing schedule. When making a decision, the coordinator has no means to assess thoroughly its possible

consequences. Three, except in the case of a grave incident, there is no feedback or retrospective analysis on the decisions taken by the coordinator.

2. The predictive and reactive disruption management problem

2.1. Introduction

Disruptions – and thus schedule modifications - are inherent in the OR schedule execution (Franklin Dexter et al. 2004). Indeed, uncertainties impact patients, human resources, and material resources. Thus, planning and scheduling article reviews show an increasing interest in stochastic approaches to scheduling. We first discuss the type of uncertainties that can be found in the surgical suite. Then, we address the strategies developed in the literature review to provide a remedy to these disruptions before they take place (predictive disruption management), and upon their occurrence (reactive disruption management).

2.2. Uncertainties

In this section, we provide a non-exhaustive review of the different types of uncertainties in the surgical suite: duration uncertainty, arrival uncertainty, resource uncertainty, and care requirement uncertainty (S. Zhu et al. 2019).

Patient activity duration in the surgical suite (preoperative care, setup, procedure...) depends on patient condition, surgeon skill, surgery type and several other factors (Molina-Pariente, Fernandez-Viagas, and Framinan 2015; Koppka et al. 2018; Kroer et al. 2018; Ng et al. 2017). Activity duration is thus highly stochastic, and its modeling can have a strong impact on the quality of both the planning and scheduling (Guda et al. 2016), and the disruption management problems. The three distributions usually used by the scientific community are the log-normal, gamma and normal ones (S. Zhu et al. 2019). Other methods exist such as using Monte Carlo simulation.

Patient arrival uncertainty include **unpredictable arrival times of outpatients** in the hospital (Kroer et al. 2018; Rachuba, Imhoff, and Werners 2022; Latorre-Núñez et al. 2016; Guda et al. 2016). Indeed, outpatients are admitted and discharged in the same day. Since they are not in the hospital at the start of the schedule execution day, it is more complicated to control their arrival times. Approaches to limit this uncertainty include adding some slack time to give more time to the patients to arrive (Cardoen, Demeulemeester, and Beliën 2010).

Patient arrival uncertainty can also refer to the **arrival of non-elective cases**. These cases can be semi-urgent (meaning they do not need to receive surgery on their admission day) or urgent (meaning they must receive surgery on their admission day).

Resource uncertainty translates the fact that human and material resources might not always be available at the right time and the right place for the patient (Hashemi Doulabi, Rousseau, and Pesant 2016; Castro and Marques 2015; Vancroonenburg, Smet, and Vanden Berghe 2015). Since the surgical suite processes heavily rely on resource synchronization, this uncertainty can lead to patient waiting times or even to case postponement. (Erdem, Qu, and Shi 2012) proposes a reactive surgery scheduling model that reschedules not only elective cases but also resources upon the arrival of non-elective cases.

Care requirement uncertainty (refer to the fact that professionals cannot always know in advance what care patients will need during their stay at the hospital. Thus, as the patient situation

evolves throughout their stay at the hospital, it can lead to their surgery being canceled or postponed. For instance, during our on-site observations, we witnessed a patient having their case cancelled while in the OR; the staff had found a rash on their leg when they were about to get a hip replacement.

In our study, we focus on uncertainties related to resource availability, activity durations and non-elective case arrivals.

2.3. The disruption management problem at the operational level

In this section, we rely on two literature reviews. (Franklin Dexter et al. 2004) review reactive disruption management methods at the online operational level, and (Kamran, Karimi, and Dellaert 2020) discuss both predictive and reactive strategies at the online and operational levels. We distinguish the articles based on whether they only tackle offline disruption management, or both offline *and* online.

2.3.1. Online Operational disruption management

At the online operational level, the objective is to take real-time decisions to ensure a smooth schedule execution despite uncertainties inherent to medical practice and surgical suite organization (Franklin Dexter et al. 2004) define OR inefficiency as “the sum of two products: hours of underutilized OR time multiplied by the cost per hour of underutilized OR time plus hours of overutilized OR time multiplied by the cost per hour of overutilized OR time” and describe OR efficiency as “the value that is maximized when the inefficiency of use of OR time has been minimized”. They propose to make online operational decisions based the following 4 ordered priorities: ensuring patient safety, not cancelling cases, maximizing OR efficiency, reducing patient waiting time. We will refer to this framework as the 4-priority framework (4PF) in the future as it comes out often in their article. They list the following online operational decisions (reactive disruption management strategy):

- Scheduling add-on cases (Zhou and Dexter 1998; F. Dexter, Macario, and Traub 1999; Franklin Dexter and Traub 2002; Franklin Dexter, Macario, and Traub 1999)
- Fill the schedule gaps (Zhou and Dexter 1998)
- Move already scheduled cases (Franklin Dexter et al. 2003) (F. Dexter 2000) (Franklin Dexter et al. 2004)
- Assign staff (F. Dexter, Macario, and O’Neill 1999; Franklin Dexter et al. 2004)
- Prioritize limited resources and personnel (F. Dexter and Traub 2000a) (Lebowitz 2003)
- Prepare patients (F. Dexter and Traub 2000b)
- Sequence urgent cases (Zhou et Dexter 1998)

We discuss some of the articles referenced in (Dexter et al. 2004a) and in the literature below.

Scheduling add-on cases. (F. Dexter, Macario, and Traub 1999) use computer simulation to assess how many hours of add-on elective cases can be scheduled into open OR time for 10 scheduling methods. The different algorithms are the following: Best Fit (with or without fuzzy constraints), Worst Fit (with or without fuzzy constraints), Best Fit Descending (with or without

fuzzy constraints), Worst Fit Descending (with or without fuzzy constraints), Worst Fit Ascending, and Hybrid. Elective cases are defined as cases which can wait at least 3 days for their surgery to be performed (e.g. an elective patient admitted on Monday can be operated during the next Thursday or after). Elective cases are considered as “Add-on” when they are scheduled after a specified cut-off time (e.g. after the weekly scheduling meeting). Their results are likely to reflect reality for surgical suites with a few add-on elective cases per day.

(Franklin Dexter and Traub 2002) assess two methods to schedule an elective case into an OR: Earliest Start Time (i.e. the case is scheduled into the first available OR) and Latest Start Time (i.e. the case is scheduled into the last available OR that allow them to finish the surgery without overtime; otherwise, the case is scheduled in the first available OR). Their study perimeter is the following: surgeons and patients choose the day of the surgery, cases cannot be cancelled, and staffing to maximize the efficiency of OR utilization. First, they show that (1) Earliest Start Time is rational economically and allows to maximize OR efficiency if the suite is already nearly full, (2) Latest Start Time is best at balancing the OR utilization between the services, (3) the difference of utilization between the two methods is only a few methods per OR. Second, they use computer simulation to assess the impact of surgery duration uncertainty on the performance of these two heuristics and show that it amounts to only a few minutes per OR. They conclude that there is no need for strong restrictions on elective add-ons for facilities which aim at ensuring (in this order) patient safety, patient and surgeon access to OR, and surgical suite efficiency.

Within the 4PF (4 priority framework), (Dexter et al. 2004a) study case sequencing decisions. They take the following example: OR#1 and OR#2 have both 8.5 h of allocated time. Turnover times are 0.5 h. A 2.5 h case is scheduled in OR#1 requiring a microscope by surgeon A and a 4 h case is scheduled in OR#2 by surgeon B. They address the following question: should we schedule a 4 h case in OR#2 requiring the same microscope after the turnover, or should we schedule multiple shorter add-ons? The first option implies a 100% utilization rate, meaning that any delay would cause an overtime. To answer that question, they propose a 1.5% accurate statistical method to compute the probability of one surgery lasting less time than another based on at least 2 historical durations for each of them.

Scheduling add-on cases and Sequencing urgent cases. (Franklin Dexter, Macario, and Traub 1999) discuss how to optimally sequence non-elective cases. They suggest different methods such as: minimizing the average patient and surgeon waiting times, applying FIFO scheduling, and ranking cases based on medical priority.

Filling schedule gaps. (Zhou and Dexter 1998) assess whether an add-on case can be added to the schedule without leading to overtime by predicting the upper bound of its duration. They conclude that the prediction bounds were accurate if based on both the surgeon and the procedure type, and if the case durations were assumed to follow a log-normal distribution.

Moving already scheduled cases. (Franklin Dexter et al. 2003) explain that although it can be constraining, moving the last case of a day from one OR to another one can improve OR efficiency. The survey they conducted with physicians show that the OR overtime should be reduced by at least an hour for the OR change to be perceived as worth it.

(F. Dexter 2000) discusses the information required to move the last case of the day in one OR to another OR that is idle to decrease overtime labor costs. They compare the overtime per case if the OR management has access to (1) the exact duration prediction of the case, and (2) historical duration data for the cases. They show that knowing the exact case duration reduces overtime by less than 5 minutes than using historical case durations. They conclude that “The use of other information technologies to assist in the decision of whether to move a case, such as real-time patient tracking information systems, closed-circuit cameras, or graphical airport-style displays, can, on average, reduce overtime by no more than only 2 to 4 min per case that can be moved”.

Assigning staff. If there are still surgeries to be performed once the OR shift is over, the surgical team can either continue in overtime or be replaced by another team. (F. Dexter, Macario, and O’Neill 1999) discuss the information required to establish a relief strategy for anesthesiologists at the end of the OR shift. They show that although knowing the exact duration remaining in cases minimizes anesthetist staffing costs, using historical case durations performs almost as well. They conclude that “Few additional staff hours would have been saved by supplementing our relief strategy with other methods to monitor case durations (e.g., real-time patient tracking systems or closed-circuit cameras in operating rooms)”.

Prioritizing limited resources and personnel. A patient pathway requires the synchronization of various human and material resources. This complexity increases with the number of patients as they rely on the same resources (although supposedly not at the same time). (F. Dexter and Traub 2000a) discuss how to use statistical decision theory based on historical case duration to decrease the impact of resources on OR scheduling, and thus increase equipment and OR utilization. They study a specific situation where resource will first be used by the first case of an OR#1, and then by the first case of another OR#2, knowing that the OR#2’s first case has a higher probability of lasting longer than the OR#1’s first case.

(Lebowitz 2003) use a Monte Carlo Simulation of a surgical suite to show that scheduling short procedures first can decrease staff overtime without reducing the number of surgeries performed.

Preparing patients. Real case durations are usually longer or shorter than their predicted value. Consequently, surgeries may need to start earlier or later than predicted. Since patients need to be prepared before going to the surgical suite, the time at which they are supposed to be ready needs to be updated throughout the day. (F. Dexter and Traub 2000b) use simulation to determine at what time a patient should be ready for surgery on the day of surgery. They assume that the historical case durations follow a log-normal distribution and compute prediction bounds while reducing to 5% the risk of OR staff having to wait for the patient.

(F. Dexter, Traub, and Lebowitz 2001) propose a method to compute the delay between two surgeons working one after the other in the same OR on the same day by using both analytical expression and Monte Carlo simulation.

Below are mother articles that discuss other decisions.

(Stuart et al. 2010, 20) propose a **robust reactive surgery assignment model** that minimizes cancellations of already scheduled patients and maximizes the throughput of non-elective cases. They focus on a single operating room suite. At the end of each surgery, they re-solve the surgery

schedule problem while considering the disruptions that occurred since the last reschedule. The scheduling strategy can be inferred a type of block scheduling policy. They model uncertainties on surgical durations (log-normally distributed), non-elective case arrivals (exponential distribution with an average inter-arrival time of 225 minutes), and resource availability (human or material). These disruptions can lead to either early or late start times for the scheduled patients.

(Stuart and Kozan 2012) suggest a **reactive scheduling model** with the goal of maximizing the weighted number of expected in-time patients. The tool can delay, reschedule, or add additional non-elective cases while respecting the constraint on a single OR suite capacity. They model uncertainties on surgical durations by adding a slack time at the end of each case, non-elective case arrivals, and resource availability (human or material).

(Erdem, Qu, and Shi 2012) study a **rescheduling problem of elective patients in case of non-elective patient arrivals**. They consider the overtime cost of the suite and/or the PACU, the cost of postponing or preponing elective cases, and the cost of turning down the non-elective cases in their objective function. They include both the surgical suite and the PACU in their study.

(He and Xiang 2013) tackle the **rescheduling problem when a lack of resources makes it unfeasible**. They consider uncertainty on resource availability, maintain the patient-surgeon coupling after the schedule modification, and aim at minimizing the duration between initial case start and modified case start.

2.3.2. Online and offline operational disruption management

(Dios et al. 2015) present a **scheduling and rescheduling decision support system for elective cases and suite resources (surgeons and nurses)** with the objective of minimizing the number of changes to already scheduled cases, the patient waiting time and the resource re-scheduling cost. They develop their tool so that they can generate the surgery schedule based on an elective patient waiting list up to 6 months in advance, while allowing for manual last-minute changes in case of disruptions such as non-elective arrivals. Their DSS is currently in use in one of the largest hospitals in Spain.

(Bruni, Beraldi, and Conforti 2015) develop a **reactive scheduling model for a multiple OR suite**. They include both non-elective arrivals and duration uncertainty. They model three reactive disruption management strategies: scheduling cases in overtime, swapping cases, and rescheduling all the remaining cases. They consider a block scheduling strategy.

(Addis et al. 2016) propose a **rolling horizon approach for the offline scheduling and rescheduling problem**. They use an elective case waiting list that considers continuously joining new patients and where each patient is assigned a maximum waiting time before being scheduled. They assume a block scheduling strategy. Their study includes two sources of uncertainty: patient arrival in the waiting list and surgery durations.

(Heydari and Soudi 2016) consider a predictive/reactive assignment and sequencing model for a multiple identical OR suite. They consider both elective and non-elective cases, and they include uncertainties on activity duration and non-elective arrivals. They build an initial schedule able to absorb disruptions with minimum effect on already elective cases. Doing so, they define two sets

of performance indicators comprising robustness (the ability to maintain performance despite disruptions) and stability measures (the ability of a schedule to not deviate despite disruptions).

(Ceschia and Schaerf 2016) propose a **dynamic patient admission scheduling** in which they integrate the constraints brought by the surgery scheduling. To do so, they include constraints on the utilization of ORs for patients requiring surgery: each OR capacity must be respected, and each OR is only assigned a set of surgical specialties. They consider elective and non-elective patients.

(Ballestín, Pérez, and Quintanilla 2019) build a **scheduling and rescheduling model for elective cases** that minimizes the percentage of late patients. First, they build a tentative schedule two weeks before the planning period with the objective of minimizing the number of tardy patients. Second, a few days before schedule execution, they rebuild the schedule based on the changes that happened since the first scheduling. They propose several strategies based on the specificities of elective cases to tackle the changes from the first to the second schedule.

As a synthesis for this part, we propose Table 9 extracted from (Kamran, Karimi, and Dellaert 2020).

In our study we focus on the disruption management at the offline and at the online operational level.

Table 9 - Review of Predictive and Reactive Disruption Management for the surgery scheduling and the disruption management problems. Taken from (Kamran, Karimi, and Dellaert 2020). The abbreviations stand for planning (P), scheduling (S), replanning (RP), rescheduling (RS), patient booking strategy (PBP), DM (disruption management), reactive disruption management (RDM), predictive and reactive disruption management (PRDM).

Reference	P and and/ or S	RP and/ or RS	PBP	DM approach	Patient		Model/Problem	
					Elec.	Emerg.	Deter.	Stoch.
Stuart et al. (2010)		x	O ¹	RDM	x	x		x
Ceschla and Schaerf (2014)	x	x	B ¹	RDM	x	x		x
Bruni et al. (2015)	x	x	B	RDM	x	x		x
Dios et al. (2015)	x	x	O	RDM	x		x	
Addis et al. (2016)	x	x	B	PRDM	x	x		x
Ballestin et al. (2019)	x	x	B	RDM	x		x	
Stuart and Kozan (2012)		x	O ¹	RDM	x	x		x
He and Xiang (2013)		x	O	RDM	x		x	x
Zhang et al. (2014)	x	x	O	RDM	x			x
Nouaouri et al. (2011)		x	O	RDM	x	x	x	
Erdem et al. (2012)		x	O ¹	RDM	x	x	x	
Shu and Subbaraj (2015)		x	B ²	RDM	x		x	
Heydari and Soudi (2016)	x	x	O	PRDM	x	x	x	x
Soudi et al. (2019)		x	O	PRDM	x		x	x
Akbarzade et al. (2019)		x	B ²	RDM	x	x	x	
Kamran et al. (2019)	x	x	MB	PRDM	x	x		x
Kamran et al. (2020)	x	x	MB	RDM	x	x	x	

O¹ The way they approach to patient booking policy can be inferred a type of block scheduling policy as well.

B¹ The way they approach to patient booking policy can be inferred a type of modified block scheduling policy as well.

B² The way they approach to patient booking policy can be inferred a type of open scheduling policy as well

3. A digital twin for the surgical suite based on discrete event simulation

3.1. Discrete-event simulation

Simulation is “the imitation of the operation of a real-world process or system over time” (Banks, n.d.; Robinson 2004). Discrete-Event Simulation (DES) is a computer-modeling technique used to model the behavior of a system as a sequence of events in time. The key components of a DES mode include entities, events, a simulation clock, queues, resources, activities, and processes. We give a brief definition of each of these components:

- An **entity** is an object that move through the modeled system (example: a patient admitted for surgery).
- An **event** is an instantaneous occurrence that change the state of the system (example: a patient arrives in the surgical suite; a patient exits the surgical suite).
- The **simulation clock** is a virtual clock that tracks the simulation time progression. It determines the order of occurrence of each event.
- **Queues** allow to model waiting entities (example: a patient waiting room).
- **Resources** are the required componaents for the system to perform its action (example: a surgeon, a nurse).
- An **activity** is considered as the smallest unit of work. It has a finite duration, and it is assumed to provoke state changes at its start and at its end (example: a procedure, a reversal).
- A **process** is a sequence of activities and events in a chronological order that allows to model all or part of the behavior of the targeted system (example: the preoperative care process).

Since the 1950s, the research community has shown great interest in the use of DES in fields such as manufacturing, supply chain management, military operations, computer, and network design. In a standard manufacturing DES model, raw materials are introduced into the system and are directed to queues for processing. Then, they undergo transformation and/or consumption through different processes, before leaving the system in the form of finished goods. A similar modeling can be applied to the healthcare sector. First, a sick or injured patient enters a hospital and is sent to a waiting room. Then, the patient is then treated (transformed) via various processes (surgery, radiological exam, etc.), before exiting the hospital as a healthy patient (Forbus and Berleant 2022).

DES has been used in the healthcare sector for more than 20 year (Evans, Unger, and Gor 1996) and several reviews are available (Thorwarth and Arisha 2009; Günal and Pidd 2010; S. Liu et al. 2020; X. Zhang 2018; Vázquez-Serrano, Peimbert-García, and Cárdenas-Barrón 2021; Forbus and Berleant 2022).

(Forbus and Berleant 2022) reviews five years of literature (2017-2021) and show that not only the interest in DES in healthcare increases by the year, but it also expands to new areas of the healthcare system. They identify four primary purposes of DES use in the healthcare area: disease progression management (study the long-term economic impact of treatments), health screening protocols

(study of the effects of properly orienting patients towards specific care pathways), health behavior modeling (study of diseases caused or exacerbated by personal lifestyle choice), and healthcare system operations (the equivalent of traditional manufacturing operations management in the healthcare sector). This later use of DES, which focuses especially on resource utilization, scheduling and capacity planning is the one that interests us in this study. (Günel and Pidd 2010) review the use of DES for performance modelling in the healthcare sector. They focus on care provided by hospitals such as outpatient, inpatient, day-case and emergency care. They address the attempts at building whole hospital simulations and the challenges it brings. They conclude that most articles are unit specific, facility specific and can only be used at an operational level.

Some these reviews highlight the fact that DES is also used in the surgical suite. Indeed, many articles can be found (Marcon and Dexter 2006; Gul et al. 2011; Saremi et al. 2013; Lehtonen et al. 2013; Niu et al. 2007; Ma and Demeulemeester 2013; Peng, Qu, and Shi 2014; J. Brown et al. 2014; Baesler, Gatica Fuentes, and Correa 2015; van der Kooij, Mes, and Hans 2014; Saadouli et al. 2015; W. Xiang, Yin, and Lim 2015a; Bam et al. 2017; Koppka et al. 2018). Subjects of interests include the assessment of the performance of OR management strategies (Schoenfelder et al. 2021; Persson et al. 2017; Allen, Taaffe, and Ritchie 2014; M'Hallah and Al-Roomi 2014) and OR scheduling (Schultz and Claudio 2014; Ewen and Mönch 2014; S. Wang et al. 2016; Roshanaei et al. 2017a). Below, we briefly discuss a few other articles where DES is applied to solve issues related to the surgical suite.

(Bovim et al. 2020) proposes to solve the MSSP with a simulation-optimization. First, they use two-stage stochastic optimization model is used to develop a MSS. Second, they use DES to test the MSS in a stochastic environment with uncertainties related to the surgery duration and the hospital length of stay, as well as to provide scenarios for the optimization model.

(Yahia et al. 2017) develop a Design and Engineering Methodology for Organization-based simulation model to provide a more comprehensive view of the planning and scheduling problem in the surgical suite. They their DES model with AnyLogic and they use it (1) to assess the operational performance of the CMP and MMSP, (2) as a simple process and ontological representation.

(Duma and Aringhieri 2015) propose to use simulation-based optimization to assesses whether a case with at risk of going overtime should be cancelled or assigned overtime. They consider elective and non-elective cases, the impact of the training level disparity among surgical teams, as well as uncertainties on patient arrivals, patient length of stay, and surgery durations. Both patient-centered and facility centered indices are used to assess the performance.

(Z. Zhang and Xie 2015) use a simulation-based optimization model to tackle the appointment scheduling problem in a mutli-OR suite. They consider uncertainties on surgery durations and assess performance through the costs generated by surgeon waiting time, OR idle time and OR overtime.

3.2. Digital twin

The notion of “digital twin” is not a recent development. Its origins track back to the 1960s when NASA’s Apollo space program introduced the idea of “twin” space vehicles. NASA built two identical space vehicles, deployed one into space and kept the other on Earth to replicate and predict the behavior of its space twin (Boschert and Rosen 2016). In 2003, Michael Grieves introduced the concept of digital twin as we know it today: “a digital equivalent to a physical system”²¹. However, it is only in 2010, that NASA provided the first definition of a digital twin within the context of their own field: “an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin”²².

Today, the development of advanced information technologies such as IoT has opened doors for a new generation of digital twins. **Although the scientific literature abounds with literature reviews on the digital twin, there is still not a single, widely accepted definition of what is a digital twin** (Jones et al. 2020; Semeraro et al. 2021; M. Liu et al. 2021; VanDerHorn and Mahadevan 2021). For instance, (Grieves and Vickers 2017; Abramovici, Göbel, and Dang 2016; Rosen et al. 2015) describe a DT as “a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level”, while (Schluse and Rossmann 2016; Schroeder et al. 2016) defines it as “an integrated multiphysics, multiscale simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin”.

Some common characteristics of what a digital twin should still be inferred from this pool of available definitions: a digital twin must be individualized, high-fidelity, real-time, and controllable (M. Liu et al. 2021). In other words, a digital twin must (1) be the virtual replica of a designated physical twin, (2) be able simulate the physical twin’s behavior in real-time or almost real-time, and (3) allow a bidirectional communication with the physical twin. Furthermore, in Novembre 2021, the International Organization for Standardization published the norm ISO 23247-1:2021²³ where they provide an overview and general principles of a digital twin framework for manufacturing (Shao, Frechette, and Srinivasan 2023).

Note that an **offline digital twin** describes the case where real-time communication is not critical. Rather, an offline digital twin would connect to the physical system periodically. This periodic connection is an important distinction between an offline digital twin and a traditional simulation model (Shao and Helu 2020).

²¹ <https://www.3ds.com/fileadmin/PRODUCTS-SERVICES/DELMIA/PDF/Whitepaper/DELMIA-APRISO-Digital-Twin-Whitepaper.pdf>

²² <https://emacromall.com/reference/NASA-Modeling-Simulation-IT-Processing-Roadmap.pdf>

²³ <https://www.iso.org/standard/75066.html>

Within this study, we define a digital twin as an individualized and high-fidelity virtual replicate of a physical twin (a product, a process, or an organization). The digital and the physical twins exchange data via a bidirectional communication canal. The physical twin provides data so that the digital twin can replicate its behavior in real or near-real time; the digital twin provides data to the user and the digital twin so that decisions can be made in the real-world.

The industrial applications of digital twin span across the different lifecycles phases: design (F. Xiang et al. 2019; Lutters 2018; Caputo et al. 2019), manufacturing (Z. Zhu, Liu, and Xu 2019; Leng et al. 2019; Knapp et al. 2017), service (Aivaliotis et al. 2019; Xie et al. 2019) and retire (X. V. Wang and Wang 2019).

Although less developed than in the industry, digital twins are also used in healthcare. (Erol, Mendi, and Doğan 2020) define a digital twin as a “digital replica that allows modeling the state of a physical asset or system”. They propose the digital twin of a patient which shows the same physical characteristics and changes that the real patient. Their tool can be used for diagnosis and treatment process monitoring. (Y. Liu et al. 2019) propose a framework of the cloud healthcare system based on digital twin (CloudDTH) in order to monitor, diagnose, and predict aspects of individual health. Their tool specifically targets the elderly population. (Elayan, Aloqaily, and Guizani 2021) define a digital twin as “a virtual replica of a physical asset that reflects the current status through real-time transformed data”. Their article proposes and implement an intelligent context-aware healthcare system using the DT framework.

The above articles describe patient focused digital twin for monitoring individual and diagnosing health problems. However, it is possible to apply this diagnosis and monitoring concept to the healthcare organization itself. (Abdallah Karakra et al. 2018; 2019; A. Karakra et al. 2020; Abdallah Karakra 2021; Abdallah Karakra et al. 2022) build a discrete event simulation based digital twin for real-time monitoring and near-future prediction of patient pathways in the hospital. (Obinna C. Madubuike and Anumba 2022; Song and Li 2022; Obinna C. Madubuike and Anumba 2023; Obinna Chimezie Madubuike, Anumba, and Agapaki 2023) tackles the discuss the application of digital twin in healthcare facility management.

In our case, we propose to build the digital twin of a multi-OR surgical suite. Our digital twin is thus the virtual replica of a group of intertwined processes that aim at answering patient demand (surgical interventions) while using specific resources (the operating rooms and the staff). Note that the study of material resources other than the operating rooms are out of scope. The digital twin is used as a decision-support system on a daily basis and thus, the daily input of data is equivalent to having real-time data input for an online digital twin. We make the hypothesis that we can build the digital twin of a surgical suite using Discrete Event Simulation.

4. Chapter synthesis

In this three-section Chapter, we have discussed the state of the art surrounding our problematic and defined our study perimeter. The goal of this chapter was to bridge between the on-site observed problematics and the current advancements and solutions provided by the scientific community to define our study perimeter.

To begin with, we have described the planning and scheduling problem linked to the working of surgical suite. Then, we discussed the reactive and the predictive levels of the disruption management problem. After that, we addressed the concept of digital twins, how they can be used in both the healthcare and industrial sectors. Finally, we presented a brief review on the use of discrete event simulation in the healthcare environment, and more precisely, in the surgical suite.

Consequently, we have set our study aim as follows: providing a decision-support system for the operational decision level to deal with both the reactive and predictive disruption management problem. To do so, we propose to build a **discrete event system digital-twin-based decisions support system (DT-DSS)**. For this purpose, we use Flexsim Healthcare®: a 3D simulation and data analysis software.

Our choice of discrete event simulation is justified by the fact that it:

- Is adapted to complex system modeling: we can model a multiplicity of resources and processes (patient pathways) in parallel.
- Inherently respects resource constraints. For instance, if a patient acquired a surgeon, the surgeon will not be able to intervene on another patient at the same time.
- Is compatible with the computation of KPIs and the construction of dashboards, and thus with performance analysis.
- Allows to model and simulate operating schedule execution.
- Is compatible with the implementation of an experimenter. This allows to easily create what-if scenarios. An experimenter allows to easily configure scenarios for multiple replications – meaning to integrate stochasticity – and to compare the global KPI for all the replications, or the KPI for a specific replication.
- Is compatible with the implementation of an optimizer.
- Allows to perform risk assessment, and sensitivity analysis.
- Allows flow visualization and provides a dynamic visual interface (we can see the system evolution across time).
- Can provide a pedagogical environment. It can enhance non-expert user trust in the tool with the visualization aspect. This is especially important as our application field is the healthcare area. 3D figures are easier to understand than mathematical equations.
- Allows uncertainties modeling such as duration variability and non-elective arrivals.
- Provides a risk-free environment and a training environment.

PART 2 - PROPOSED
METHODOLOGY AND TOOL

CHAPTER III. SOLUTION PROPOSAL

In Chapter II, we have described the four different planning and scheduling decision levels of a surgical suite. First, the long-term strategic level deals with the capacity planning, the capacity allocation, and the case-mix problems. Second, the medium-term tactical level tackles the master surgery schedule problem (MSSP). Third, the short-term offline operational level related to the surgery scheduling problem (which can be divided into the advanced and the allocation scheduling problems). Fourth and finally, the real-time online operational level consists in the schedule execution problem. We have then discussed the disruption management problem that takes place at the operational levels. It is divided into two main issues: (1) in predictive disruption management (PDM), disruptions are anticipated and dealt with before they occur; (2) in reactive disruption management (RDM), the disruptions are only tackled after they have been already realized.

Upon studying the on-site and scientific problematics linked to the surgical suite, we have decided to focus on the disruption management at the operational level and have thus made the following hypotheses: we consider the allocated resources (strategic level), the master surgical schedule (tactical level) and the provisional schedule (offline operational level) to be fixed and staff-validated in advance. In other words, we do not wish to build nor to improve the provisional schedule. This has led us to address the following general research question: “How can we promote and maintain the performance of a surgical suite’s organization under uncertainties?” which we have divided into 5 more specific research questions:

- Q1. How can we anticipate disruption before schedule execution?
- Q2. How can we assess the quality of the predictive disruption management?
- Q3. How can we assess the quality of the reactive disruption management?
- Q4. How can we identify whether performance lack stems from offline or online decisions?
- Q5. How can we train OR managers to disruption management?

This has required us to specify the study perimeter. Thus, we have chosen to:

- Assess the performance using 3 KPI’s: (1) the maximum patient waiting time in the surgical suite, (2) the average utilization of the surgical suite’s ORs and (3) the average staff overtime in the surgical suite.
- Focus on three types of uncertainties: non-elective patient arrivals, activity duration variability and resource availability.
- Study one type of online operational decision: the scheduling of non-elective patient arrivals.
- Use Discrete Event Simulation and Digital Twins to tackle our research questions.

To provide decision support on online operational decisions, we can either:

- (1) **Before schedule execution (offline tool):** anticipate what would be the best online operational decision strategy to follow based on the specific provisional schedule.
- (2) **During schedule execution (online tool):** provide insights into what online operational decision to take in real-time.
- (3) **After schedule execution (offline tool):** provide feedback on the online operational decisions that were taken during schedule execution.

Either way, the principal function of our tool will be: “Maintain and improve the performance of a surgical suite’s organization under uncertainties”. **Note that the term “maintain” is particularly important.** We make the hypothesis that the provisional schedule is staff-validated and fixed. Thus, we cannot change the provisional schedule - even if we show before schedule execution that the performance targets may not be reached. This means that, with certain provisional schedules, it might be impossible to obtain a performant performed schedule. In other words: the fact that the performed schedule is not performant does not always mean that the online operational management was not performant; it could also indicate that the provisional schedule was suboptimal.

Example: if the provisional schedule utilization is at 95% and several non-elective cases are added to the schedule, the overtime resulting from it might not be avoidable.

Based on our literature review and on-site observations, we have decided to propose a digital twin-based offline decision support system to improve the decisions taken at the online operational level. This means that we propose a decision support system that directly supports the analysis of the provisional and the performed schedules, and that thus indirectly prepares the schedule execution and provides feedback on it. Indeed, to the best of our knowledge, the offline decision support system we propose does not exist today. Indeed, in most surgical suites, the staff has access to an OR software to build the provisional schedule and to extract data to retrospectively compute KPIs. However, there has not been any tool developed to anticipate and assess different decision strategies to follow during the real-time execution of the schedule, or to provide feedback on how the schedule execution was carried out.

In the remainder of this Chapter we describe a methodology for a prospective analysis of the provisional schedule (contribution #1), a methodology for a retrospective analysis of the performed schedule (contribution #2), and a methodology for real-time decision-making virtual training destined to OR managers (contribution #3).

In Chapter IV, V and VI, we propose as a proof of concept a study case in which we apply the three first methodologies to a surgical suite inspired by the *Hôpital Privé de La Baie*. To do so, (1) we develop a digital twin-based decision support system for the prospective and retrospective simulation and analysis of the operating room schedule execution, and (2) we infer from this prototype a standardized methodology to conceive and build such a tool in any surgical suite (contribution #4). We describe this contribution #4 in the last section of the Chapter.

1. Prospective analysis of the provisional schedule

In this section, we propose a methodology for a prospective analysis of the provisional schedule. The objectives are to anticipate disruptions before schedule execution (**Q1**), and to assess the quality of the predictive disruption management (**Q2**). This methodology corresponds to our contribution #1.

We propose a five-step analysis of the provisional schedule. To begin with, we simulate the provisional schedule execution to assess the resource synchronization (step #1) and compute the schedule performance (step #2). Then we consider the impact of stochastic durations on the performance to assess the schedule robustness (step #3). After that, we include additional non-elective arrivals, and compute the schedule performance for different scheduling strategies (step #4). Finally, we simulate the provisional schedule execution in a stochastic environment that has both stochastic durations and stochastic non-elective arrivals to assess both the robustness and resilience of the provisional schedule at the same time (step #5).

We synthesize these four steps in Table 10. Each row corresponds to one analysis step, and each column corresponds to a model parameter.

Table 10 – Prospective analysis steps

#	Objective	Activity durations	Additional Non-elective arrivals
1	Assess feasibility (resource synchronization)	Deterministic	No
2	Compute Performance	Deterministic	No
3	Assess robustness	Stochastic	No
4	Assess resilience	Deterministic	Yes
5	Assess the best non-elective case scheduling strategy based on the provisional schedule	Stochastic	Yes

A detailed study case will be presented in Chapter VIII. We briefly describe each of these steps below:

- **Step 1 - Resource synchronization.** The material and human resources are synchronized if it made such that the patient does not have to wait for them. For example, there will be waiting time if: (a) Two patients are scheduled for surgery in the same OR at the same time (therefore material resource constraints are not respected), or (b) Two patients are scheduled for surgery with the same surgeon at the same time (therefore human resource

constraints are not respected). We discuss the modeling and simulation of resources in a surgical suite digital twin in Chapter IV.

- **Step 2 – Performance.** We run the provisional schedule in a deterministic environment and compute the KPIs. We compare each of them to the ANAP targets. The KPIs' description is available in Chapter I.
- **Step 3 – Robustness.** For the robustness (definition in Chapter 1 we run the provisional schedule with stochastic durations and compute the gap between the new KPI values and the ones of step 2, and to the ANAP targets.
- **Step 4 – Resilience.** For the resilience (definition in Chapter 1), we run the provisional schedule using deterministic durations, and we test different combinations of non-elective arrival scenarios with non-elective scheduling scenarios. The resulting KPIs are compared with the ones of step 2, and to the ANAP targets.
- **Step 5 – Simulating the provisional schedule execution.** We run the provisional schedule in a stochastic environment where the durations are variable and where there are non-elective arrivals, and we test the non-elective scheduling strategies. We compare the KPIs with the ones of step 2, and to the ANAP targets.

As a side note, the results of the provisional analysis can be used as feedback for the offline operational decisions (surgery scheduling problem), although this was not our primary goal.

2. Retrospective analysis of the performed schedule

In this section, we propose a methodology for a retrospective analysis of the performed schedule. The objectives are to assess the quality of the reactive disruptions management (**Q3**), and to identify whether performance lack stems from offline or online decisions (**Q4**); we aim at providing feedback on the schedule execution that led to obtain the performed schedule. This methodology corresponds to our contribution #2.

In this section, we propose a three-step methodology for a retrospective analysis of the performed schedule: (1) replay the performed schedule as-is (i.e. in a deterministic environment) to assess whether the resource constraints are respected in the performed schedule, (2) assess the performed schedule performance, and (3) identify the performance gap between the performed and the provisional schedule and assess whether they are a consequence of offline or online operational decisions. We synthesize these three steps in Table 11. Each row corresponds to one or several analysis steps, and each column corresponds to a model parameter.

Table 11 - Retrospective analysis steps

#	Objective	Activity durations	Additional Non-elective arrivals
1	Compute Performed Schedule Performance	Deterministic	No
2	Assess the impact of implementing other decisions to tackle the disruptions.	Deterministic	No
3	Identify performance gap root causes	Deterministic	No

A detailed study case will be presented in Chapters VII and VIII. We briefly describe each of these steps below:

- **Step 1 – Performed schedule performance.** We run the performed schedule in a deterministic environment and compute the KPIs. The KPIs' description is available in Chapter I.
- **Step 2 – Test other decisions.** We simulate the performed schedule in a deterministic environment to assess the impact of different solutions to tackle the disruptions. For instance, we test other scheduling decisions for non-elective arrivals. We compute the KPIs and compare them with the ones of step 1.
- **Step 3 – Performance gap root causes.** The performed schedule performance is strongly dependent on the provisional schedule performance. For instance, if there is scheduled overtime in the provisional, there is a high probability that there will be overtime in the performed schedule too. Consequently, we identify the performance gap and study whether they result from improvable surgery scheduling (offline level), or from the real-time OR management (online level).

3. A training environment for the OR manager

In this section, we propose a methodology for training an OR manager on disruption management. This answers our research question: how can we train OR managers on disruption management? (Q5). This methodology corresponds to our contribution #3.

We have described a decision support system able to model the execution of an operating suite schedule in a stochastic environment (duration variability and additional non-elective arrivals) while following a specific OODS. But what if we allowed the user to test their own personal non-elective schedule strategies themselves? We propose to use this virtual environment to train the OR coordinator on schedule execution.

We represent this in Figure 20.

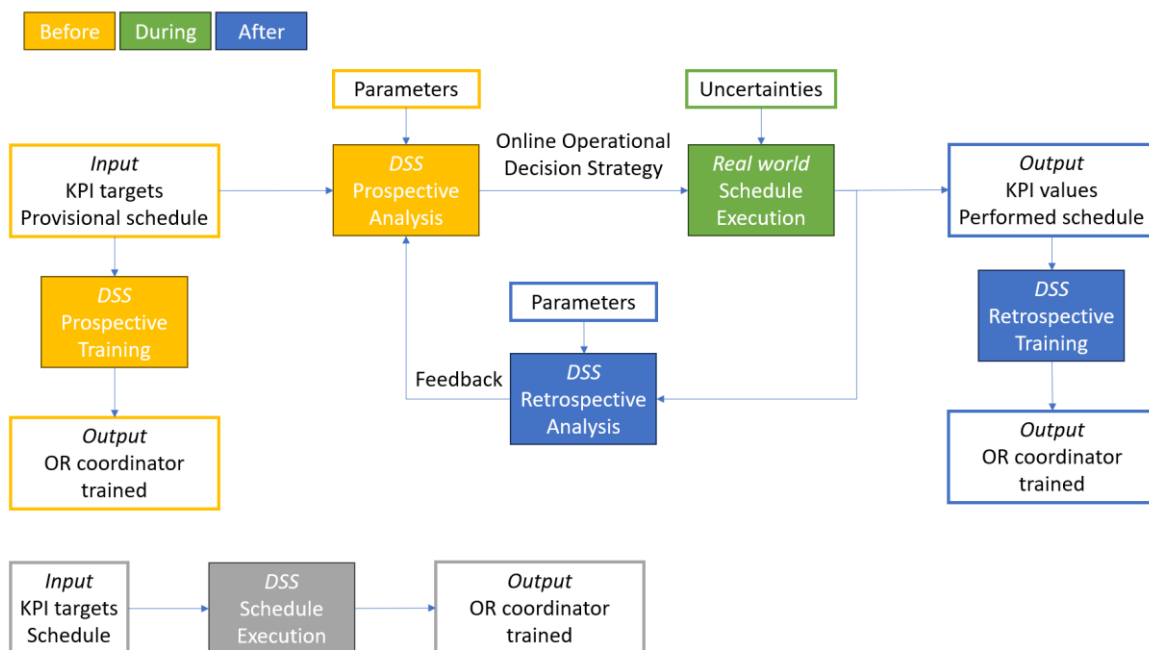


Figure 20 - Complete framework

4. Proposition of a standardized method to build a surgical suite digital twin

We propose a 5-step standardized method to build the digital twin of a surgical suite using discrete event simulation. We illustrate it in Figure 21, and describe its steps below.

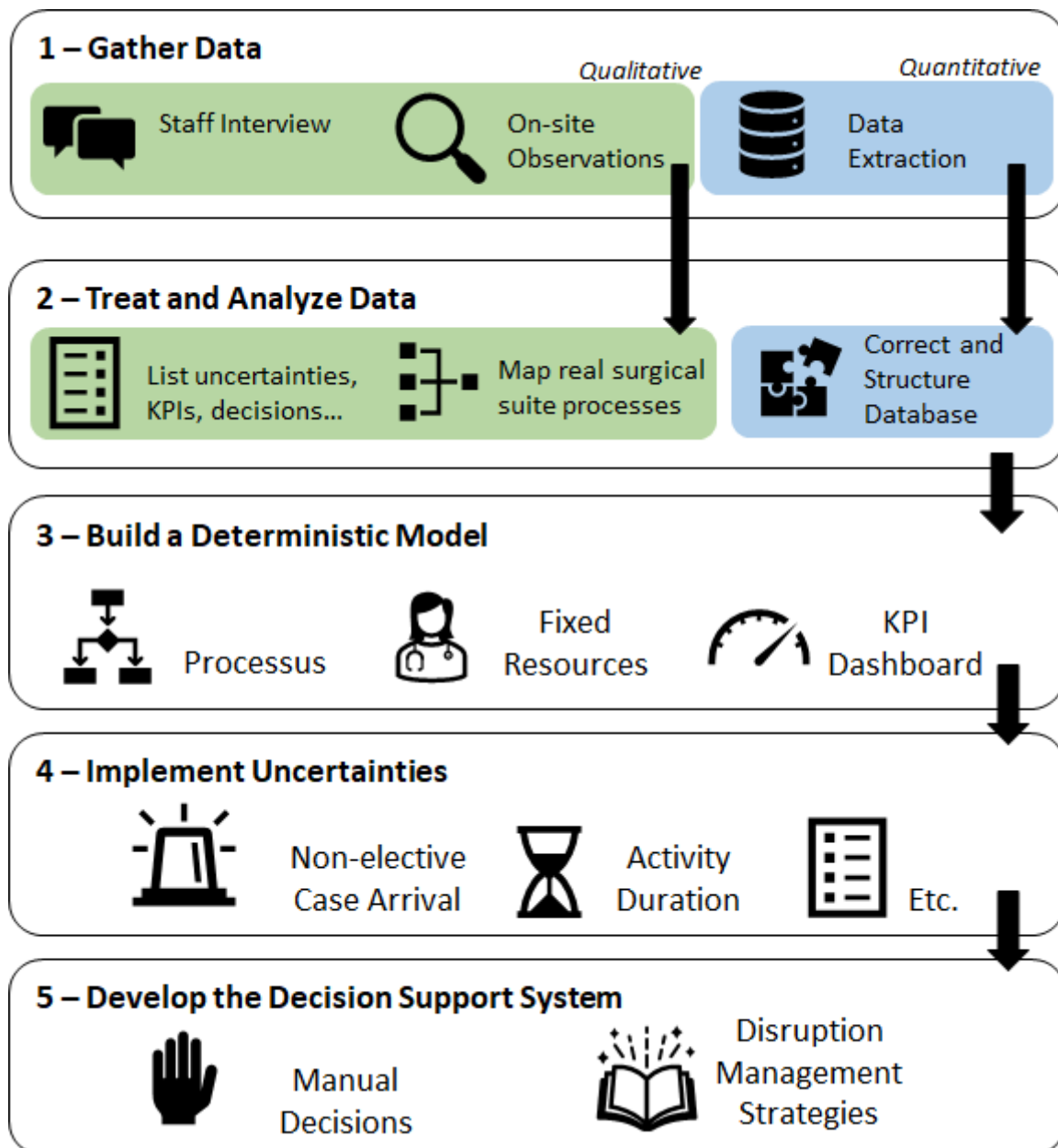


Figure 21 - Illustration of the steps of a standardized method to build to build a surgical suite digital twin.

1 – Gather data - Qualitative. The first step consists in gathering data related to the targeted surgical suite. To do so, we perform interviews with the surgical suite staff and perform on-site observations. The objective is to have a deep understanding of how the specific suite works. Indeed, although all suites share some common processes, they also all display some local solutions that can be interesting to model. For instance, the process to ask the stretcher-bearers to bring the next patient to the surgical suite usually changes from one suite to the other. First, we recommend speaking with at least one representative of each profession in the suite, namely: a surgeon, an anesthesiologist, an OR nurse, an anesthesiologist nurse, a nurse assistant, and a PACU nurse. It

can be interesting to understand how services in contact with the surgical suite function as well (i.e. the inpatient and outpatient wards, the sterilization, the stretcher-bearer services, etc.). Second, we also suggest starting by mapping the three operational suite processes (the preoperative, perioperative and post-operative phases), then to move on the supporting and decision-making processes related to them. Finally, it is interesting to assist in the surgery scheduling meetings and to exchange with the OR manager or the staff responsible for the reactive management disruption.

1 – Gather data - Quantitative. We extract quantitative data from the OR software database. This step can be delicate as patient data are sensitive and must be anonymous. At the end of this first step, we propose a tentative study perimeter in terms of the process, resources, uncertainties, disruptions, decisions, and KPIs are all considered.

2 – Treat and analyze data. This step focuses on the data extracted from the OR software database. They usually include timestamps which are a must when modeling the surgical suite activity. These timestamps can however be incorrect and must be corrected (Chapter V). It might be possible that the data available in the database does not allow to study the perimeter proposed in the first step so some adjustments can be made.

3 – Build a determinist model. Once we have all the data, we build the deterministic model of the studied surgical suite. First, we map the observed process. Second, we add the fixed resources. Third and finally, we build the KPI dashboard.

4 – Implement uncertainties. Depending on the study perimeter, we implement uncertainties in the surgical suite processes. This include thinking of the number of replications required for each stochastic scenario to be representative of reality.

5 – Develop the decision support system. As for step 4, we implement the decisions based on the perimeter that was previously identified. We suggest proposing two decision-making modes to the user: a manual mode in which the user can configure the model reaction to any disruption in a flexible way, and an automatic mode in which the DT-DSS tries many already modeled disruption management strategies.

This tool (A) models schedule execution of either a provisional or a performed schedule, (B) in either a deterministic or a stochastic environment, while (C) respecting the resources and the patient constraints, (D) applying online operational scheduling strategies, and (E) computing KPIs. In the following Chapters, we describe how we develop the DT-DSS for our specific study case. In Chapter IV, we describe how we model the schedule execution based on the operational processes (patient pathway), and the supporting processes (sub-functionalities A & C). In Chapter V, we detail how we model stochastic decisions (sub-functionality B). In Chapter VI, we explain how we model stochastic additional non-elective arrivals and the scheduling strategies to add them to the ongoing schedule (sub-functionalities B & D).

5. Chapter synthesis

In this Chapter, we have presented our solution proposal: a methodology for prospective analysis, a methodology for a retrospective analysis, a training methodology and a standardized method to build a surgical suite digital twin. In the following chapters of this part II, we will describe how we build a prototype to apply these first three methodologies.

CHAPTER IV. MODELING AND SIMULATION OF THE SCHEDULE EXECUTION

In the previous Chapter, we have proposed a framework for the continuous improvement of online operational decisions in a surgical suite, and we have justified that a digital-twin based decision support is a satisfactory tool to perform all the functionalities required by this framework. We developed a digital twin-based decision support system for the prospective and retrospective simulation and analysis of the operating room schedule execution, and we inferred from this prototype a standardized methodology to conceive and build such a tool in any surgical suite.

In this new Chapter, we describe how we model and simulate the schedule execution for either a provisional or a performed schedule. We use the available information in the OR database to model the surgical suite's processes, while respecting the constraints imposed by patients and the availability of resources. Note that lack of data in the OR database is a constraint that one might face in most of the existing surgical suites.

At this stage of the study, we consider a deterministic environment and we do not model uncertainties. Consequently: (1) the durations are deterministic, (2) there are no additional non-elective arrivals and (3) we only consider operational and supporting processes. Indeed, since we are modeling the execution of schedules in a deterministic environment, all the events are known in advance and there is no need to make decisions throughout the execution.

Our objective is to model the execution of either a provisional or a performed schedule. Ideally, we would like a model that considers the totality of the operational processes, the supporting processes, the human resources, and the material resources. However, as we show in Table 12, we only have access to 7 patient pathway timestamps as well as the surgeon, the anesthesiologist, and the operating room IDs. We therefore limit our modeling process to what can be derived from the available data.

In this Chapter, we first propose a solution to model schedule execution despite a lack of data. We use and justify different models for provisional schedule execution (detailed process with strict constraints on resources) and performed schedule execution (aggregated process with flexible constraints on resources). Second, we illustrate this method with our study case. We provide a synthetic conclusion at the end of the Chapter.

Table 12 – Difference between the required and the available information in our study case

Type of information	Required Information	Information available in the database
Patient pathway timestamps	<p>Start time and end time for all the activities of the patient pathway; the activities being:</p> <p>A - For surgery with induction in the OR: Patient Reception, Patient Checklist, Setup, Induction, Procedure, Reversal, Move to PACU, PACU Monitoring</p> <p>B - Surgery with induction in the PACU: Patient Reception, prepare patient for Induction, Induction, Wait for anesthesia to work, Patient Checklist, Setup, Procedure, Reversal, Move to PACU, PACU Monitoring</p> <p>C - Surgery without the need of the anesthesia team: Patient Reception, Patient Checklist, Setup, Procedure, Reversal, Move to PACU, PACU Monitoring</p>	<p>For all patients: Suite Entry, OR Entry, Incision, Suture, OR Exit, PACU Entry, PACU Exit</p>
Supporting process timestamps	<p>OR cleanup start, OR cleanup end, etc.</p>	<p>/</p>
Human Resources	<p>Surgeon ID, Anesthesiologist ID, All nurses ID (OR, anesthesia, PACU), Nurse Assistant(s) ID, Stretcher-bearers ID</p>	<p>Surgeon ID, Anesthesiologist ID</p>
Material Resources	<p>OR ID, Preoperative bed ID, PACU bed ID, Other material resource ID: transportation means surgical instruments, surgical supplies, imaging and visualization equipment, surgical support equipment.</p>	<p>OR ID, Preoperative bed type</p>

1. Proposal of different modelling approaches depending to available data

1.1. Surgical suite process

The surgical suite's process (SSP) is complex and require the intervention of various professions and equipment at different times and locations. Since it is common to not have the data required to model them available in hand, let **“aggregated SSP”** be a model based on the available timestamped data in the OR software, and let **“detailed SSP”** be a model based on the available timestamped data in the OR software *and* our on-site observations. These SSP models differ in terms of the exhaustivity of the process mapping and in terms of timestamps' value plausibility: the aggregated SSP includes less steps, but has more plausible timestamps value than the detailed SSP.

We illustrate the difference between an aggregated process and a detailed process for the preoperative phase of a surgery requiring an LRA in Figure 22. The aggregated process (blue) consists in one activity, while the detailed process consists in 4 activities (green). The aggregated process relies on timestamps recorded in the database (blue), while the detailed process relies on timestamps recorded in the database (blue) *and* on timestamps that are not recorded in the database (green). Therefore, to simulate a detailed process, we need to estimate the value of the missing timestamps (green) based on on-site observations.

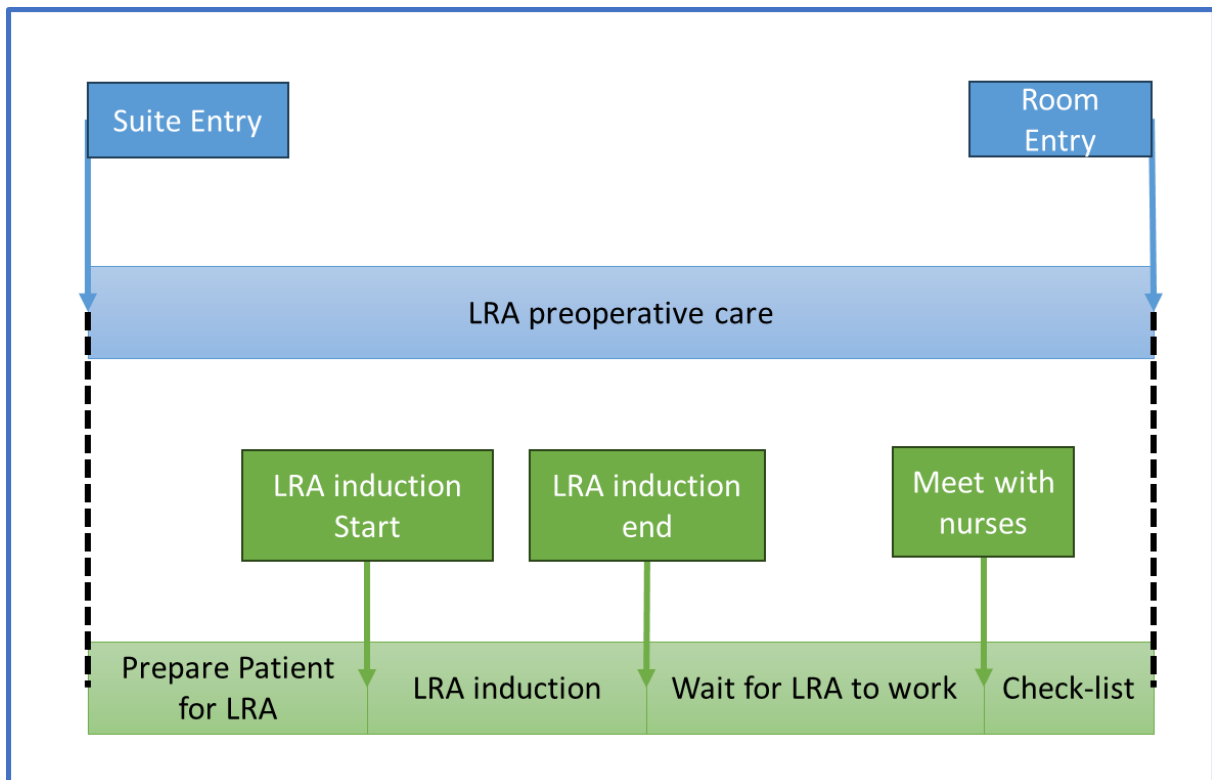


Figure 22 – Illustration of the difference between an aggregated process (top) and a detailed process (bottom) for the preoperative care of a surgery requiring an LRA.

We propose different approaches for the provisional and the performed schedules because their simulation have different goals.

The objective when simulating the performed schedule execution is to acquire a simulated execution which is as close as possible to the performed schedule execution. (i.e. the performed and the real patient room entry times are identical), *then* to exhaustively model the activity (i.e. model the different steps for the whole preoperative patient pathway).

On the other hand, the provisional schedule is naturally based on estimations and hypotheses. For instance, timestamps and durations are estimated because they are not known in advance and the resource synchronization is assessed in an empirical manner. On the other hand, the simulating the surgical suite schedule exhaustive is a priority as we are trying to where and when the schedule could be disrupted (gives a better idea).

Consequently, we model the provisional schedule execution using the detailed SSP, and we model the performed schedule execution using the aggregated SSP.

1.2. Resource constraints

To exhaustively model the surgical suite's processes, we need information on the resources used: what resource is needed? When? Where? For how long? However, as for the timestamps, the information related to resources is not always available in the OR database. Furthermore, it is common for the staff to not always follow the best practices (e.g. joint patient reception by the OR nurses and the anesthesia nurse) or to adapt their process to the ongoing state of the surgical suite (e.g. during a slow day, the anesthesiologist can perform all their patients' induction while during a busy day they might let the anesthesia nurse induce patient).

We illustrate this in Figure 23 for the perioperative phase of a patient requiring induction in the operating room: in the best-case scenario (left), the surgeon, the anesthesiologist and the nurses are all present from the "room entry" to the "room exit". In reality (right), it is possible that the surgeon is only present for the procedure and that the anesthesiologist completely delegates the induction and the patient monitoring to the nurse anesthetist. Thus, applying resource constraints to the SSP is a complex task.

Let "**strict resource constraints**" be the (possibly incomplete) constraints described in the OR database and let "**flexible resource constraints**" be the constraints on the operating room only. During the schedule execution of the performed schedule, we consider the recorded timestamps to be representative of the reality of what actually took place and must therefore be respected during the simulation. As we mentioned, applying resource constraints is tricky. Since the resource that is less likely to be inaccurate is the OR ID, **we use flexible resource constraints during the schedule execution of the performed schedule.** When we prospectively simulate the provisional schedule execution, we make the hypothesis that the processes are perfectly performed, thus **we use strict resource constraints for the provisional schedule execution.**

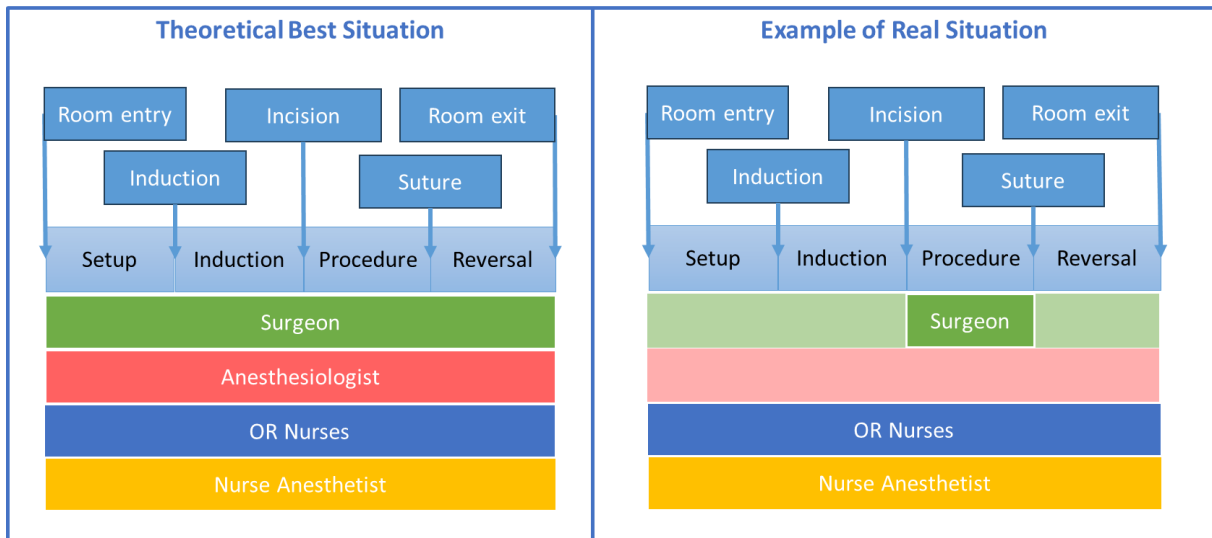


Figure 23 – Illustration of the difference between the theoretical best situation (left) and an example of real situation (right) of the human resource presence during the perioperative phase of a patient requiring induction in the operating room.

2. Application to our study case

2.1. Introduction

In the previous section, we proposed a method to model the surgical suite organization despite the missing data in the OR software database. We have suggested to use a detailed process with strict constraints on resources for the provisional schedule execution, and to use an aggregated process with flexible constraints for the performed schedule execution.

In this section, we first describe how these two types of resource constraints can be translated to our study case. Second, we present the aggregated and the detailed processes we use. Third and finally, we add technical notes on specific hypotheses we had to make because of our simulation tool and study case.

2.2. Flexible and strict resource constraints

As we mentioned in Table 12, for each patient in the schedule, the OR database provides us with information related to human resources (surgeon ID and anesthesiologist ID), and material resources (OR ID and preoperative care bed type). Depending on the resource constraints we apply to the surgical suite's process, we can decide whether or not resources are: considered in the study, nominative or non-nominative, and limited or unlimited.

To model resources in our model, we create entities that we gather in a “resource group”. Thus an instance of the resource groups is any entity part of that group. Examples of resource groups are surgeons, anesthesiologists, PACU beds...

2.2.1. Resources to be included

In agreement with our expert committee (P1C3), we decided to simplify the study and not consider all the material resources:

H1. The study only considers the OR, the preoperative care location beds, and the PACU beds as material resources. Therefore, we do not consider the following material resources: transportation means, surgical instruments, surgical supplies, imaging and visualization equipment, and surgical support equipment.

Based on our on-site observations, we know that the anesthesia process in the OR can involve (1) the anesthesiologist alone, (2) the anesthesia nurse alone, (3) both at the same time. Since the OR database does not specify which option is followed, we make the following hypothesis:

H2. The study considers all surgical suite human resources except the anesthesia nurse: the surgeons, the anesthesiologists, the OR nurses, the PACU nurses, the OIP nurse, the nurse assistants, and the stretcher-bearers.

Based on our on-site observations, we know that the OR cleanup is performed by either (1) nurses that were in the OR, (2) assistant-nurses, (3) both at the same time. Since the OR database does not specify neither the cleanup start and cleanup end timestamps nor which option is followed, we make the following hypothesis:

H3. There is one assistant-nurse per OR that systematically performs the OR cleanup once the patient exits the OR.

Based on our on-site observations, we know that the OR nurses are systematically assigned an OR, and thus the patients that are scheduled within. They are also assigned a role (circulating, scrub, or instrumentist). However, since the OR database does not mention this information, we make the following hypothesis:

H4. Each OR is assigned one OR nurse. This nurse is assigned to all patients assigned to that specific OR.

H5. The nurse schedule is identical to the OR schedule.

2.2.2. Resources to be modeled as nominative

We make the difference between nominative and non-nominative resources. Resources are nominative when they are linked to a unique ID. When a resource is nominative, the patient can be only cared for by the assigned resource in the schedule. When a resource is not nominative, the care is provided to the patient by any resource of the same type available at that point.

Using nominative resources in a model is more constraining than using non-nominative ones: in the first case you can only pick *one specific* instance of the resource group, while in the second case you can pick *any* instance of the resource group. Using nominative resources when possible in the model also provides a simulation closer to reality: the specific resource that was used in real-life is used in the model.

In real life, the surgeon, the anesthesiologist, the anesthesia nurse, and the OR nurse know to which OR they are assigned and thus which patient they are assigned to as well: they are all nominative resources. However, in the OR database, only the surgeon and the anesthesiologist IDs are mentioned, thus:

H6. Surgeons and anesthesiologists can be modeled as nominative resources.

H7. Anesthesia nurses and OR nurses cannot be modeled as nominative resources.

Human resources such as OIP nurses, PACU nurses and stretcher-bearers participate regularly in the patient pathway. The rule of the thumb is usually the following: idle staff takes care of patients in demand of care. Their IDs are not included in the database; thus we make the following hypothesis:

H8. PACU nurses, OIP nurses, and the stretcher-bearers are modeled as non-nominative resources.

The same can be said for material resources such as PACU beds and the preoperative care bed: the ones idle are used when needed; they are not assigned to a specific patient. The OR is the only material resource that is assigned to the patient.

H9. Preoperative beds and PACU beds are modeled as non-nominative resources.

H10. ORs can be modeled as nominative resources.

2.2.3. Limited or Unlimited Resources

In this section and the remaining of the manuscript, we talk about limited or unlimited resources through misuse of language. By limited/unlimited resources, we mean limited/unlimited entities in a resource group. If resources are limited during schedule execution, a patient can try to acquire an already busy resource and must wait until the resource is idle again. If resources are unlimited, this waiting state never occurs.

We illustrate the impact of limited resources in Figure 24 with the example of a single anesthesiologist working in two ORs at the same time – note that this is common practice in surgical suites. We consider two operating room shifts (grey) that each have one scheduled patient (dark blue and light blue) which both require an anesthesiologist for their induction. In the first case, the anesthesiologist resource is unlimited, and the two induction steps are performed simultaneously. In the second case, the anesthesiologist resource is limited: the anesthesiologist starts by the Patient #1 induction, then moves to the Patient #2 induction (green). Patient #2 must wait for the anesthesiologist to perform their induction because they are already occupied with performing the induction of Patient #1 (orange).

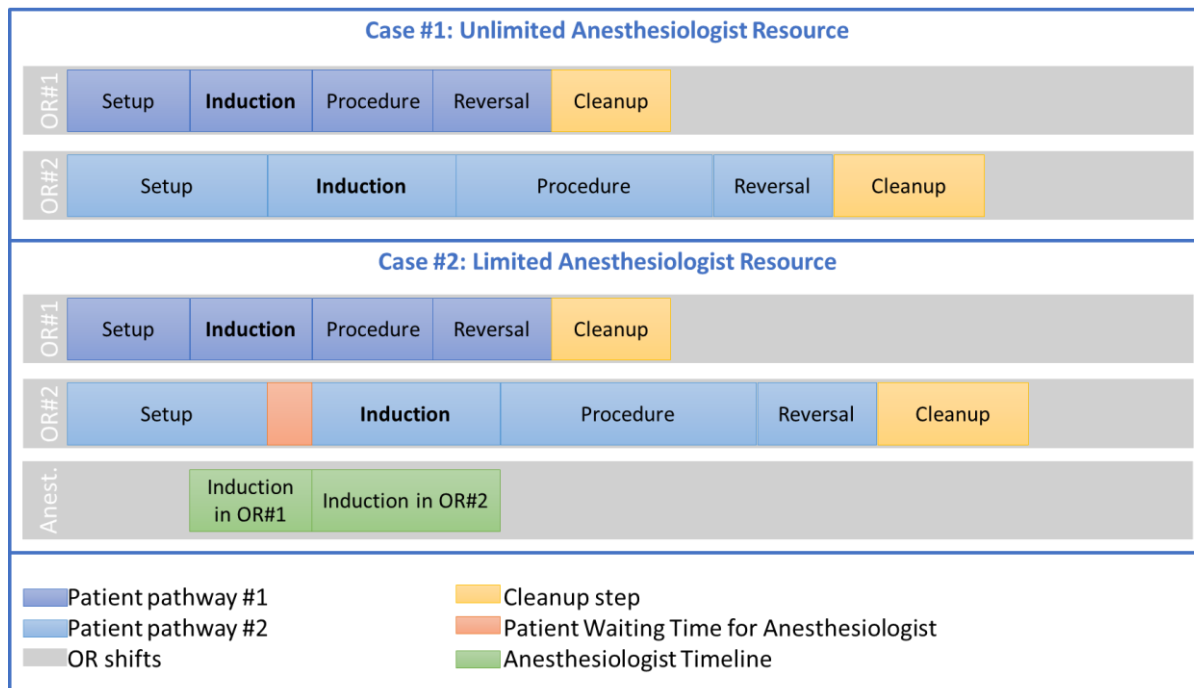


Figure 24 - Example of the Impact of the Anesthesiologist Being a Limited Resource

Now we briefly address the difference between unlimited resources and not considered resources. If a resource is modeled as unlimited, it will never provoke waiting times. If the resource is not even considered (i.e. not present in the model), the model will not even require the resource. In other words, in either case, the steps' timestamps and durations do not change. The difference resides in the fact that with unlimited resources, we can still compute KPIs for the resource (such as the utilization rate, the idle rate, etc.) and visualize the resource interactions with the rest in the model. Modeling unlimited resources can be an intermediate step between not modeling resources and modeling limited resources.

Concerning the human resources in our model: (1) we do not have access to the number of OIP nurses and the number of PACU nurses, (2) each OR is assigned an OR nurse, (3) we have the list of surgeon and anesthesiologist IDs. Since we can decide to hypothesize the number of OIP nurses and PACU nurses, all human resources can be considered either limited or unlimited based on what our goal is.

Concerning the material resources: we do not have access to the number of beds dedicated to the preoperative care, nor the number of PACU beds. However, we can make a hypothesis on this number. Besides, we know exactly how many ORs exist.

Note that nominative resources are always limited.

We summarize the way we model resources in Figure 25. Blue resources are always modeled as non-nominative resources. Green resources *can* be modeled as nominative resources. Resources with an infinite sign are always unlimited if they are considered in the model. Resources without an infinite sign *can* be modeled as limited resources.

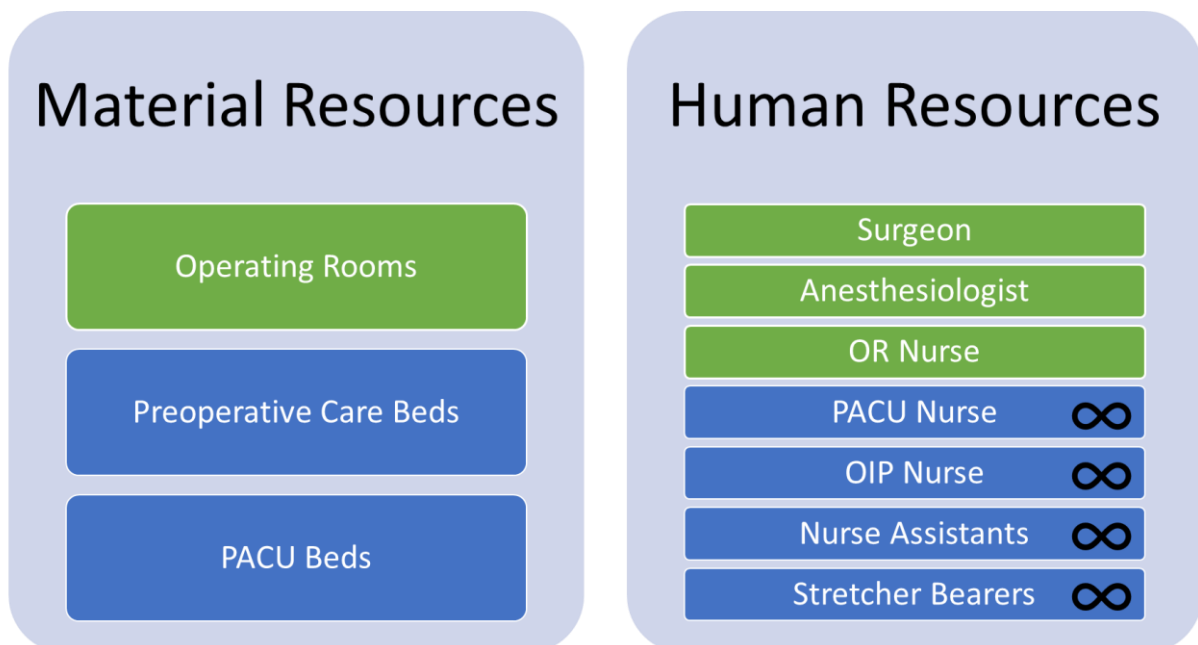


Figure 25 - Which resources can be modeled as infinite resources?

2.2.4. Resource Constraints for Our Specific Study Case

We apply the solution proposed in 1.2 to model our resource constraints based on the available data and mix it with the notion of nominative/non-nominative resources, and limited/unlimited resources. **Strict resource constraints** are the (possibly incomplete) list of constraints described in the OR database and **flexible resource constraints** are the ones imposed on the operating room only.

We remind the reader that in our study case:

- Each patient is linked to a nominative surgeon, a nominative anesthesiologist (if needed), a nominative OR, and a preoperative care location type (the bed used however is non-nominative).
- Since each OR is assigned an OR nurse, and each patient is assigned an OR: each patient is consequently assigned an OR nurse.
- Patients can require a PACU nurse or an OIP nurse depending on their patient pathway.

Table 13 and

Table 14 describe the flexible and the strict constraints on resources for our study case.

For the **performed schedule execution**, we use **flexible constraints** to respect the database timestamps: human resources are not considered, and material resources are non-nominative and unlimited, except for the OR that are nominative and limited. We decided to keep the OR nominative and limited as this is the most trustable resource-related information and that it is at the core of the schedule: it would not make sense to attempt to replay a performed schedule by using different ORs than the ones that were used. Not that we could have modeled human resources as non-nominative and unlimited but that we decided to not consider them for simplification. This could be a work perspective.

For the provisional schedule execution, we use strict constraints as we try to envision the schedule execution in its globality and in the perfect case. Human resources are nominative, when possible (surgeon, anesthesiologist and OR nurse), and non-nominative + unlimited in the other case. Regarding material resources: we kept nominative ORs and made an estimation of how many beds are available in the preoperative area in the PACU; beds are thus limited resources.

Table 13 – Description of the flexible and strict constraints on material resources

Resource	Flexible Constraint	Strict Constraint
Operating Rooms	Nominative + Limited	Nominative + Limited
Preoperative beds	Non-nominative + Unlimited	Non-nominative + Limited
PACU beds	Non-nominative + Unlimited	Non-nominative + Limited

Table 14 – Description of the flexible and strict constraints on human resources

Resource	Flexible Constraint	Strict Constraint
Surgeons	/	Nominative + Limited
Anesthesiologists	/	Nominative + Limited
OR nurse	/	Nominative + Limited
PACU nurses	/	Non-nominative + Unlimited
OIP nurse	/	Non-nominative + Unlimited

In the next section, we will describe the surgical suite's process and show for which steps resources are necessary.

2.3. Aggregated surgical suite process with flexible constraints on resources

To model the performed schedule execution, we use an aggregated surgical suite process with flexible resource constraints. The process we describe in this section is the one we modeled in our simulation tool.

Based on the proposition in 1.1, we use the timestamps available in the database (Suite entry, OR entry, incision, suture, OR exit, PACU entry, PACU exit). Since they are all part of the patient pathway, the surgical suite processes are reduced to the patient pathway.

We add a step "Move to Suite" at the start of the process, and a step "Exit Suite" at the end of the pathway. These steps are used to model the patient being transported in and out of the surgical suite. "Move to Suite" provides time for the patient to be created at the suite entry, and to walk towards the preoperative area. "Exit suite" provides time for the patient to move from the PACU to the suite exit and disappear. This has two advantages: (1) the patient does not appear at the preoperative location, but at the suite entry, (2) the patient does not disappear at the PACU but at the suite exit. This requires us to make the following hypotheses:

H11. The timestamp labeled "Suite entry" in the database marks the start of the preoperative care. We rename it "Preoperative Care Start".

Consequently, the aggregated pathway follows the 7 initial timestamps available in the database plus the suite entry and the suite exit. Is it made of 10 steps: (1) move to suite, (2) preoperative care, (3) setup *or* setup + induction, (4) procedure, (5) reversal, (6) move to PACU, (7) PACU monitoring, and (8) exit suite. Steps 1-2 are preoperative, steps 3-5 are perioperative, and steps 6-8 are post-operative. Steps 1 and 10 are added to facilitate the modeling (see technical notes below). The aggregated patient pathway and its related resources is presented in Figure 26, and each step is described in Table 15. In Figure 26, the timestamps with an asterisk are modified/added timestamps, the steps with two asterisks are added steps.

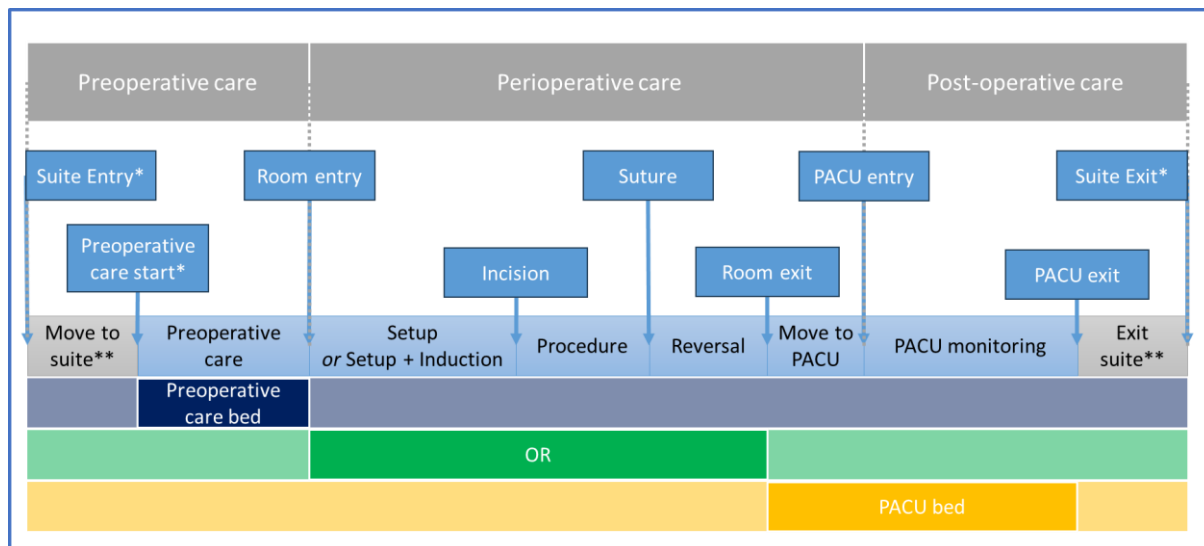


Figure 26 - Description of the aggregated surgical suite process with flexible resource constraints: timestamps, steps and required resources of the patient pathway.

Note that in Figure 26 we represented all the different possible patient pathway types. First, during the preoperative care, the patient can either (1) receive LRA induction in a dedicated LRA bed, (2) receive sedation induction in a dedicated sedation bed, (3) not receive induction and wait in a dedicated waiting area bed. Second, in the operating room the patient can either (1) receive an induction, or (2) not receive an induction. Since all combinations are possible, this amounts to 6 different patient pathways. During the preoperative care, the patient can either lie down on a LRA dedicated bed, sedation dedicated bed or waiting area bed. On a side note, the PACU bed is required during the “Move to PACU” step because the patient cannot leave the OR before being sure there is a PACU bed available for them.

In Table 15, we describe the different steps of the aggregated patient pathway: the first column numbers the steps, the second names the steps, the third describes what happens in the model during the step (and thus what we can see in the 3D view), and the fourth details the resource acquisition and release mechanics. In the step description we make a difference between acquiring the “first available” (non-nominative) resource, or the “assigned” (nominative) resource.

Patients trying to acquire already used resources must wait. For example, a patient who has finished the reversal step will stay in the OR if they did not acquire a PACU bed. To navigate the process, each patient is assigned an OR ID, an anesthesia type, a duration for each step (see Chapter V), and an arrival time.

Now that we have described how we the model performed schedule execution using an aggregated surgical suite process with flexible constraints on resources, we discuss how we model the provisional schedule execution using a detailed surgical suite process with strict constraints on resources.

Table 15 – Description of the Steps of the Aggregated patient pathway

#	Step name	Step Description	Resources
1	Move to Suite	The patient is created at the suite entry. The patient walks to the <i>first available</i> preoperative bed and lays on it.	To acquire: preoperative bed
2	Preoperative care	The patient stays in their preoperative bed.	Already acquired: preoperative bed
3	Setup <i>or</i> setup + induction	The patient walks to their <i>assigned</i> OR and lays on it.	To acquire: OR To release: preoperative bed
4	Procedure	The patient stays in the OR.	Already acquired: OR
5	Reversal	The patient stays in the OR.	Already acquired: OR
6	Move to PACU	The patient walks from the OR to the <i>first available</i> PACU bed and lays on it.	To acquire: PACU bed To release: OR
7	PACU monitoring	The patient stays in their PACU bed.	Already acquired: PACU bed
8	Exit Suite	The patient walks to the suite exit and disappears.	To release: PACU bed

2.4. Detailed surgical suite process with strict constraints on resources

We have explained how we modeled an aggregated SSP by using only the timestamps available in the OR software. Now, we explain how we map the SPP based on the OR software data, on-site observations, and interviews with the staff.

To obtain the aggregated pathway, we (1) started with the aggregated process, (2) detailed the preoperative care phase, (3) implemented the strict resource constraints, and (4) added the OR cleanup phase. We obtain 6 different patient pathways: the preoperative phase change depending on the patient anesthesia type, and the perioperative care and the post-operative care phases only differ in terms of the resource constraints applied.

First, we describe the perioperative and post-operative phases that are common to all patient pathways (Figure 27), then we represent the preoperative patient pathway in case of no induction before entering the OR (Figure 28), LRA induction (Figure 29), and ophthalmologic sedation preparation (Figure 30).

In the perioperative and post-operative phase of the detailed SSP with strict resource constraints, the patient requires both material (OR and PACU bed) and human (surgeon, anesthesiologist and OR nurse) resources. During the perioperative phase, the surgical team can either perform a setup (case a) or perform a setup *and* an induction (case b). The anesthesiologist is required for case b only. To model this patient pathway, we made the hypothesis that human resources are needed for the shortest time possible, meaning that the surgeon must only be here for the surgical procedure and the anesthesiologist for the induction:

H12. Human resources are required in the model when their absence would stop the process in real-life.

In the preoperative phase without induction, the checklist is long because this is the first time that the patient meets with a surgical suite staff member:

H13. Modeling: The checklist performed by the OR nurse is “long” if the OR nurse is the first staff member that the patient meets; otherwise it is considered “short”.

H14. In the preoperative phase for LRA induction and the preoperative phase for OIP, the checklist is short because the patient has met the suite staff before.

Concerning the supporting process that are not included in the patient pathway, we add the simulation of OR cleanup during provisional schedule execution – and not in the performed schedule execution.

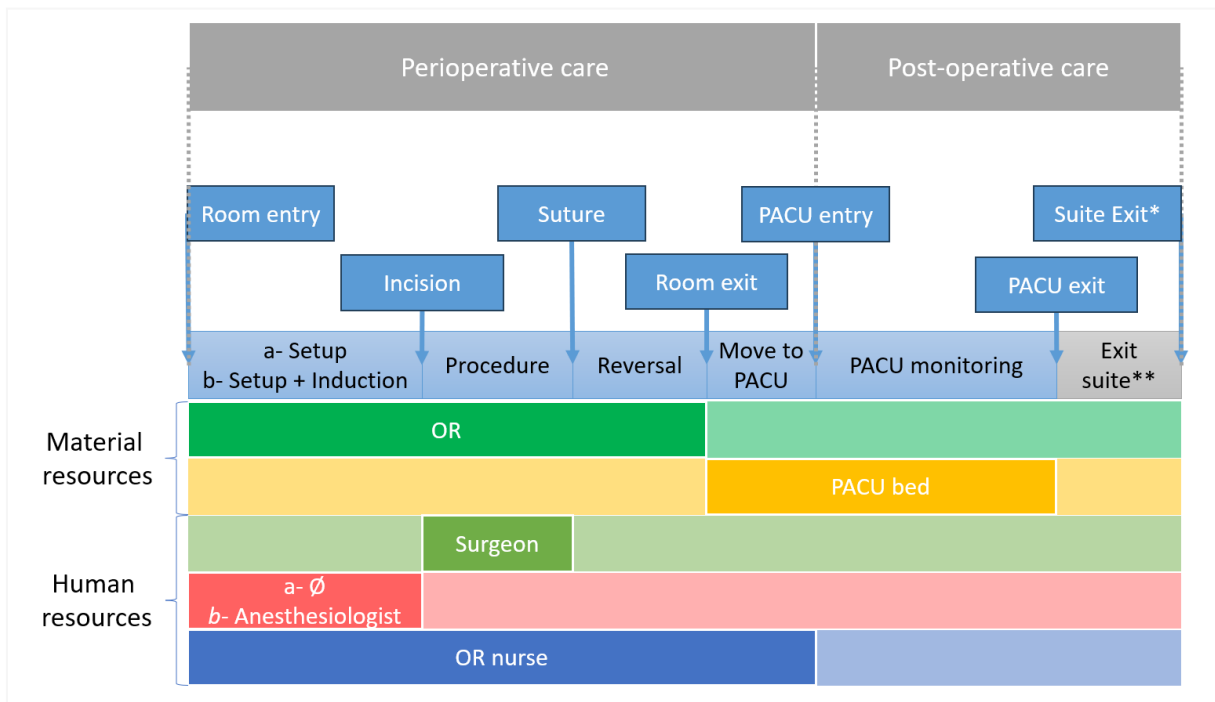


Figure 27 - Description of the detailed surgical suite process with strict resource constraints: timestamps, steps and required resources of the patient pathway (perioperative and post-operative phases)

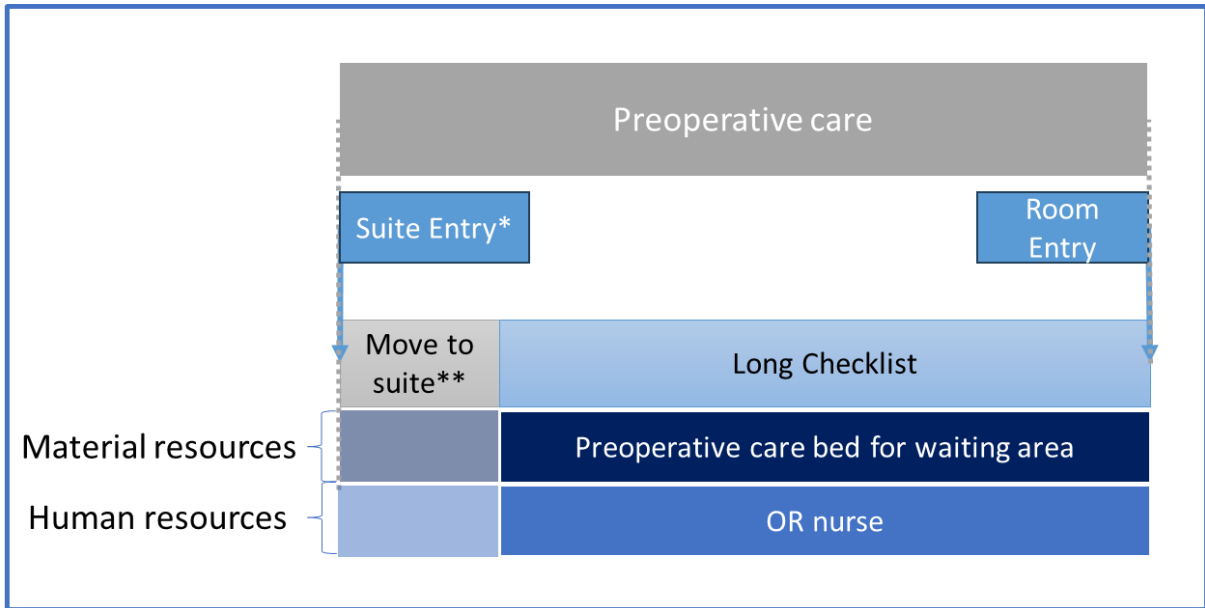


Figure 28 - Description of the detailed surgical suite process with strict resource constraints: timestamps, steps and required resources of the patient pathway (preoperative phase without induction).

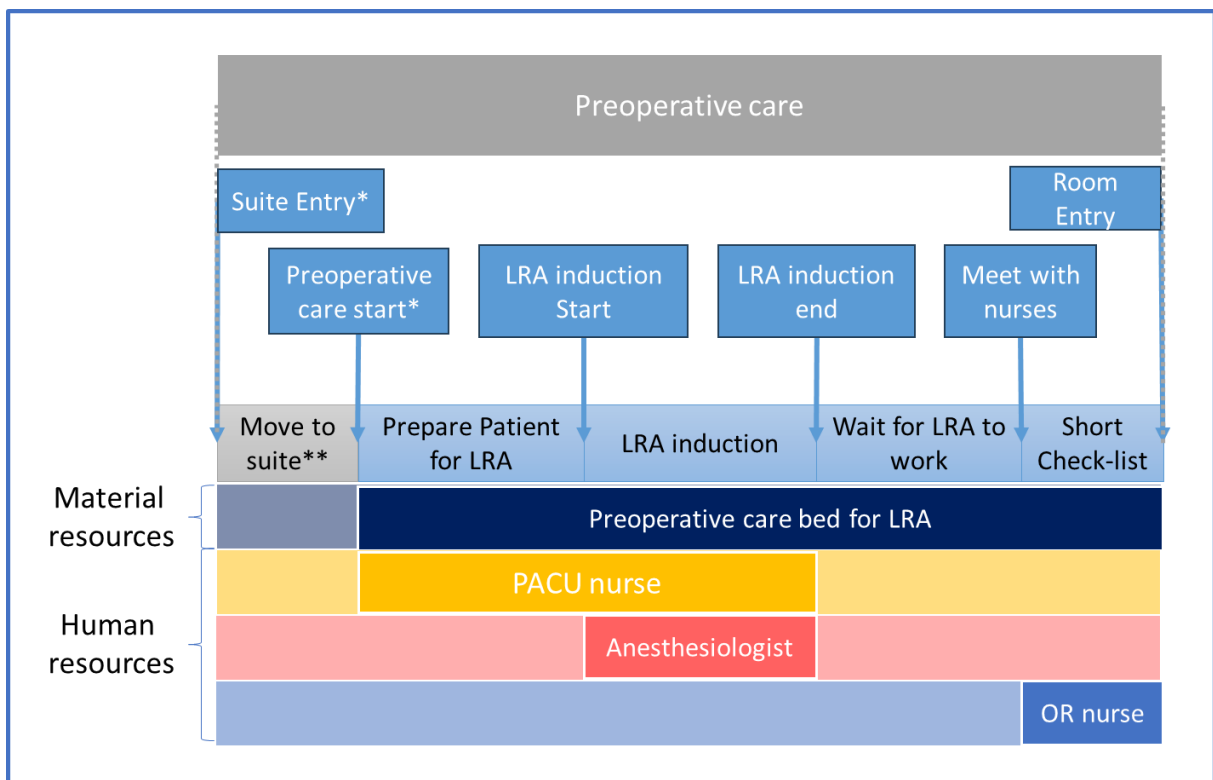


Figure 29 - Description of the detailed surgical suite process with strict resource constraints: timestamps, steps and required resources of the patient pathway (preoperative phase for LRA induction).

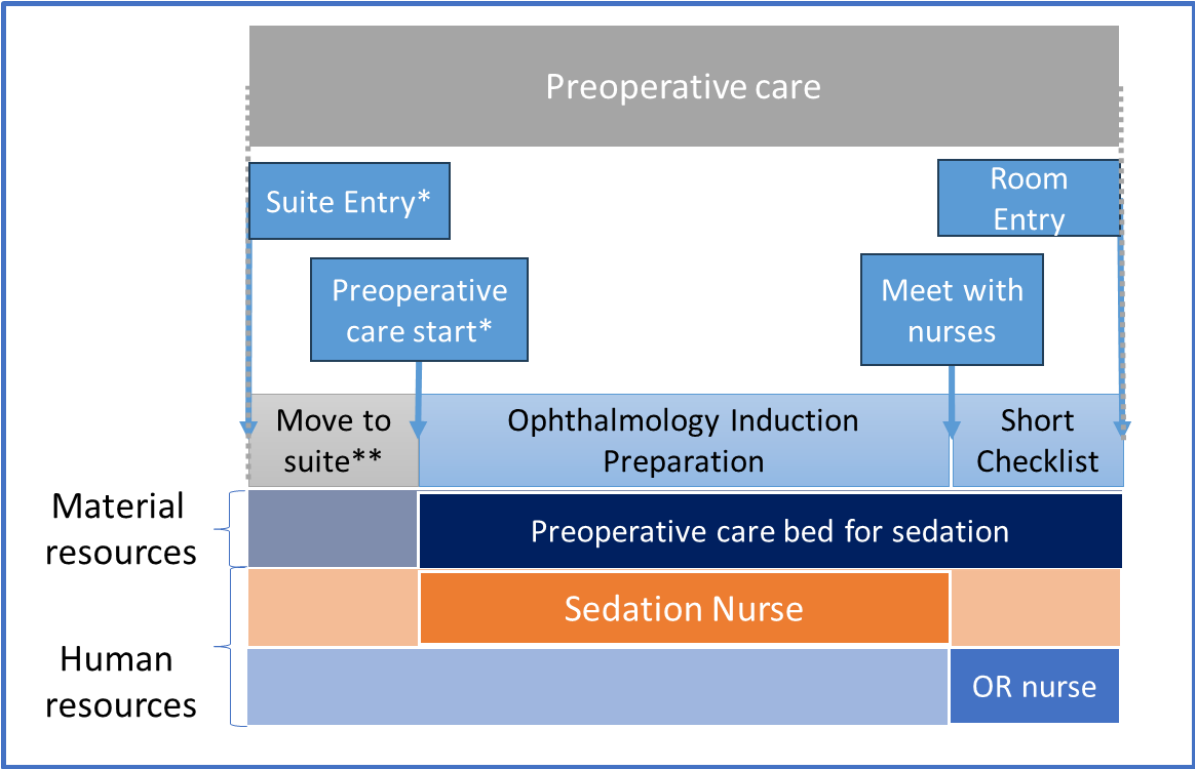


Figure 30 - Description of the detailed surgical suite process with strict resource constraints: timestamps, steps and required resources of the patient pathway (preoperative phase with ophthalmology sedation induction)

3. Additional modeling hypotheses applied to our simulation tool

In this section we discuss modeling hypotheses that are not directly linked to the process mapping of the schedule execution.

3.1. Anesthesia type label and preoperative care option

During the provisional schedule execution, we propose (1) three preoperative care options: no induction, LRA, and OIP, and (2) two perioperative care options during setup: with induction, and without induction. These options are based on the anesthesia type that the patient is receiving. We briefly explain how we treated the patient anesthesia type to define which preoperative and perioperative care pathway they would be assigned to.

We find 24 different anesthesia labels in the database. We note that:

- Patient’s anesthesia type label can either be “none” or one of 23 anesthesia types.
- Some labels include notes such as “wished by the patient”, “to be decided on the day before the surgery”, “to be decided with the patient on the day of the surgery”.
- Either one or two anesthesia types can be recorded per labels (i.e. “General anesthesia + Truncular block under ultrasound”).

Based on our on-site observations, patients with different anesthesia types can follow the same patient pathway. We make the new hypothesis related to database treatment:

*H15. **Data treatment:** When the label is an anesthesia type plus a note similar to “wished by the patient” or “to be decided”, we use the anesthesia type.*

*H16. **Data treatment:** We use general anesthesia when: (1) there is only the note “to be decided”, (2) there is a hesitation between general anesthesia and another type of anesthesia.*

*H17. **Data treatment:** We group the anesthesia under the following global anesthesia types: GA, LRA, OPH, SED and AL (see Table 16)*

In Table 17, we display how the anesthesia type conditions the patient pathway. For instance, GA, SED and SA imply that the patient will receive preoperative care in a waiting area bed, and that an anesthesiologist will be required during the setup step in the OR in order to perform an induction.

Table 16 – Anesthesia Type Grouping

Anesthesia type	Abbreviation	Labels included
General anesthesia	GA	General Anesthesia
Local-regional anesthesia	LRA	Axillary Block, Popliteal Sciatic Block, Truncular Block, Nerve Block Under Ultrasound, Loco-Regional Anesthesia, Peribulbar Anesthesia, Sciatic Block, Crural Block, Catheter
Ophthalmologic induction	OPH	Sub-Tenon Anesthesia ²⁴
Sedation	SED	Sedation
Local anesthesia	LA	Local Anesthesia, WALANT ²⁵
Spinal anesthesia	SA	Spinal Anesthesia, Short Spinal Anesthesia, Epidural

Table 17 – Patient Pathway Options based on Anesthesia Type.

Anesthesia type	Preoperative bed type	Induction in room required?
General anesthesia, Sedation, Spinal anesthesia.	Waiting Area bed	Yes
Local-regional anesthesia	LRA bed	No
Ophthalmologic induction	OIP bed	No
Local anesthesia	Waiting area bed	No

²⁴ https://eyewiki.aao.org/Sub-Tenon_Anaesthesia

²⁵ <https://www.ncbi.nlm.nih.gov/books/NBK570646/>

3.2. Patient movements modeling

In this subsection, we explain how we model patient movements in the surgical suite during schedule execution. Patients must change location throughout the pathway:

1. From the Suite entry to the preoperative location
2. From the preoperative location to the OR
3. From the OR to the PACU
4. From the PACU to the Suite exit.

Concerning movements #1 and #4, we know that:

- The preoperative step duration is from the Suite Entry to the OR entry timestamps and is realized in a preoperative bed.
- The PACU monitoring duration is from the PACU Entry to the PACU Exit timestamps and is realized in a PACU bed.
- We want the patient to start the preoperative step and finish the PACU monitoring at the expected times in the expected place.
- In our model, patients spawn at the Suite entry location and disappear at the Suite exit location.

Thus, we add a one-minute step called “Suite Arrival” step after patient creation and another one-minute step “Suite Exit” after PACU monitoring (so before patient disappearance). During these steps, the patient walks from one location to another. This allows to respect both the time and the location of Preoperative Care and PACU Monitoring. In other words, we rename Suite Entry in Preoperative Care Start and add a new Suite Entry one minute before, and we add Suite Exit one minute after PACU Exit.

Secondly, since movement #2 is short and has not related timestamps in the OR software, we include it in the step that follows it. Moving the Patient to the OR is included in the Setup (*or* Setup and Induction).

Finally, movement #3 has its own timestamps (OR exit and PACU entry) so we modeled it as an independent step of the pathway.

3.3. Modeling OR schedules

Note that in our model, the operating rooms are the only resources on a schedule. All other resources (staff and beds) are available at any time if they are not already acquired by a patient. We model ORs schedules such that:

- Simulated and real operating room schedules (opening time, closing time and shift durations) are identical.
- All patients scheduled for the day will either undergo surgery on that specific date or be canceled/postponed. Since patients can exit the model by either finishing their pathway or by being canceled (at the entrance of the Suite or before the OR entry), this means that even if the OR shift is supposed to be over, scheduled patients will still receive surgery. This is referred to as “overtime” and can also take place in real-life.

For each performed case, we have access to the operating room ID, the shift's start time and the shift's end time. We obtained a total of 14925 shifts. However, upon further analysis, we note occurrences of shifts either overlapping each other or succeeding each other without a break. The cases are the following:

- (1) Shifts A and B are identical.
- (2) Shift B starts before the end of shift A (or shift A ends after the start of shift B).
- (3) Shift A and shift B start at the same time.
- (4) Shift A and shift B end at the same time.

Therefore, we delete shifts duplicates and merge overlapping and successive shifts. This allows us to have a clean database for the OR shifts.

4. Chapter synthesis

In this Chapter, we have described how we model the schedule execution for either a provisional or a performed schedule.

To model the **performed schedule execution**, we use an **aggregated process** that solely uses the information available in the database after schedule execution. Preoperative and post-operative processes are the same for each patient. The perioperative process varies depending on whether the patients need an induction in the OR, or not. The **resource constraints are flexible**: we do not consider human resources, and we consider a limited number of nominative operating rooms; there are no other material resources. Consequently, patient waiting times can only happen if two patients require the same OR at the same time.

To model the **provisional schedule execution**, we use a detailed process that relies on database information, staff interviews and on-site observations. Patients can have different preoperative care (no induction, LRA, OIP), and different perioperative care (induction, no induction). Post operative care is identical for each patient. We apply **strict constraints** on human and material resources' usage. Patient waiting time can occur for two reasons: (1) two patients require access to the same OR, the same surgeon, the same anesthesiologist, or the same OR nurse, or (2) if there are no more preoperative/post-operative beds available.

We synthesize this in Table 18 and Figure 31. We use the DT-DSS to simulate schedule execution, whether it is provisional or performed. First, we added surgical suite processes, human resources, and material resources in the virtual environment (simulation tool). Second, we implemented parameters (schedule type, process type, constraint type) to be able to change the environment configuration. Third and finally, we inputted the schedule description in the model. All this allows us to extract the description of the schedule execution as the output.

Table 18 – Description of process type and resources for the performed and the provisional schedule execution.

#	Schedule Type	Process Type	Human resources	Material Resources
1	Performed	Aggregated: relies on database information	None	Limited and Nominative OR
2	Provisional	Detailed: relies on database information, staff interview and on-site observations	- Limited and Nominative Surgeon, Anesthesiologist and OR Nurse - Unlimited PACU nurse and OIP nurse	- Limited and Nominative OR - Limited and not-nominative preoperative and post-operative beds

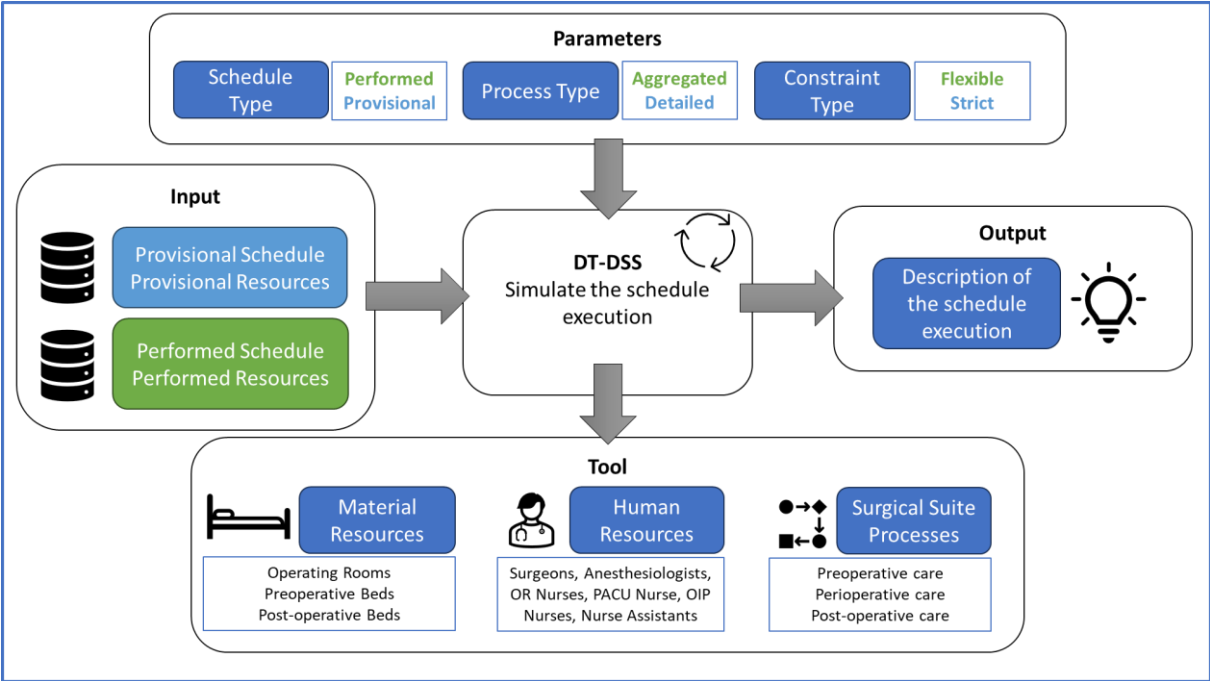


Figure 31 – Representation of our DT-DSS so far.

CHAPTER V. COMPUTING DURATIONS

In Chapter III, we have identified which functionalities our DT-DSS must perform to support our analysis framework, and we have shown that our study case environmental constraints require to adapt these functionalities. In Chapter IV we have described how we model the schedule execution of either provisional or performed schedules. **In this Chapter, we describe how we compute the deterministic and stochastic durations of each activity of the surgical suite processes.**

Activity durations can be either deterministic or stochastic. A **deterministic duration** is a discrete value known in advance. A **stochastic duration** is a value gathered from a statistical or empirical law. Using the pseudo-random number generator algorithm, we are able to generate a sequence of values to be assigned to the stochastic duration variable. This can be done after providing a certain “seed” number to the algorithm. We are able to re-run the exact same scenario with the exact same sequence of pseudo-random duration values upon providing the same seed value. This serves for the purpose of replicability of experiments. Upon providing different seed numbers however, we are able to run multiple replications of a scenario, each of which possess a different sequence of duration values. Our discrete-event simulation model allows us to run scenarios in multiple ways: deterministic scenarios in which durations remain the same, or stochastic scenarios in which durations change from one replication to another by automatically varying the previously mentioned seed number. The performed schedule can only have deterministic durations as we are only replicating something that already happened. However, the provisional schedule can be modeled either in a deterministic or stochastic manner.

In Chapter IV, we discuss how we model schedule execution and list the timestamps and the activities that we model in our DT-DSS. Some of these timestamps are recorded in the database, others are not.

In Figure 32, we represent the detailed patient pathway timeline (Chapter II). The color code is the following: green for timestamps and durations provided by the database, blue for timestamps and durations *not* provided by the database, and grey for timestamps and durations added for modeling purposes (section 3-Chapter IV). **To compute the deterministic and stochastic durations of each activity, we need to ensure the coherence of the green data and to estimate the blue data.** This will be later detailed and explained in the remainder of this Chapter.

A general correction and computation process is illustrated in Figure 33. Each step corresponds to a section of this Chapter. Indeed, since the staff's priority is providing care to the patient, timestamps can be omitted or recorded earlier or later than when they occurred. **Consequently, we need to ensure the coherence of timestamps recorded in the database and compute the missing ones before being able to use them in the DT-DSS.**

Table 19 – Who records the surgical suite processes’ timestamps?

#	Timestamps	Recorded in database by...
1	Suite Entry	Nurse assistant(s) responsible for welcoming the patient in the suite
2	PACU Entry, PACU Exit	PACU nurses
3	Suite Entry, Room Entry, Incision, Suture, Room Exit	OR nurses
4	LRA induction Start, LRA induction end, Meet with nurses, Suite Exit	Not recorded

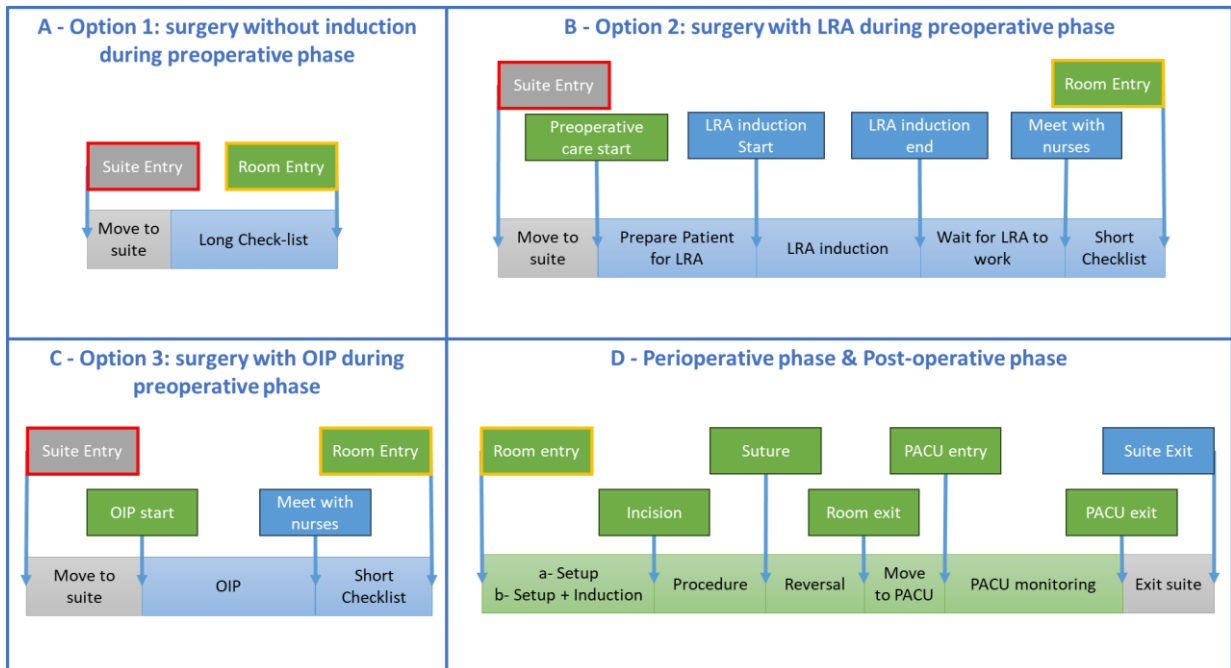


Figure 32 - Detailed Patient Pathway Timeline

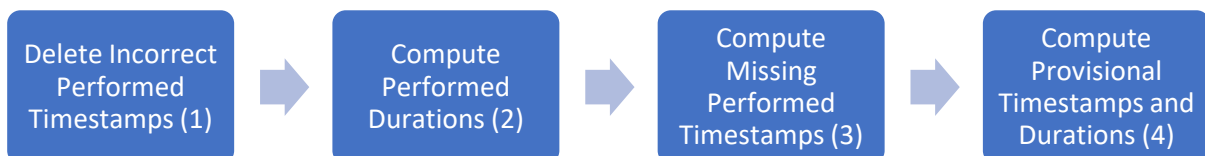


Figure 33 – Steps followed to correct and compute timestamps and durations

1. Correcting the initial timestamps

1.1. Introduction

As mentioned in the introduction, the staff is responsible for manually recording the timestamps in the database. Since this task is not their priority, it can sometimes be neglected: timestamps can be recorded at the activity start time, before it, after it, or not at all. This can lead to computing erroneous durations and thus to not being able to simulate schedule execution in a reliable manner.

It should be noted that since we are studying the performed schedule, we use the aggregated patient pathway (Figure 34) with flexible resource constraints. The aggregated patient pathway in the surgical suite is divided into three main phases: preoperative care (before surgery), perioperative care (during surgery) and post-operative care (after surgery, recovery). These processes can be divided into steps (preoperative step, setup, procedure, reversal, moving to PACU, PACU monitoring), that are delimited by timestamps (suite entry, room entry, incision, suture room exit, PACU entry and PACU exit).

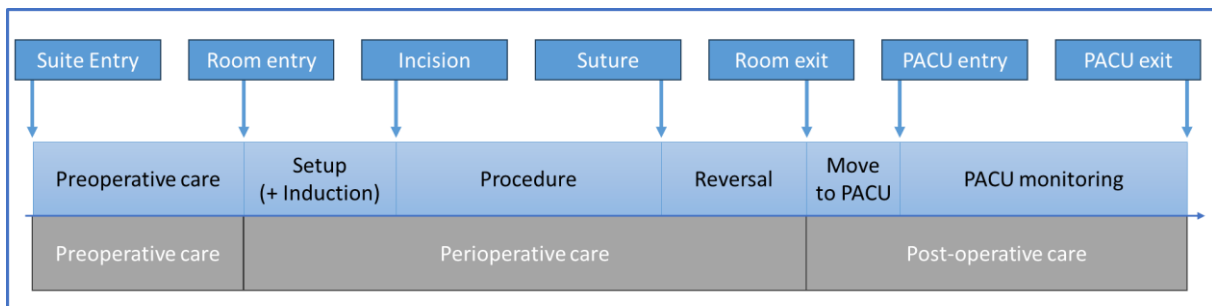


Figure 34 – Timestamps and Steps of an Aggregated Patient Pathway

We cannot determine whether an isolated timestamp is wrongly or rightly recorded because we have no comparison point. We can observe the surgical suite processes from several points of views (POV): the patient, the human resources (surgeon, anesthesiologist, OR nurse, PACU nurse, OIP nurse), or the material resources (preoperative bed, operating room, PACU bed). Ensuring timestamp coherence would require checking whether the patient pathway timestamps are in the right order, and whether each resource is used only by one patient at a time.

However, as we mentioned before, we study the aggregated patient pathway with flexible resource constraints, which is a model that only considers the patient and the ORs (Chapter IV). **Consequently, we ensure the coherence of the timestamps from the patient POV and the OR POV.** We describe both POV in Figure 35. The first describes the patient POV (patient pathway), and the second timeline describes the OR POV. It is a succession of “operating times” (patient in room) and “turnovers” (waiting for patient to enter the room).

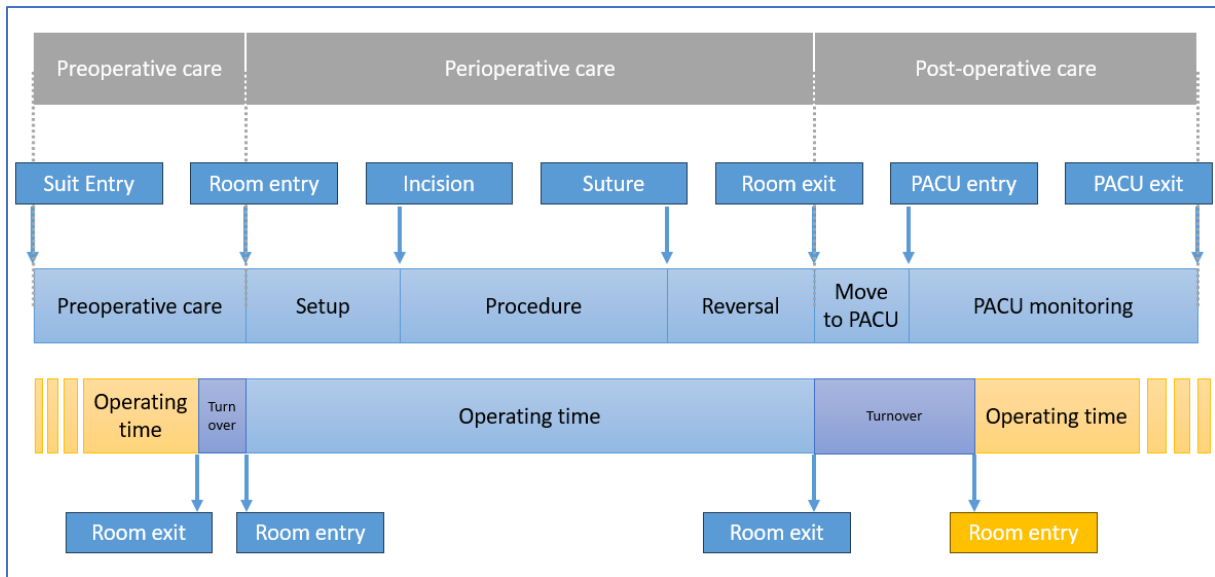


Figure 35 – Illustration of the surgical suite processes from the patient POV (top) and the operating room POV (bottom)

We illustrate timestamp incoherence using patient POV in Table 20. On the first row, the timestamps were recorded one after the other: they are all coherent. On the second row, the incision, suture, and room exit timestamps were also recorded one after the other and are thus coherent with each other. However, we can see that room entry was allegedly performed *after* the incision, which is impossible. Thus the room entry and the incision timestamps are not coherent with each other. A question remains, which one should we keep?

Table 20 - Example of coherent and incoherent timestamps.

#	Room Entry	Incision	Suture	Room Exit
1	9:00	9:15	9:45	10:00
2	9:20	9:15	9:45	10:00

Based on our on-site observations and staff interviews, we noted that the staff may not have time to record the timestamp of a specific step (n) at the right time. When recording the timestamp of the next step (n+1), they may realize their omission and record a late timestamp for step n. Consequently, we make the following hypothesis:

H18. Data treatment: For two supposedly successive timestamps, if the first one is recorded later than the second one, then we delete the first timestamp.

In our Table 20 example, this means that we consider the incoherent timestamp to be the room entry from row#2. Thus we delete it and keep the incision timestamp.

In this subsection, we consider timestamps from the patient POV. We correct them by ensuring that, for each patient pathway, for two consecutive timestamps, the successor should always come after the predecessor one (e.g., the patient leaves the room after the reversal, not the contrary). When it is not the case, we delete the supposedly preceding timestamp and keep the successor.

In this section, we study timestamp incoherence within each patient pathway (are all the timestamps in the right order?) and for each OR (is there always only one patient in the OR?).

1.2. Finding incoherent timestamps using the patient point of view

Let us consider the examples displayed in Table 21. Room entry and incision are recorded for two patients. In the first case, the OR nurse recorded the values of the timestamps successively (9:15am is after 9am). In the second case, the OR nurse either forgot to record room entry or had another more urgent task to do. When the surgeon incised the patient, the OR nurse recorded the incision and then the room entry. Thus the room entry is recorded after incision. This can occur for any consecutive timestamps.

Table 21 – Example of coherent and incoherent values two consecutive timestamps in the same patient pathway

#	Room Entry Time	Incision Time	Reversal Duration	Observation
1	9:00	9:15	15minutes	Coherent: keep both timestamps.
2	9:20	9:15	-5minutes	Incoherent: delete t_room_entry.

1.3. Finding incoherent timestamps using the operating room point of view

For two patients A and B using the same OR successively, we delete Room Exit (A) if Room Entry (B) is recorded before Room Entry (A). In Figure 36, we represent the timelines of two patients using the same OR. The records show that patient B enters the OR before patient A leaves it, which is impossible. Thus, we keep Room Entry (B) and delete Room Exit (A).

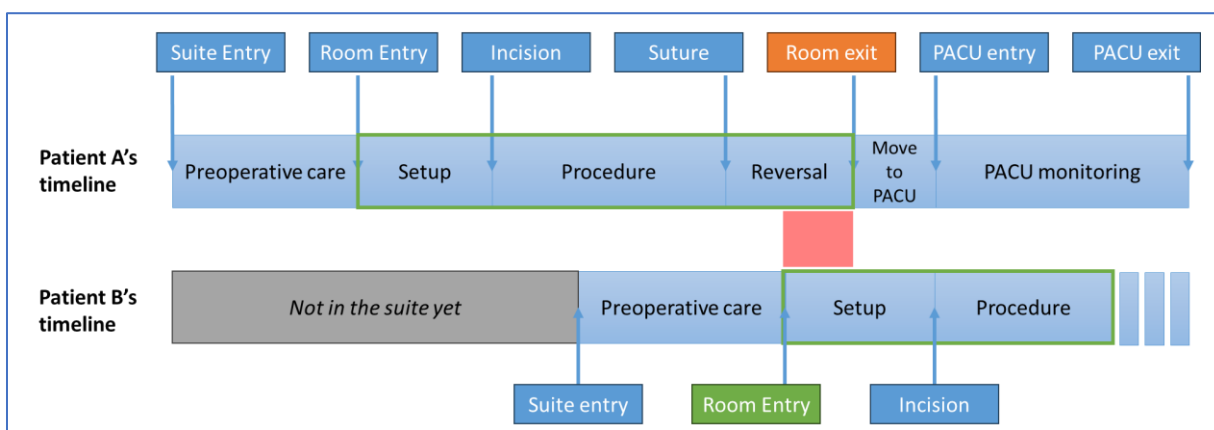


Figure 36 – Illustration of incoherence timestamps in the light of operating room usage (OR POV).

1.4. Correction

In Figure 37, we show the number of timestamps recorded in the database initially (blue), after the correction using patient POV (orange), and after the correction using OR POV (grey). Table 22 displays the number of timestamps at each step, and the gap between the initial number and the number after correction #2. Table 23 does the same but under the form of percentages. We focus on the results displayed in the column “Percentage after correction #2 (OR POV)” of Table 23: all timestamps are recorded more than 78% of the time, except suite arrival which is recorded at 17%. This is because suite arrival was only recorded one year compared to 4 years for the other timestamps. These 17% still amount to 12,238 timestamps, which is sufficiently large for what we want to do.

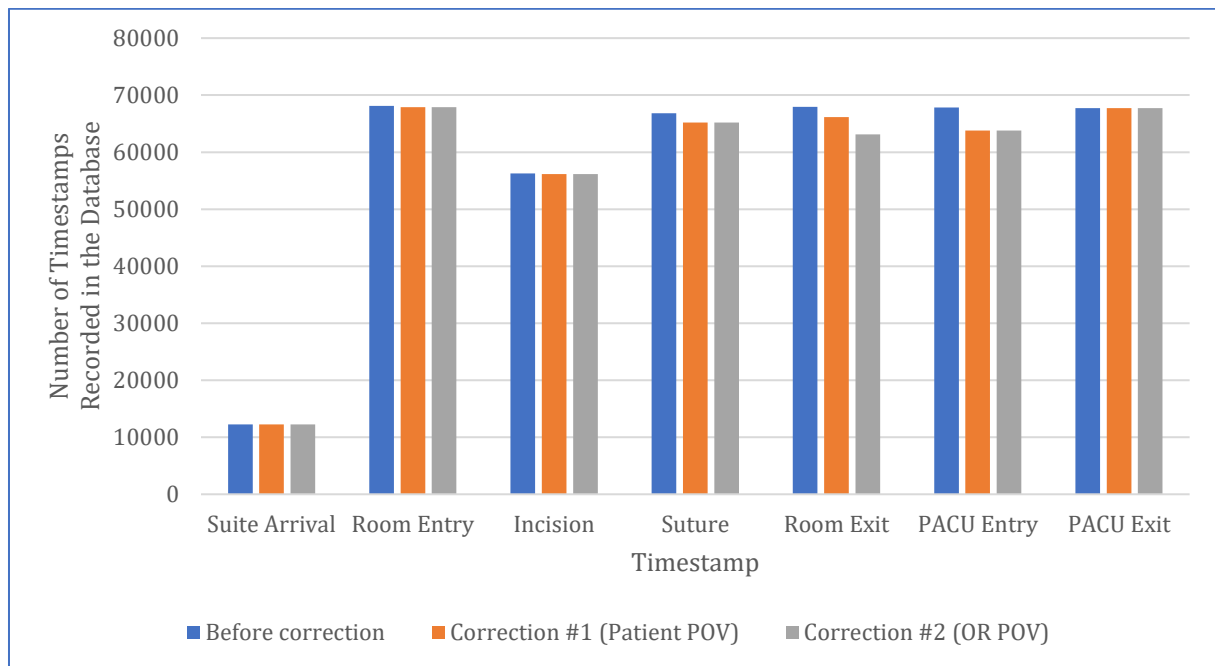


Figure 37 - Comparison of the Number of Timestamps after Correction from the Patient POV (orange) and the OR POV (grey).

Table 22 – Number of timestamps before correction, after correction using patient POV, and after correction using OR POV.

Timestamps	Initial Number	Number after correction #1 (Patient POV)	Number after correction #2 (OR POV)	Gap between initial and correction #2 number
Suite Arrival	12,278	12,238	12,238	40
Room Entry	68,091	67,864	67,864	227
Incision	56,255	56,154	56,154	101
Suture	66,829	65,176	65,176	1,653
Room Exit	67,947	66,138	63,143	4,804
PACU Entry	67,842	63,776	63,776	4,066
PACU Exit	67,723	67,723	67,723	0

Table 23 - Percentage of timestamps before correction, after correction using patient POV, and after correction using OR POV.

Timestamps	Initial Percentage	Percentage after correction #1 (Patient POV)	Percentage after correction #2 (OR POV)	Gap between initial and correction #2 Percentage
Suite Arrival	17.16	17.10	17.10	0.06
Room Entry	95.15	94.83	94.83	0.32
Incision	78.61	78.47	78.47	0.14
Suture	93.38	91.07	91.07	2.31
Room Exit	94.94	92.42	88.23	6.71
PACU Entry	94.80	89.12	89.12	5.68
PACU Exit	94.63	94.63	94.63	0

2. Computing durations

2.1. Introduction

Now that we have deleted the incoherent timestamps from our database, we can compute the performed discrete durations between each remaining couple of timestamps. These durations will allow to: (1) simulate the performed schedule execution in our DT-DSS, (2) compute discrete provisional durations, and (3) compute stochastic provisional durations.

2.2. Computing initially available durations

For each two consecutive timestamps, we compute the duration between them. Table 24 displays the number and the percentage of durations we can compute based on the current available timestamps. As we can see, some durations are missing. For instance, we only have access to 17% of the preoperative phase duration, and the highest percentage of durations recorded is 88% (PACU monitoring). In the remaining of this section, we explain how we computed the missing durations.

Table 24 – Number and percentage of computed durations per duration type.

#	Duration Type	Number of duration computed in the database	Percentage of durations computed in the database
1	Preoperative care	12,195	17.04
2	Setup (+ induction)	55,827	78.01
3	Procedure	53,943	75.38
4	Reversal	60,469	84.50
5	Moving to PACU	59,279	82.83
6	PACU Monitoring	63,657	88.95

2.3. Impactful criterion of the operating duration

Based on our staff interviews, we know that the surgeon, the anesthesiologist, the anesthesia type, and the surgery type can have a strong influence on the patient pathway durations. We cannot base our study on the surgery type because it is not standardized in the database we are using. Thus, we use the CCAM codes instead - the CCAM is the Common Classification of Medical Procedures (*Classification Commune des Actes Médicaux*). It is used by the French social security system (*Sécurité Sociale*) to pay doctors and reimburse insured people²⁶. **Consequently, we use the surgeon ID, the anesthesiologist ID, the CCAM codes and the anesthesia type to group patients.**

Upon trying to create patient groups based on all four criteria, we notice that very few cases have all four-information recorded. Thus, we group patients based on what data is available and end up with 6 possible combinations. Table 25. describes the grouping criteria we use. The last column

²⁶ <https://www.dictionnaire-juridique.com/definition/ccam-classification-commune-des-actes-medicaux.php>

specifies in which patient group is attached a cataract surgery described by the CCAM code “BFPP001”, performed by **surgeon A** and **anesthesiologist B**, and receiving and **OIP**.

Table 25 – Proposition of grouping criteria.

#	Surgeon ID	Anesthesiologist ID	CCAM codes	Anesthesia type	Example of grouping criterion
1	No	No	No	No	/
2	Yes	Yes	No	Yes	[A, B, OIP]
3	Yes	No	No	Yes	[A, OIP]
4	Yes	No	No	No	[A]
5	No	No	Yes	No	[BFPP001, OIP]
6	Yes	Yes	Yes	Yes	[A, B, BFPP001, OIP]

2.4. Method for each correction

For each grouping criterion, for each duration type, we follow these steps:

1. We extract the cases where (i) the grouping criterion is respected, and (ii) the duration is not null.
2. We randomly split the obtained sample in two subsets (30% - 70%).
3. We compute the median and the mean of the durations in the 70% subset.
4. We compare the true value of the duration in the 30% subset to the estimated value (median and mean) in the 70% subset.
5. Let k be a gathering criterion, j an activity, i a patient respecting the criterion and having the activity duration computed, and n the number of patient i . We compute the Weighted Absolute Percentage Error $WAPE(j,k)$ according to the formula:

$$WAPE_{duration\ type, criterion} = \frac{\sum_{t=1}^n |A_t - F_t|}{\sum_{t=1}^n |A_t|},$$

where A_t is the actual (true) value of the median or mean durations in the 30% subset and F_t is the forecasted median or mean duration computed from the 70% subset. The reasoning behind our choice of error metric is to provide ourselves with an easily understandable percentage value without having to worry about the effect of short near-zero values on the overall percentage metric.

We display our results in Table 26. The durations are abbreviated as D1 (preoperative care), D2 (setup + induction), D3 (procedure), D4 (reversal), D5 (move to PACU), D6 (PACU monitoring). The grouping criterion is abbreviated as S (surgeon ID), A (anesthesiologist ID) and T (anesthesia type) and C (CCAM codes). The methods are abbreviated as MED (median) and AVG (average or mean).

Table 26 – Values of the WAPE for each duration type (column) and each estimation method (row). The worse the WAPE is the more the colors tend to be red; the better the WAPE is the more the colors tend to be green.

#	D1	D2	D3	D4	D5	D6	Grouping Criterion	Method
0	3.43	5.42	12.58	17.16	8.84	7.04	S + A + T	MED
1	5.78	5.78	14.98	16.85	8.42	6.41	S + T	MED
2	10.79	8.18	21.12	21.2	11.16	9.68	S	MED
3	5.78	4.95	5.64	13.09	6.49	5.64	C	MED
4	3.13	2.85	3.7	11.08	6.89	4.33	C + S + A + T	MED
5	0.73	0.23	0.2	0.64	2.47	0.2	S + A + T	AVG
6	0.34	0.4	1.48	1.62	0.3	0.15	S + T	AVG
7	0.66	0.25	0.81	0.8	1.33	0.08	S	AVG
8	0.3	0.39	0.44	0.47	0.13	0.71	C	AVG
9	0.68	1.06	0.52	0.1	1.07	0.62	C + S + A + T	AVG
10	0.24	0.31	2.63	0.83	0	0.47	/	AVG
11	13.16	16.28	35.01	37.87	10.56	21.16	/	MED

2.5. Estimate missing durations

For each duration type, we rank the correction methods according to the WAPE (the lower being the better). For each case, for each duration, we associate the best correction type available. If correction is based on more than 2 values (3 or more), then we apply the correction. If not, we move on the next best correction type. We can compute all the durations. **However, we are not sure yet that they are coherent with the available timestamps.**

3. Computing missing timestamps

3.1. Introduction

In the previous sections we have cleaned the database of incoherent timestamps, computed durations between each remaining couple of successive timestamps, and used these newly computed durations to estimate the value of the remaining missing.

We now have access to a discrete duration for each activity of each patient. However, we do not know whether these durations guarantee the coherence of timestamps that we had established in section 1. Consequently, in this section, we compute each missing timestamp based on the durations and assess whether it keeps the processes coherent.

We remind our reader that:

- When dealing with two supposedly successive timestamps, we consider the successor to be more reliable than the predecessor. Therefore, if these two timestamps are incoherent with each other, we delete the earlier timestamp and keep the latter one (H18).
- The notion of coherence is based on the respect of the surgical process from the patient POV and from the OR POV.

To compute our missing timestamps, we implement the following steps:

1. Correct pathway extremities: suite entry and PACU exit (section 3.2).
2. Correct each patient pathway independently: incision, suture and PACU entry (section 3.3).
3. Correct patient pathways by considering them dependent on each other: room exit and room entry (section 3.4).

The steps are all repeated until the number of timestamps corrected stops increasing. Indeed, as we will see, the timestamps are dependent on each other, so correcting one can help correct another one. We detail each of the steps below.

In this section, we will constantly use the same color code in each figure: we want to compute the missing timestamps (orange), based on the available previous/following timestamps (green) and the available durations between them (green).

3.2. Correct pathway extremities: suite entry and PACU exit

For each patient, when both the $t^{room\ entry}$ and the $d^{preoperative\ care}$ are available, we compute $t^{suite\ entry} = t^{room\ entry} - d^{preoperative\ care}$. We illustrate this in Figure 38.

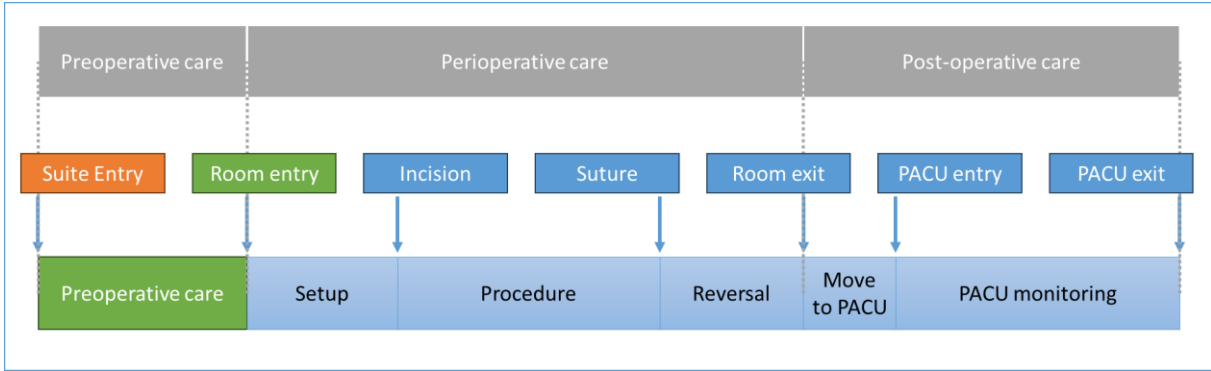


Figure 38 – We compute “Suite Entry Time” based on “Room Entry Time” and “Preoperative Care Duration”.

For each patient, when both the $t^{PACU\ entry}$ and the $d^{PACU\ monitoring}$ are available, we compute $t^{PACU\ exit} = t^{PACU\ entry} + d^{PACU\ monitoring}$. We illustrate this in Figure 39.

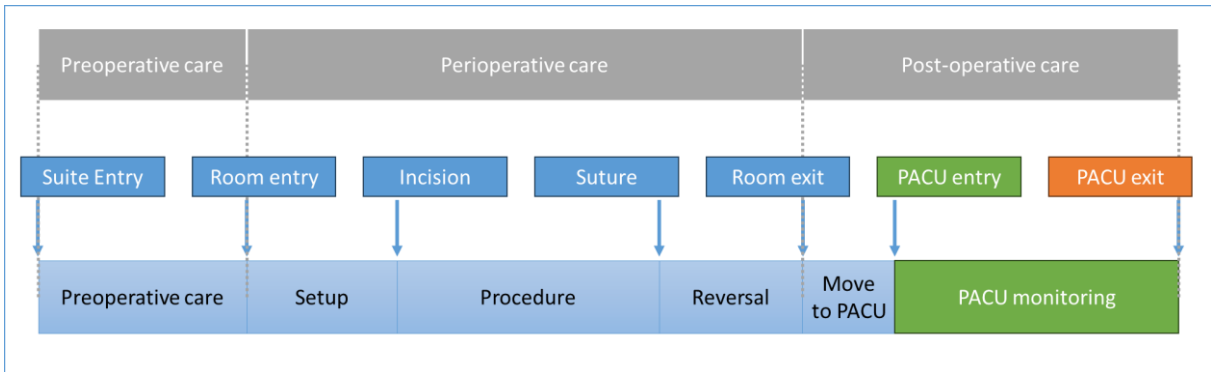


Figure 39 - We compute “PACU Exit Time” based on “PACU Entry Time” and “PACU Monitoring Duration”.

3.3. Correct each patient pathway independently: incision, suture, PACU entry

For each missing timestamp that is not at the patient pathway extremity ($t^{suite\ entry}$ or $t^{PACU\ exit}$), we identify whether we have the required elements to correct it. To correct t_i , we need to respect the following conditions (illustrated in Figure 40 and Figure 41):

$$\begin{aligned}
 t_{i-1} &\neq 0 \\
 d(t_i, t_{i+1}) &\neq 0 \\
 d(t_{i-1}, t_i) &\neq 0 \\
 t_{i+1} - d(t_i, t_{i+1}) &> t_{i-1} \text{ (condition 1)} \\
 t_{i-1} + d(t_{i-1}, t_i) &< t_{i+1} \text{ (condition 2)}
 \end{aligned}$$

If all conditions are respected, we compute $t_i = t_{i+1} - d(t_i, t_{i+1})$. Note that we correct the timestamps based on the latest timestamp. This is coherent with the fact that for two consecutive timestamps, we consider the second one to be more reliable.

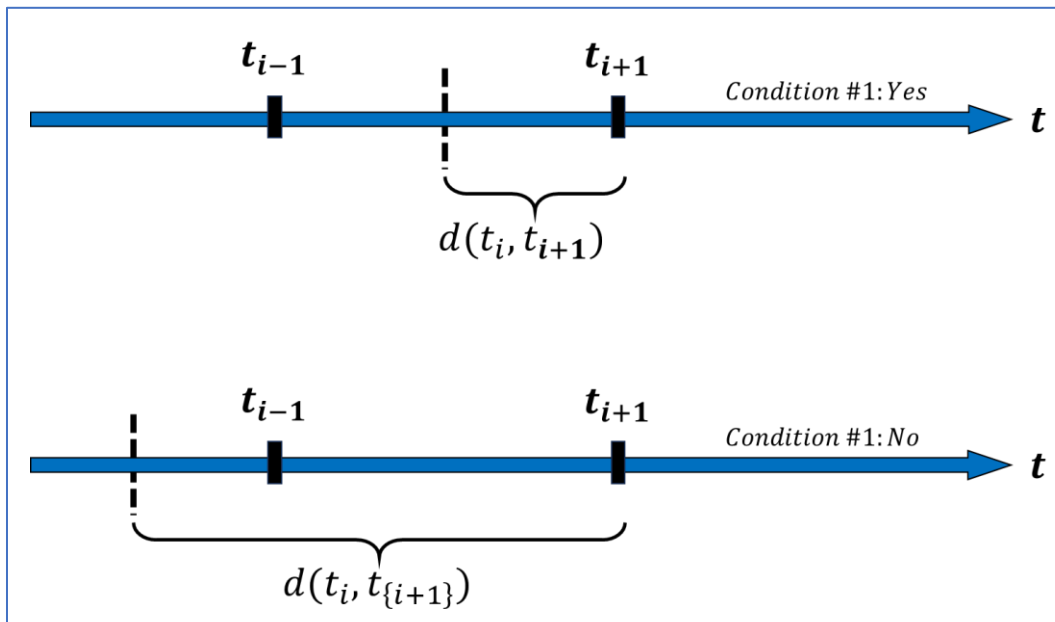


Figure 40 – Illustration of cases where $t_{i+1} - d(t_i, t_{i+1}) > t_{i-1}$ is respected (top timeline) or not respected (bottom timeline).

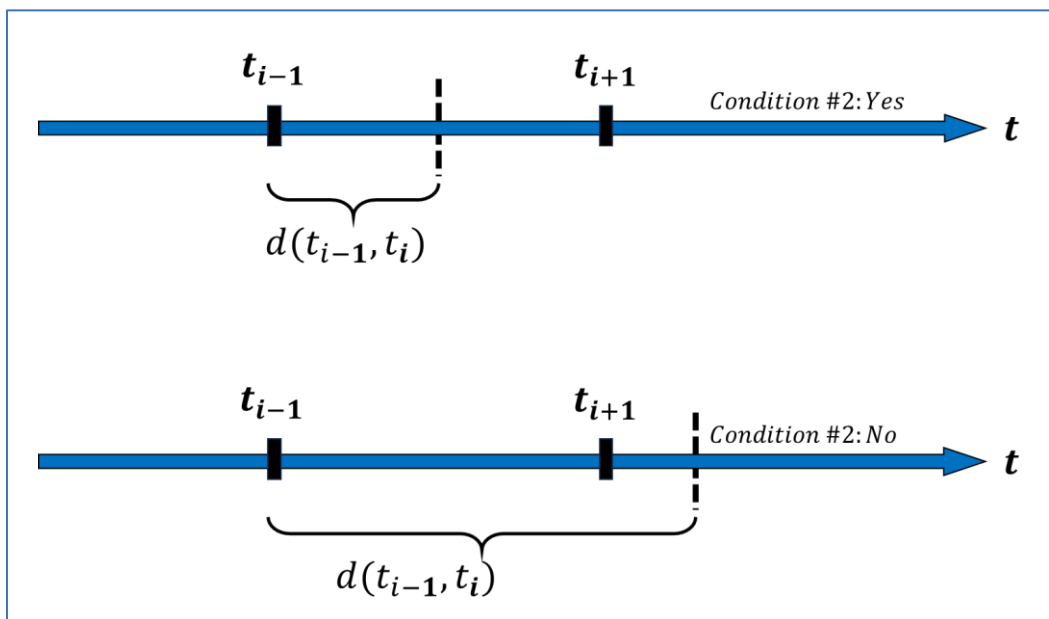


Figure 41 – Illustration of cases where $t_{i-1} + d(t_{i-1}, t_i) < t_{i+1}$ is respected (top timeline) or not respected (bottom timeline).

In the following figures, we illustrate how to respectively compute:

- $t^{incision}$ based on t^{suture} and $d^{procedure}$ (Figure 42).
- t^{suture} based on $t^{room\ exit}$ and d^{suture} (Figure 43).
- $t^{PACU\ entry}$ based on $t^{PACU\ exit}$ and $d^{PACU\ monitoring}$ (Figure 44).

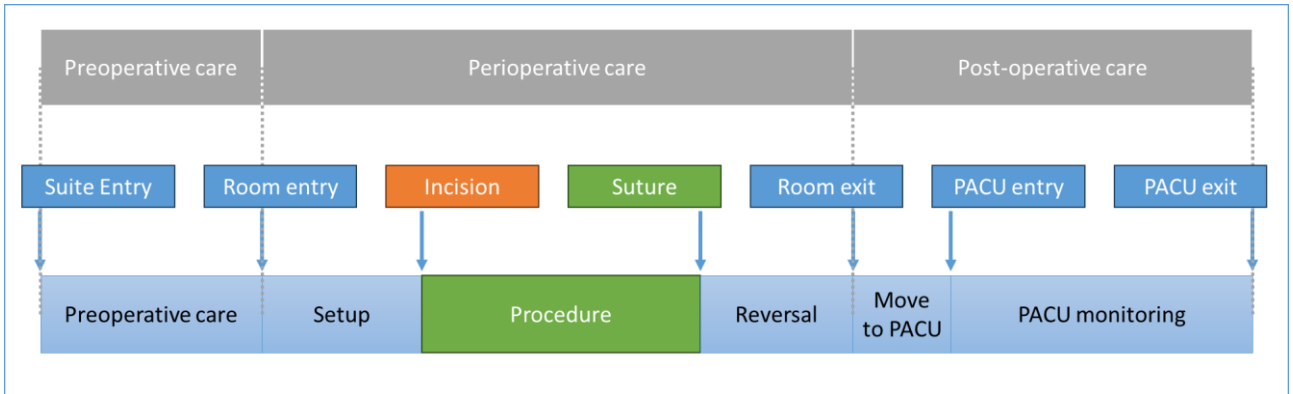


Figure 42 – We compute “Incision Time” based on “Suture Time” and “Procedure Duration”.

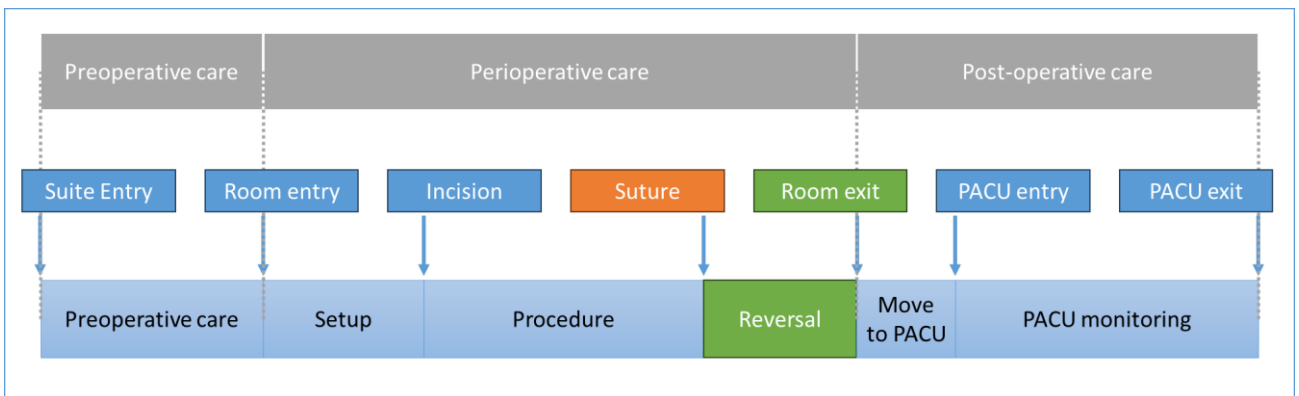


Figure 43 - We compute “Suture Time” based on “Room Exit Time” and “Reversal Duration”.

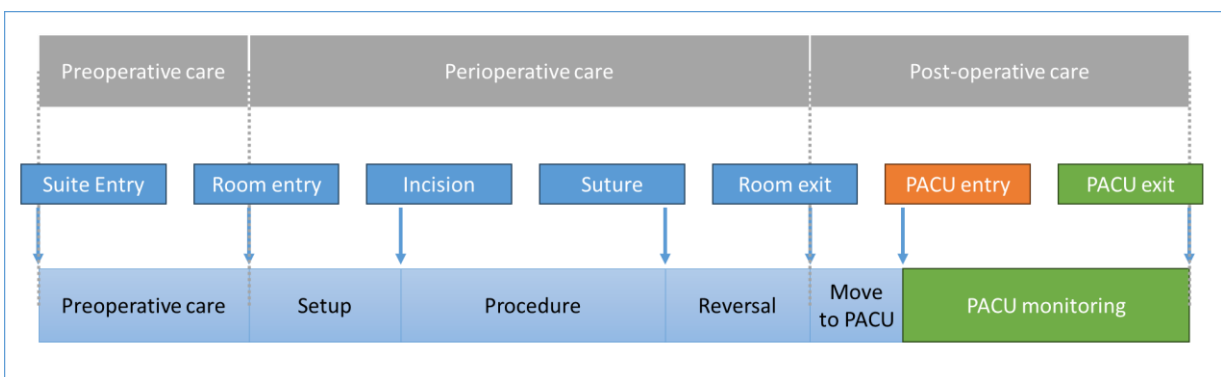


Figure 44 - We compute “PACU Entry Time” based on “PACU Exit” and “PACU Monitoring Duration”.

3.4. Correct patient pathway by considering them dependent on each other: room entry, room exit

3.4.1. Correction of room exit time

We try to correct $t_i^{room\ exit}$ using the following methods:

- (1) Relying on its successor (Figure 45).
- (2) Relying on its predecessor (Figure 46).
- (3) Making the hypothesis that moving to the PACU takes 30 seconds (Figure 45) based on on-site observations.

Each of the methods requires to respect a set of constraints. When one set of constraints is not respected, we move on to the next method. If no set is respected, we cannot correct the timestamp.

Method 1. If the following constraints are respected, we compute $t^{room\ exit} = t^{PACU\ entry} - d^{move\ to\ PACU}$.

$$\begin{aligned}
 &t_{i+1}^{room\ entry} \neq 0 \quad | \quad case_i \text{ is the last case} \\
 &t_i^{suture} \neq 0 \\
 &t_i^{PACU\ entry} \neq 0 \\
 &d_i^{move\ to\ PACU} \neq 0 \\
 &t_i^{PACU\ entry} - d_i^{move\ to\ PACU} < t^{suture} \\
 &t_i^{PACU\ entry} - d_i^{move\ to\ PACU} \leq t_{i+1}^{room\ entry} \quad | \quad case_i \text{ is the last cas}
 \end{aligned}$$

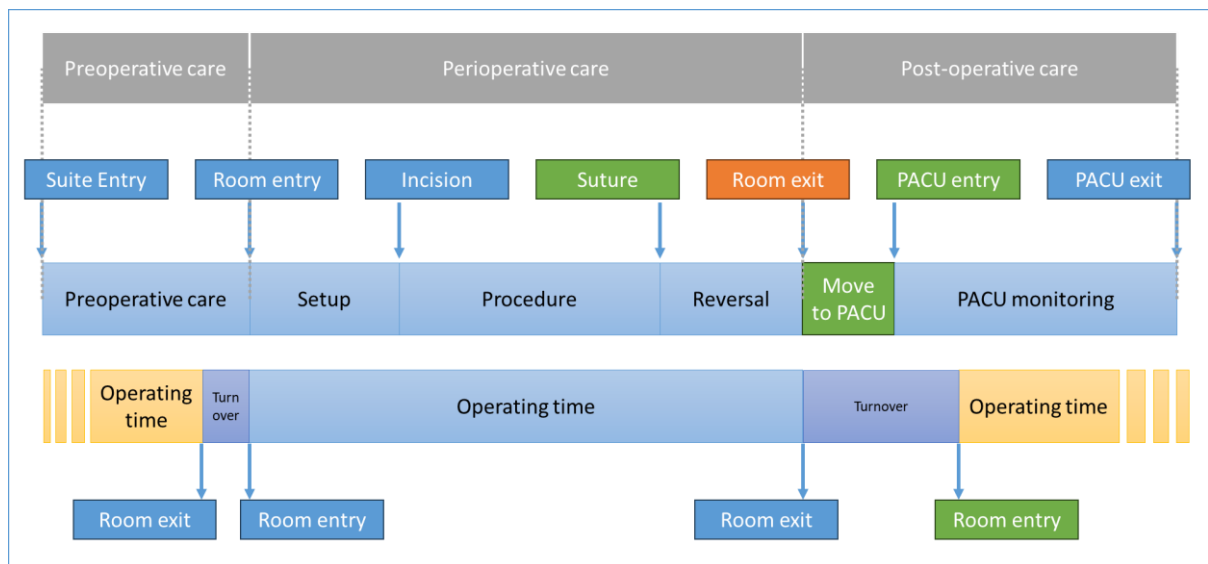


Figure 45 – We compute “Room Exit Time” based on “Suture Time”, “PACU Entry Time” and “Move to PACU Duration” of the same patient, as well as “Room Entry Time” of the next patient.

Method 2. If the following constraints are respected, we compute $t^{room\ exit} = t^{suture} + d^{reversal}$:

$$\begin{aligned}
 t_{i+1}^{room\ entry} &\neq 0 \quad | \quad case_i \text{ is the last case} \\
 t_i^{suture} &\neq 0 \\
 t_i^{PACU\ entry} &\neq 0 \\
 d_i^{reversal} &\neq 0 \\
 t_i^{suture} + d_i^{reversal} &\leq t_{i+1}^{room\ entry} \quad | \quad case_i \text{ is the last case} \\
 t_i^{suture} + d_i^{reversal} &\leq t_i^{PACU\ entry}
 \end{aligned}$$

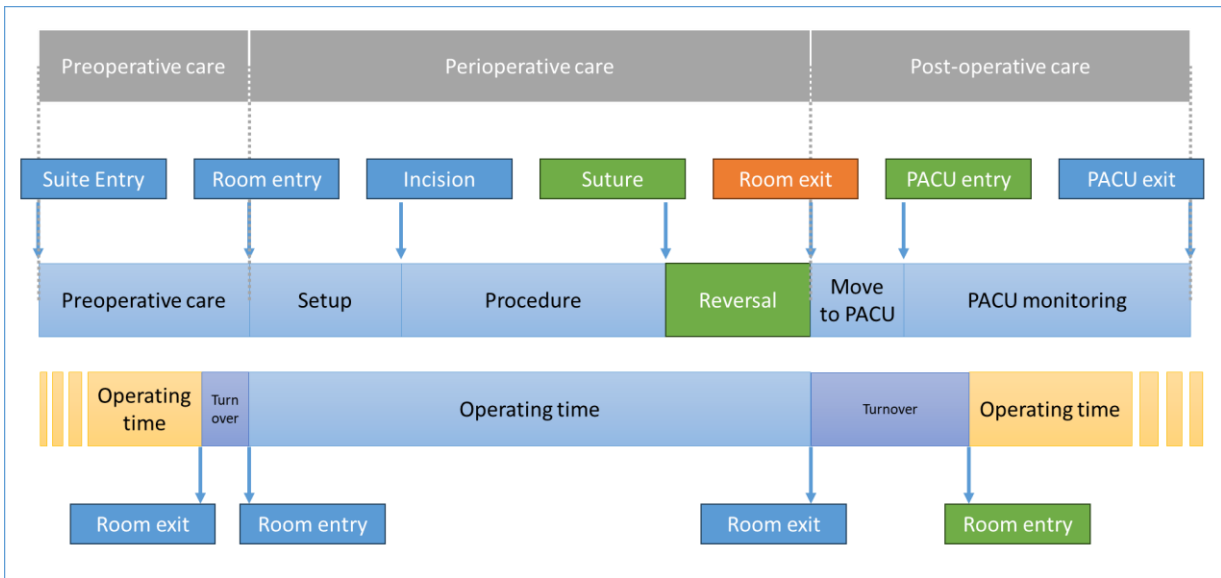


Figure 46 - We compute “Room Exit Time” based on “Suture Time”, “PACU Entry Time” and “Reversal Duration” of the same patient, as well as “Room Entry Time” of the next patient.

Method 3. We make the hypothesis that $t_i^{move\ to\ PACU} = 30$ seconds. If the following constraints are respected, we compute $t_i^{room\ exit} = t_i^{PACU\ entry} - d_i^{move\ to\ PACU}$:

$$\begin{aligned}
 t_{i+1}^{room\ entry} &\neq 0 \quad | \quad case_i \text{ is the last case} \\
 t_i^{suture} &\neq 0 \\
 t_i^{PACU\ entry} &\neq 0 \\
 t^{PACU\ entry} - d^{move\ to\ PACU} &> t^{suture} \\
 t^{PACU\ entry} - d^{move\ to\ PACU} &\leq t_{i+1}^{room\ entry} \quad | \quad case_i \text{ is the last case}
 \end{aligned}$$

3.4.2. Correction of room entry time.

As for $t_i^{room\ exit}$, We try to correct $t_i^{room\ entry}$ using the several methods:

- (1) Relying on its successor (Figure 47).
- (2) Relying on its predecessor (Figure 48).

Each of the methods requires to respect a set of constraints. When one set of constraints is not respected, we move on to the next method. If no set is respected, we cannot correct the timestamp.

Method 1. If the following constraints are respected, we compute $t_i^{room\ entry} = t_i^{incision} - d_i^{setup}$:

$$t_i^{suite\ entry} \neq 0$$

$$t_i^{incision} \neq 0$$

$$d_i^{setup} \neq 0$$

$$t_{i-1}^{room\ exit} \neq 0 \mid \text{case}_i \text{ is the first case}$$

$$t_i^{incision} - d_i^{setup} > t_i^{suite\ entry}$$

$$t_i^{incision} - d_i^{setup} \geq t_{i-1}^{room\ exit} \mid \text{case}_i \text{ is the first case}$$

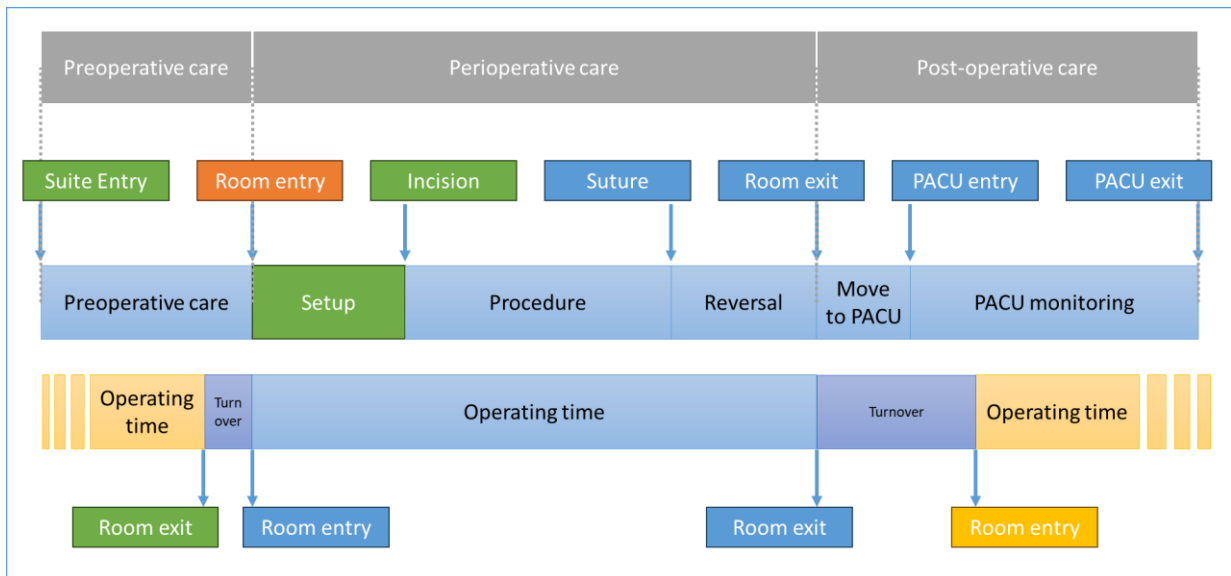


Figure 47 - We compute “Room Entry Time” based on “Suite Entry Time”, “Incision Time” and “Setup Duration” of the same patient, as well as “Room Entry Time” of the previous patient.

Method 2. If the following constraints are respected, we compute $t_i^{room\ entry} = t_i^{suite\ entry} + d_i^{preoperative\ care}$:

$$t_i^{suite\ entry} \neq 0$$

$$t_i^{incision} \neq 0$$

$$d_i^{preoperative\ care} \neq 0$$

$$t_{i-1}^{room\ entry} \neq 0 \mid \text{case}_i \text{ is the first case}$$

$$t_i^{suite\ entry} + d_i^{preoperative\ care} \leq t_{i-1}^{room\ exit}$$

$$t_i^{suite\ entry} + d_i^{preoperative\ care} < t_i^{incision}$$

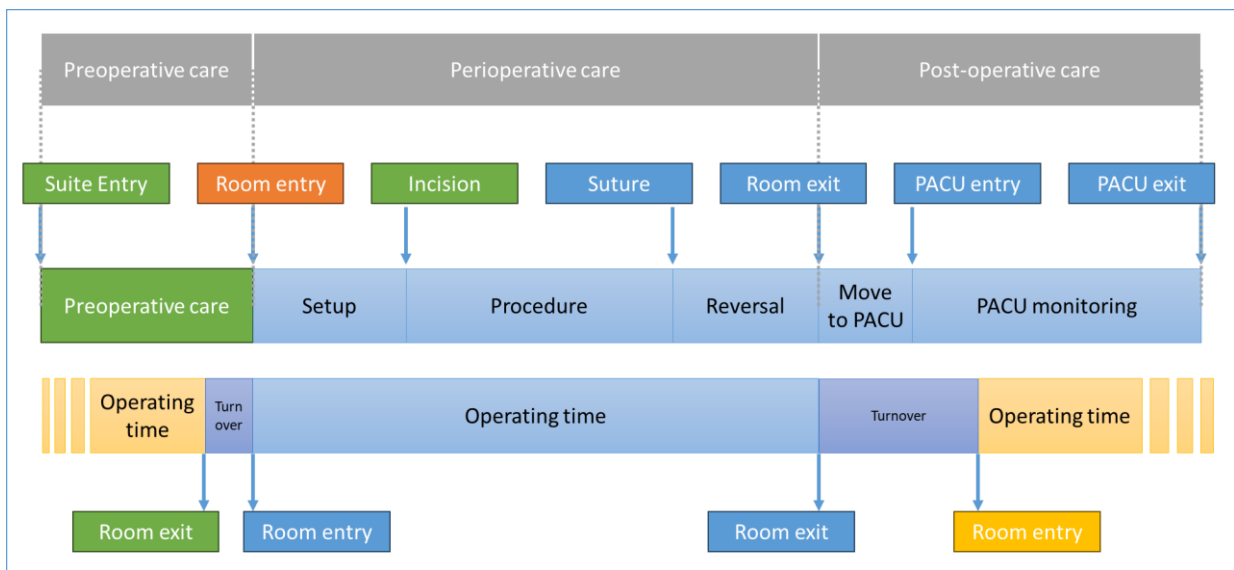


Figure 48 - We compute “Room Entry Time” based on “Suite Entry Time”, “Incision Time” and “Preoperative care Duration” of the same patient, as well as “Room Entry Time” of the previous patient.

3.5. Results after trying to compute the missing timestamps

We display the number and percentage of total timestamps obtained after trying to compute missing timestamps in Figure 49, Table 27 and Table 28. We are not able to reach 100% because the correction requires to have access to already recorded durations and other timestamps which is not always the case. However, we still increase the incision percentage record by 15% and the suite arrival one by 78%. This is non-negligible as incomplete patient pathways cannot be simulated in our surgical suite digital twin.

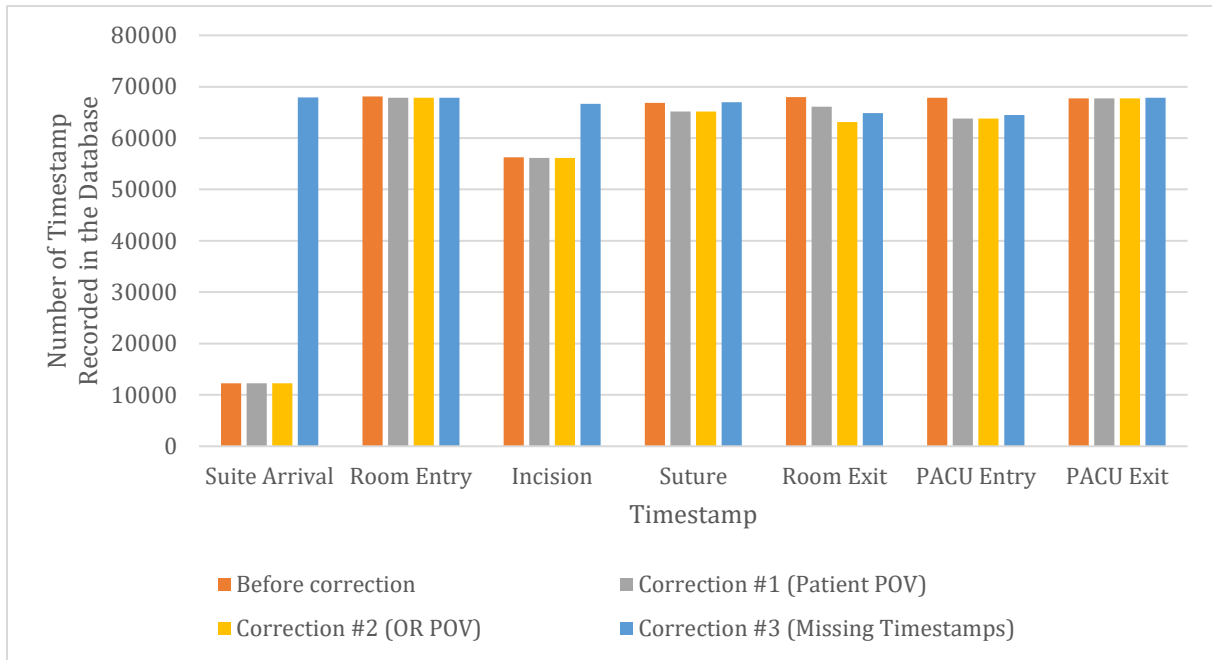


Figure 49 – Number of timestamps recorded in the database: before correction (orange), after the correction from the patient POV (yellow), after correction from the OR POV (grey), and after computation of the missing performed timestamps using performed durations (blue).

Table 27 - Number of timestamps recorded in the database.

Timestamps	Before correction	Correction #1 (Patient POV)	Correction #2 (OR POV)	Correction #3 (Missing Timestamps)	Gap between initial schedule and correction #3
Suite Arrival	12,278	12,238	12,238	67,907	55,629
Room Entry	68,091	67,864	67,864	67,864	-227
Incision	56,255	56,154	56,154	66,686	10,431
Suture	66,829	65,176	65,176	66,973	144
Room Exit	67,947	66,138	63,143	64,832	-3,115
PACU Entry	67,842	63,776	63,776	64,473	-3,369
PACU Exit	67,723	67,723	67,723	67,842	119

Table 28 - Percentage of timestamps recorded in the database.

Timestamps	Before correction	Correction #1 (Patient POV)	Correction #2 (OR POV)	Correction #3 (Missing Timestamps)	Gap between initial schedule and correction #3
Suite Arrival	17.16	17.10	17.10	94.89	77.73
Room Entry	95.15	94.83	94.83	94.83	-0.32
Incision	78.61	78.47	78.47	93.18	14.57
Suture	93.38	91.07	91.07	93.58	0.20
Room Exit	94.94	92.42	88.23	90.59	-4.35
PACU Entry	94.80	89.12	89.12	90.09	-4.71
PACU Exit	94.63	94.63	94.63	94.8	0.17

4. Compute timestamps and durations for the provisional schedule

4.1. Introduction

In the previous section, we corrected the performed timestamps, computed the performed durations of the aggregated surgical suite processes, and used them to compute missing timestamps.

In the database, we have access to the provisional ranks, provisional OR and provisional suite arrival times. However, the timestamps and the durations of the provisional schedule are not recorded. In this section, we describe the computations carried out for the provisional schedule: the stochastic timestamps and durations (to simulate its execution in a stochastic environment), and the discrete timestamps and durations (to simulate its execution in a determinist environment).

The provisional schedule durations can be estimated in several ways: surgeon estimate, empirical distribution, statical distribution-fitting, etc. Each of these methods require to group the cases by their surgery label – and even better, by their surgery label *and* their surgeon.

However, in the database provided by our collaboration partner, the surgery labels are not standardized: the name of each procedure is manually written by the staff in the OR software. The same surgery type can be referred to by several labels. For instance, a cataract can be referenced as: “cataract”, “Cataract”, “cataract with sedation”, “cataract at 8am”, “cataract that had previously been canceled”, etc. **This non-standardization of the surgery label makes it complicated for us to group the totality of the database cases by their procedure.**

To build the provisional schedule of our study case despite this lack of data, we apply steps illustrated in Figure 50.

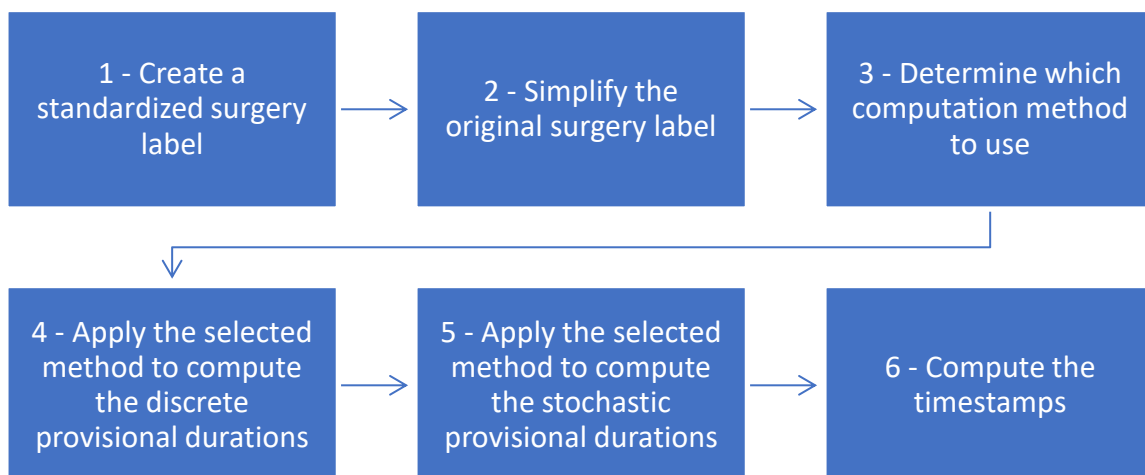


Figure 50 - Compute Timestamps and Durations for the Provisional schedule

4.2. Step description

1 – Create a standardized surgery label. First, we create a standardized name for each surgery type of the study case. The standardized name is a one-word label in lowercase that describes as accurately as possible the real surgery label. For simplification reasons, if there are several procedures, we only focus on the first one. We give examples in Table 29.

Table 29 – Example of Proposed Standardized Label for surgical procedures

#	Original Database Label	Proposed Standardized Label
1	Cure d’hydrocèle droite selon lord	hydrocele, hydrocèle
2	Urétrotomie interne endoscopique	uretrotomie, urétrotomie
3	Rtuv + biopsies de vessie	rtuv
4	Rtuv + jj droite	rtuv

2 – Simplify the original surgery label. Second, we simplify the original surgery label by replacing all capitals by lowercase, and by deleting any space before or after the text.

3 – Determine which computation method to use. The methods are explained in the next step. We illustrate this using Figure 51. Our objective is to compute all the determinist and stochastic durations required to simulate the provisional schedule execution. Thus, for each process step (Ex: preoperative duration), for a specific surgery type (Ex: cataract) performed by a specific surgeon (Ex: surgeon A), we count the number of times the step duration is recorded in the database (How many **cataracts** performed by **surgeon A** have a **preoperative duration?**). If there are more than 100 datapoints, we use method 1, else, we count the number of times the value is recorded for the specific surgery type only (How many **cataracts** have a **preoperative duration?**). If there are more than 100 datapoints, we use method 2, else we use method 3. The idea is that Method 1 allows us to compute a better estimation than Method 2, that itself allows us to obtain a better duration than Method 3. We have chosen the threshold of a 100 datapoints with the expectation of having a representative sample of cases.

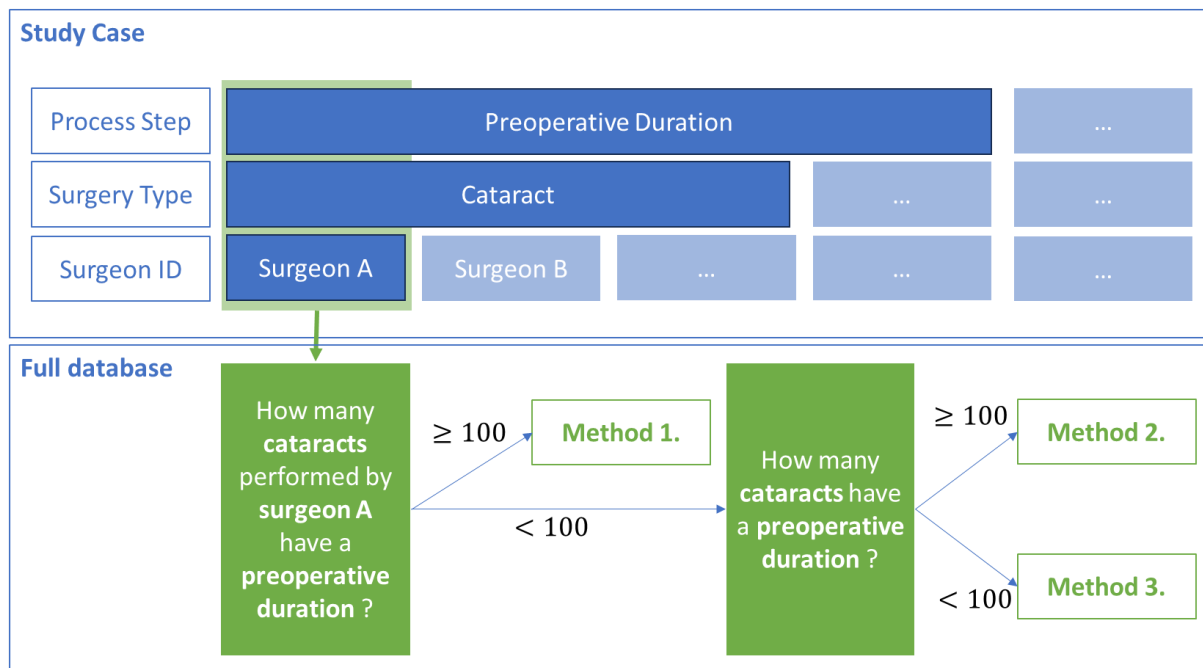


Figure 51 – How do we chose the computation method for the durations of the provisional schedule?

4 – Apply the selected method to compute the discrete provisional durations. Fourth and finally, we compute the provisional durations by applying the previously selected method. The formulas are all detailed in

Table 31 (deterministic durations) and Table 32 (stochastic durations). In each of these methods, we identify groups of durations:

- (1) **Suite arrival and suite exit:** these durations are never recorded in the OR software. They are only used in the model to ensure that the patient starts and ends their pathway at the right time and place. The duration of these steps is always equal to 1 minute.
- (2) **Preoperative care, patient in room, moving patient to PACU, and PACU monitoring:** the durations of all these steps is recorded in the OR software. They are not strongly correlated.
- (3) **Setup (+ induction), procedure, reversal:** these steps are all recorded in the OR software. They are strongly correlated (usually a long procedure requires a long setup and a long reversal; the contrary is true too).
- (4) **Putting a drip, long reception, short reception, LRA preparation, LRA, LRA waiting, OIP, OR cleanup:** these durations are never recorded in the or software. Thus, based on our observations and interviews, we estimated their average durations: putting a drip (5 minutes), long reception (15 minutes), short reception (5 minutes), LRA preparation (15 minutes), LRA (30 minutes), LRA waiting (30 minutes), OIP (15 minutes), suite arrival (1 minute), suite exit (1 minute).

As a side note:

- The OR cleanup duration depends on the perioperative duration (
- Table 30).
- If $t_i^{cleanup} > t_{i+1}^{OR\ entry}$ then $t_i^{cleanup} = t_{i+1}^{OR\ entry}$

Table 30 – Computing cleanup duration.

#	Condition on perioperative phase duration D	Cleanup Durations
1	$D < 30\ minutes$	5 minutes
2	$30 \leq D \leq 120\ minutes$	15 minutes
3	$D > 120\ minutes$	30 minutes

Group#2 durations are computed as follows:

- Method#1. Each step duration is computed as the average step duration of cases with **the same surgery and the same surgeon**.
- Method#2. Each step duration is computed as the average step duration of cases **with the same surgery only**.
- Method#3. Each step duration is computed as a random value extracted once from the uniform distribution $d_{all\ surgeons} * U(min, max)$, when min and max are model parameters and $d_{all\ surgeons}$ is the average step duration of cases **with the same surgery only**.

Group#3 durations are computed following the same formulas except that they are also multiplied

by $\%d_{surgeon} = AVG\left(\frac{d_{surgeon}}{d_{patient\ in\ room}}\right)$ for method#1, and $\%d_{all\ surgeon} =$
 $AVG\left(\frac{d_{all\ surgeon}}{d_{patient\ in\ room}}\right)$ for method#2 and method#3.

Group#4 durations are always equal to their constant value.

5 – Apply the selected method to compute the stochastic provisional durations. We keep the same step grouping.

Group#2 durations are computed as follows:

- Method#1. Each step duration is a random value extracted from the histogram made of all the steps' durations of cases with **the same surgery and the same surgeon**.
- Method#2: Each step duration is a random value extracted from the histogram made of all the steps' durations of cases with **the same surgery**.
- Method#3. Same as for the discrete duration.

Group#3 durations are computed following the same formulas except that they are also multiplied

by $\%d_{surgeon} = AVG\left(\frac{d_{surgeon}}{d_{patient\ in\ room}^{surgeon}}\right)$ for method#1, and $\%d_{all\ surgeon} = AVG\left(\frac{d_{all\ surgeon}}{d_{patient\ in\ room}^{all\ surgeon}}\right)$ for method#2 and method#3.

Each step duration from group#4 durations is a random value extracted from $d_{constant} * U(min, max)$, where *min* and *max* are model parameters, and $d_{constant}$ is the discrete duration.

6 – Compute the timestamps. The database provides us with the provisional room entry time. Using this and the provisional durations, we can compute the other provisional timestamps if necessary.

Table 31 – Synthesis of the methods used to compute the deterministic durations for the provisional schedule.

Duration Group	Method 1	Method 2	Method 3
1	<i>1 minute</i>		
2	The average step duration of cases with the same duration and the same surgeon: $AVG(d_{surgeon})$	The average step duration of cases with the same duration: $AVG(d_{all\ surgeons})$	A random value extracted once from $d_{all\ surgeons} * U(min, max)$ where <i>min</i> and <i>max</i> are model parameters.
3	$\%d_{surgeon} * AVG(d_{surgeon}^{patient\ in\ room})$ $\%d_{surgeon} = AVG\left(\frac{d_{surgeon}}{d_{surgeon}^{patient\ in\ room}}\right)$	$\%d_{all\ surgeon} * AVG(d_{all\ surgeon}^{patient\ in\ room})$ $\%d_{all\ surgeon} = AVG\left(\frac{d_{all\ surgeon}}{d_{all\ surgeon}^{patient\ in\ room}}\right)$	Random value extracted once from $\%d_{all\ surgeon} * d^{patient\ in\ room} * U(min, max)$ Where <i>min</i> and <i>max</i> are model parameters and $\%d_{all\ surgeon} = AVG\left(\frac{d_{all\ surgeon}}{d_{all\ surgeon}^{patient\ in\ room}}\right)$
4	$d_{constant}$		

Table 32 - Synthesis of the methods used to compute the stochastic durations for the provisional schedule.

Duration Group	Method 1	Method 2	Method 3
1	<i>1 minute</i>		
2	Random value extracted from the histogram made of $d_{surgeon}$.	Random value extracted from the histogram made of $d_{all\ surgeon}$.	Random value extracted from $d_{all\ surgeons} * U(min, max)$ where <i>min</i> and <i>max</i> are model parameters.
3	Random value extracted from the histogram made of $\%d_{surgeon} * d_{surgeon}^{patient\ in\ room}$ $\%d_{surgeon} = AVG\left(\frac{d_{surgeon}}{d_{surgeon}^{patient\ in\ room}}\right)$	Random value extracted from the histogram made of $\%d_{all\ surgeon} * d_{all\ surgeon}^{patient\ in\ room}$ $\%d_{all\ surgeon} = AVG\left(\frac{d_{all\ surgeon}}{d_{all\ surgeon}^{patient\ in\ room}}\right)$	Random value extracted from $\%d_{all\ surgeon} * d_{patient\ in\ room} * U(min, max)$ where <i>min</i> and <i>max</i> are model parameters and $\%d_{all\ surgeon} = AVG\left(\frac{d_{all\ surgeon}}{d_{all\ surgeon}^{patient\ in\ room}}\right)$
4	Random value extracted from $d_{constant} * U(min, max)$ where <i>min</i> and <i>max</i> are model parameters.		

5. Chapter synthesis

In this section, we proposed and illustrated a methodology to correct and complete the performed and provisional schedule timestamps and duration values extracted from the real-life database to feed the digital twin. Our contribution #6 is therefore two-fold. We begin by preprocessing our available database values and then proceed to use these values with the surgical suite processes described in Chapter IV to simulate both the performed and the provisional schedule with discrete durations, as well as the provisional schedule with stochastic durations.

CHAPTER VI. MODELING AND SCHEDULING NON-ELECTIVE CASES

In Chapter IV, we have discussed how we model schedule execution in our DT-DSS using Flexsim Healthcare®. This amounts to modeling operational and supporting processes. In Chapter V, we have explained how we modeled the stochastic duration for each activity of the surgical suites' processes. In this new Chapter (Chapter VI), we describe how we model and simulate non-elective cases.

In this research, we have defined two types of non-elective cases: semi-urgent cases which must be performed maximum three days after their admission, and urgent cases which must be performed the same day of their admission. We do not consider elective add-on (Chapter I). In Figure 52, we illustrate how the schedule evolves from the weekly staff meeting (D-1 week) to the end of the execution day (D+1). The color code is the following: elective cases (green), semi-urgent cases (yellow), urgent cases (orange). We represent:

1. **The staff-validated provisional schedule at D-1 week:** it only consists in elective cases.
2. **The provisional schedule between the weekly staff meeting and the day before schedule execution:** it consists of the same elective cases plus semi-urgent non-electives cases that were added throughout the week.
3. **The provisional schedule at the start of the execution day:** idem.
4. **The performed schedule at the end of the execution day:** on top of the previous elective and semi-urgent cases, urgent case(s) have been scheduled.

In Table 33, we describe when and why we must perform non-elective case scheduling during the application of our methodologies. We represent these steps on a timeline in Figure 53 to make it more visual. It should be noted that the schedule at the start of the execution day, and the schedule before the execution day are usually the same – they only differ if a case was added during the night. The Training can take place at any time. Finally, in Table 34, we remind the reader of the DT-DSS configuration for each of these instances.

In this Chapter, we describe our solution proposal, discuss how we modeled non-elective case arrival, and non-elective case scheduling.

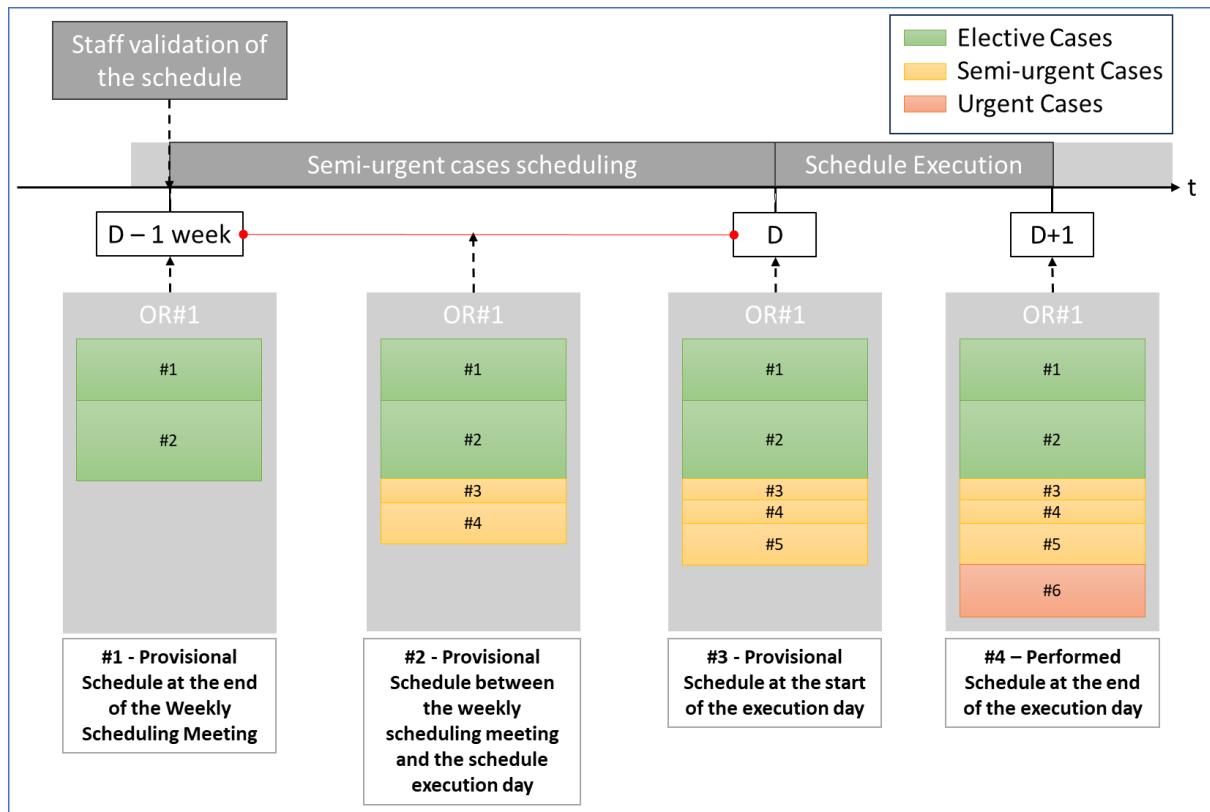


Figure 52 – Illustration of how the schedule evolves from the weekly staff meeting to the end of the execution day.

Table 33 - When and why do we perform non-elective case scheduling?

#	Methodology	Step	Objective
1	Prospective Analysis	4	Assess the provisional schedule resilience.
2	Training on a Provisional Schedule	/	Practice scheduling urgent cases during scheduling execution based on a specific provisional schedule.
3	Retrospective Analysis	2	Test other scheduling solutions for the non-elective cases that arrived during the schedule execution day (i.e. urgent cases).
4	Training on a Performed Schedule	/	Practice scheduling the real urgent cases that arrived during scheduling execution based on a specific performed schedule.
5	Regular Training	/	Practice scheduling urgent cases based on a specific schedule.

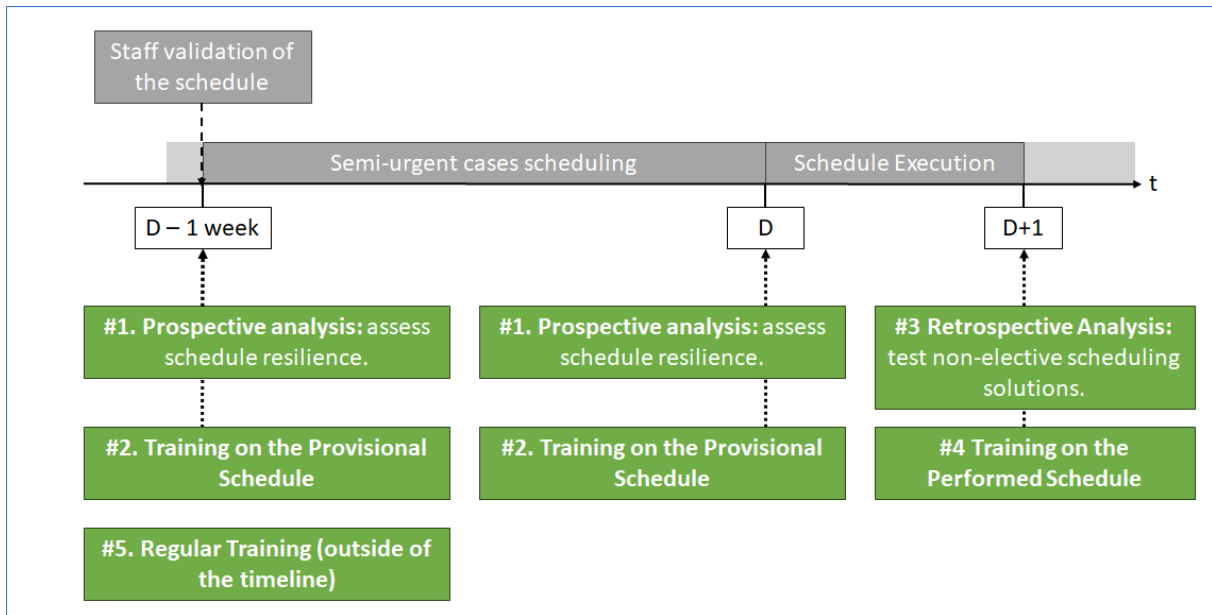


Figure 53 - When and why do we perform non-elective case scheduling?

Table 34 – Description of the DT-DSS configuration for each time we must perform non-elective case scheduling.

#	Methodology	Step	Schedule Type	Constraint Type	Pathway Type	Duration Type
1	Prospective Analysis	4	Provisional	Strict	Detailed	Determinist
2	Training	/	Provisional	Strict	Detailed	Stochastic
3	Retrospective Analysis	2	Performed	Flexible	Aggregated	Determinist
4	Training	/	Performed	Flexible	Aggregated	Determinist
5	Training	/	Any	Any	Any	Any

1. Solution proposal

First, for the **prospective analysis and for the training on a provisional schedule**, we want to model non-elective arrivals at two moments: (1) after the weekly scheduling strategy, and (2) on the day before schedule execution. In the first case, the provisional schedule consists in elective cases. Consequently, we model the arrival of both semi-urgent and urgent non-elective cases. In the second case, the provisional schedule consists in elective cases and semi-urgent cases that were added throughout the week. Thus we model the arrival of only urgent non-elective cases. We call these non-elective cases that were not in the initial schedule **additional non-elective (ANE) cases**. An ANE case can either be a semi-urgent case or an urgent case.

Second, for the **retrospective analysis and for the training on a performed schedule**, we want to model the same non-elective arrivals that were in the initial schedule to find other scheduling solutions. Consequently, we do not use ANE cases for the retrospective analysis.

Finally, for **regular training**, the user is free to practice on a provisional or a performed schedule, and to use either ANE or non-elective cases from the initial schedule depending on what they aim to achieve.

We propose two types of non-elective scheduling in our DT-DSS: (1) an **automatic mode** where the tool will schedule the non-elective case according to a specific strategy specified by the user (first fit, best fit, worst fit), or (2) a **manual mode** where for each non-elective case to schedule the tool will run the different possible scheduling scenarios, provide the results to the user and let them choose which one they want to implement. **The automatic mode is used for analysis and the manual mode for training.** We synthesize this in Table 35.

Table 35 - Description of non-elective modeling and scheduling parameters for the DT-DSS configuration for each time we must perform non-elective case scheduling.

#	Methodology	Time	Schedule Type	Initial Schedule	NE Source	NE Scheduling Strategy
1	Prospective Analysis	After the weekly meeting	Provisional	Elective	ANE (semi urgent + urgent)	Automatic
2	Training on a Provisional Schedule	After the weekly meeting	Provisional	Elective	ANE (semi urgent + urgent)	Manual
1	Prospective Analysis	Day before schedule execution	Provisional	Elective + Semi-urgent	Initial schedule (semi-urgent) + ANE (urgent)	Automatic
2	Training on a Provisional Schedule	Day before schedule execution	Provisional	Elective + Semi-urgent	Initial schedule (semi-urgent) + ANE (urgent)	Manual
3	Retrospective Analysis	After schedule Execution	Performed	Elective + Semi-urgent + Urgent	Initial Schedule (semi urgent + urgent)	Automatic
4	Training on a Performed Schedule	After schedule Execution	Performed	Elective + Semi-urgent + Urgent	Initial Schedule (semi urgent + urgent)	Manual

1.1. Modeling additional non-elective (ANE) arrivals scenarios

Let “initial schedule” be either the provisional or the performed schedule that would have been simulated in a deterministic environment. An ANE case is a non-elective case that is not in the initial schedule. Our goal is to model scenarios of ANE arrivals in the surgical suite.

Upon entering the surgical suite, each ANE case is defined by (1) a suite entry time, (2) the list of surgeons able to perform the surgery, (3) the list of ORs in which the case can be scheduled, (4) an anesthesia type, (5) the case urgency level, and (6) the activities durations. Thus, before being scheduled an ANE do not have an assigned surgeon, an assigned anesthesiologist, nor an assigned OR. The anesthesia type defines which patient pathway the ANE case is going to follow.

Since (a) the operating rooms of the surgical suite we consider are different and cannot receive all surgical specialties, and (b) in some very rare instances a case can be scheduled in a room that is not suitable for it, we make the following hypotheses:

H19. A case of specialty 'a' can be placed in room 'b' only if at least 10 cases of the same specialty were scheduled in that room in the database.

In the database, since some specialties are similar to each other (orthopedics, orthopedics - upper limbs, orthopedics – lower limbs, etc.) we do not associate each surgeon to one specialty. Instead, we make the following hypothesis:

H20. A surgeon 'a' can perform a case from specialty 'b' only if they do a case from that specialty at least once in the database.

H21. A surgeon can only perform a case of their specialty/ specialties.

As a side note:

H22. There are very few vital emergencies at HPB, so we focus on non-vital ANE cases.

H23. Our case study occurs during a weekday. Thus, we only include weekday ANE cases. We do not consider weekend ANE cases.

H24. We maintain our focus on the surgical suite. Consequently, we model the ANE cases from suite entry to suite exit – meaning we do not model their pathway in the emergency department.

1.2. Creating ANE arrival scenarios

Each ANE scenario is defined by (1) the urgency level of the cases, (2) the number of incoming cases, and (3) the cases' arrival times window in the suite.

Urgency level and number of incoming cases. We consider the non-elective cases recorded in the database to have realistic scenarios. First, we create two sets of cases: (a) days with at least one semi-urgent case, and (b) days with at least one semi-urgent case or urgent case. Second, we compute the number of cases per weekday for each separated set. Third, we divide these number of days into 4 quartiles:

- The first quartile (Q1) consists in the days with the least number of arrivals (note that they still have at least one arrival).
- The fourth quartile (Q4) consists in the days with the highest number of arrivals.
- The second and third quartile (Q2 and Q3) consists of the rest of the days.

The repartition into quartiles allows us to test different scenarios of NE arrivals. A day in Q1 can be considered as a good day, Q2 and Q3 as a regular day, and Q4 as a bad day. Indeed the more arrivals we have (and this disruptions), the worse the day non-elective cases are not trivial to schedule. Note that we do not consider the weekdays as we have stated in a previous section.

Cases' arrival time window. We propose 5 options for the arrival time window of ANE cases: the arrivals can be randomly distributed between: (1) midnight and midnight, (2) 7am and 7pm, (3) 7am and 12am, (4) 12am and 2pm, (5) 2pm and 7pm. 7am is an hour before the earliest shift start. 7pm is one hour after the latest shift ends. The staff takes the lunch break between 12am and 2pm. These scenarios correspond to ANE cases arriving during the entire day, during the OR shifts,

during the morning, during the lunch break, during the afternoon. This allows us to model up to: $(4 \times 2 \times 5) + 1 = 41$ scenarios of additional non-elective arrivals.

1.3. Synthesis

Table 36 synthesizes the different parameters available to model ANE arrival scenarios.

Table 36 – Description of the parameters options to create ANE arrivals scenarios.

Urgency level of the ANE	Number of incoming ANE	Time window during which these ANE enter the suite
Semi-urgent + urgent	None	Midnight/midnight
Urgent	Based on all days,	7am-7pm
	Based on Q1 days	7am-12am
	Based on Q2Q3 days	12am-2pm
	Based on Q4 days	2pm-7pm

2. Modeling non-elective scheduling scenarios

In the preceding section, we have described how we model ANE arrival scenarios. We now describe how we schedule non-elective cases. We propose 6 scheduling strategies: (1) maintain the initial scheduling (if possible), (2) first fit, (3) best fit, (4) worst fit, (5) manual scheduling, and (6) push the case to a waiting line. Note that it is possible to maintain the initial schedule if we are simulating a performed schedule execution; indeed in that case we already know where, and when the non-elective has been scheduled in real life.

2.1. Automatic scheduling mode

The available automatic strategies in our DT-DSS are the following:

- **First Fit (FF):** schedule the case in the **first** available allowed OR. This means that the non-elective case will be introduced between already scheduled cases.
- **Best fit (BF):** schedule the case after already scheduled cases in the allowed OR that will have the **least** shift duration left at the end of the schedule execution.
- **Worst fit (WF):** schedule the case after already scheduled cases in the allowed OR that will have the **most** shift duration left at the end of the schedule execution.

Note that in case the strategy is set to best fit or worst fit *and* that there is no OR with a shift duration long enough to fit the non-elective case that needs to be scheduled, *then* the strategy changes to minimizing the overtime. Consequently, it is possible for best fit and worst fit to produce the same scheduling strategy. We illustrate these three strategies in Figure 54.

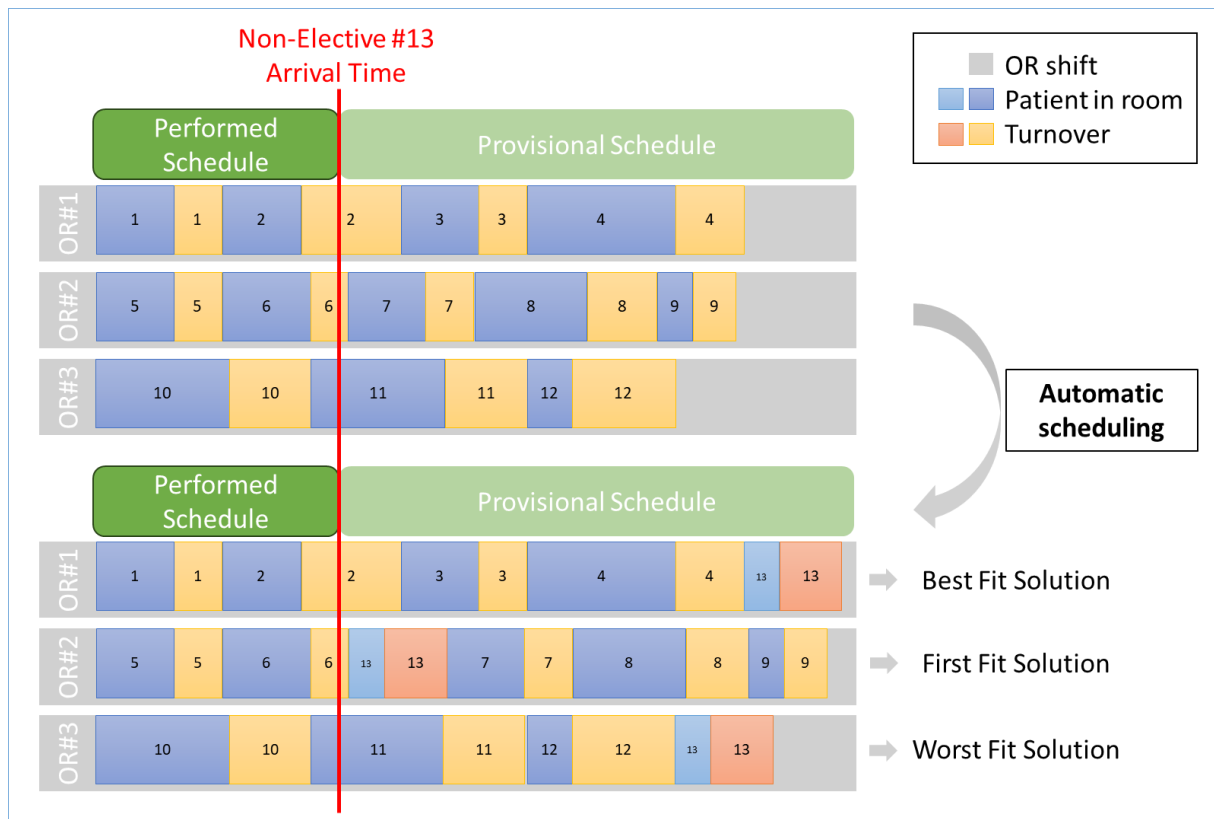


Figure 54 - Illustration of The Three Non-Elective Scheduling Strategies Allowed in our DT-DSS.

In Figure 54, the initial schedule consists in three ORs with a total of 12 patients. The simulation runs until a non-elective case arrives (non-elective arrival time, red). At that time, OR#1 is performing turnover #2, OR#2 is performing turnover #6 and OR#3 is performing surgery #11.

Depending on the simulation parameters the model will schedule the non-elective case in an OR. We make the hypothesis that in this specific example all ORs are allowed for the case, but this might not always be the case.

Case #13 can fit in any of the three ORs displayed in Figure 54 with the Best Fit strategy, case #13 is scheduled in OR#1 because it has the shortest shift duration left (first row). With the Worst Fit strategy, case #13 is scheduled in OR#3 because it has the longest shift duration left (last row). Finally, with the First Fit Strategy, case #13 is scheduled in OR#2 because it is the first room to finish its ongoing case.

Once the non-elective case has been assigned to an OR# m at the n^{th} rank, we assign it a surgeon and an anesthesiologist. We follow these rules:

- For the surgeon:
 1. If the surgeon performing the surgery $(n - 1)$ of OR# m can perform surgery n , then it is assigned to the case.
 2. If not, if there is a surgeon that is present at the suite that day that can perform surgery n , then it is assigned to the case n .
 3. If not, a surgeon from the pool of surgeons allowed to perform surgery n pool is randomly assigned to the case n .
- For the anesthesiologist:
 - If there is an anesthesiologist performing an induction for the case $(n - 1)$, then it is assigned to the case n .
 - If not, if there are anesthesiologists present at the suite that day, one is randomly assigned to the case n .
 - If not, an anesthesiologist from the anesthesiologist pool is randomly assigned to the case n .

2.2. Manual scheduling mode

In this section, we describe how the user can manually schedule non-elective cases. The principle is the following: while running the simulation of a schedule execution, the user might not want to rely on the strategies described in the previous subsection (FF, BF, WF), or might want to compare its own scheduling strategy with the suggested ones. The environment can be either deterministic (we know the durations and the non-elective cases to be scheduled in advance), or stochastic. We describe the process in a stochastic mode as it is slightly more complicated. Indeed, with a stochastic environment, we have to save the description of the disruptions in order to be able to replay them, while in a deterministic environment, we do not need to do so since neither the arrivals nor the durations change from one scenario/replication to another.

To begin with, the user starts the schedule execution simulation. Since it is a stochastic environment, every activity duration is saved so that the schedule execution can be replicated later on.

The simulation runs until the arrival of the first non-elective case to schedule (Disruption #1 Time in Figure 55. This disruption is called the “triggering disruption”. The simulation resets and the experimenter is launched.

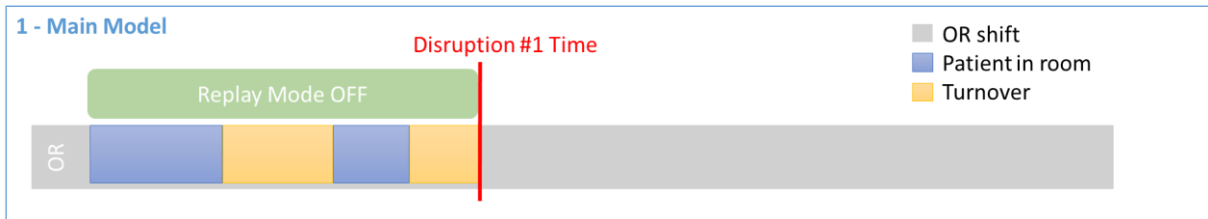


Figure 55 - Illustration of manual non-elective scheduling (1/3). At the first disruption, the main simulation resets, and the experimenter is automatically launched.

In the Experimenter, the DT-DSS tries all the scheduling solutions possible:

- Scheduling strategies proposed by the model (FF, BF, WF).
- Exhaustive list of all the (rank, OR) possible for the case to be scheduled. For instance, if the case arrives when OR#1 is performing its 2nd surgery, then the tool will try the rank 3, 4, 5, etc. until the last possible rank in the OR#1.

In Figure 56, we give the example of 2 replications for 2 different scenarios. The durations before the disruption arrival time are all the same because they are considered as having already happened; they have been saved and replayed. The durations after the disruption are stochastic: there is the same number of cases but the durations are different.

Scenario 1 is an example of FF scheduling. Scenario 2 is an example of scheduling the case in OR#n at rank 5. Once presented with the results, the user can choose which scenario they wish to implement. In our case, it is scenario 1 (yellow start).

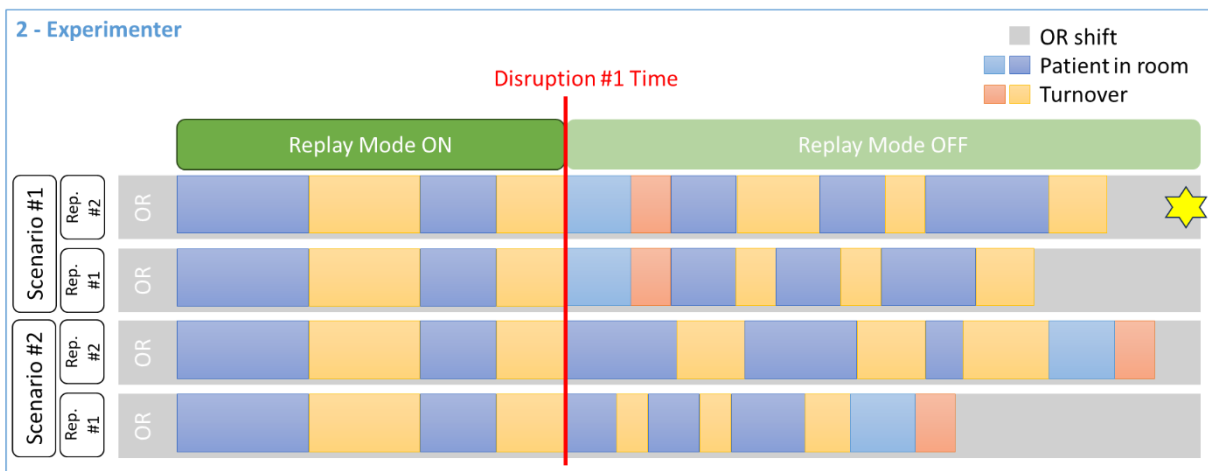


Figure 56 - Illustration of manual non-elective scheduling (2/3). The experimenter launches n scenarios of m replications to test all the possible scheduling solutions for the non-elective. The user chooses to implement one of the scheduling scenarios (yellow star).

The Experimenter then closes automatically, and the simulation starts over from $t = 0$. The performed schedule is replayed until $t =$ “disruption #1 time”. The DT-DSS automatically schedules the disruptions as previously stated by the user and runs until the next disruption. Note

that the durations of the case after the disruption are not the same as in the Experimenter: This is due to the stochastic nature of the environment. We illustrate this in Figure 57.

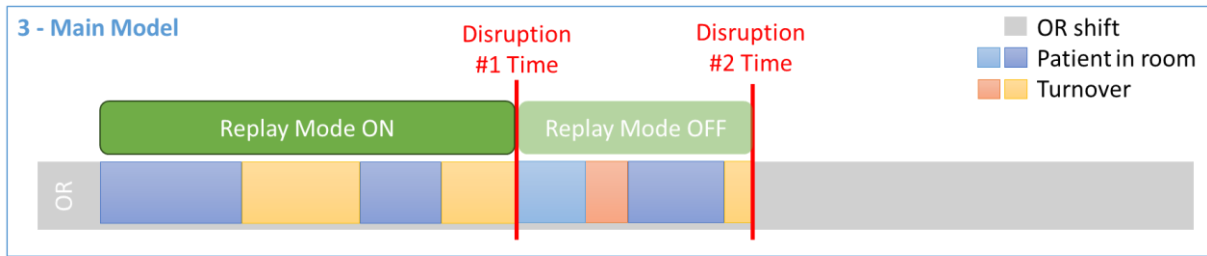


Figure 57 - Illustration of manual non-elective scheduling (3/3). The scheduling scenarios chosen by the user is implemented in the main simulation. The simulation restart from $t=0$ until the next new disruption.

3. Chapter synthesis

In this Chapter, we have presented how we model non-elective arrivals and how we add them to the ongoing schedule. The first fit strategy is what the OR managers usually do when an urgent case arrives (i.e. a case which needs to be operated as soon as possible). Best fit and worst fit strategies are simplified strategies compared to the ones used in (Van Riet and Demeulemeester 2015) (i.e. BF descending, BF ascending, WF ascending, and WF descending). We consider a flexible scheduling where (1) both elective and non-elective cases can be scheduled in each OR, and (2) non-electives can be scheduled at any point of the schedule (Van Riet and Demeulemeester 2015).

PART 3 - PROOF OF CONCEPT

CHAPTER VII. PRESENTATION OF THE STUDY CASE

In Part 1, we have presented the context and the problematic of our research. In Part 2, we have described our solution proposal. In this third and last part, we provide a proof of concept based on a study case.

First, we describe our partners' healthcare facilities. Second, we discuss the database they provided us with and explain how we structured and treated the data. Third, we present the method and the criterion set used to choose a study case. Fourth, we present the study case we use for this research.

1. Presentation of our partners and their facilities

The *Vivalto Santé* French group was created in 2009. It consists in 91 private healthcare facilities distributed between 6 countries (France, Switzerland, Portugal, Spain, Czech Republic, and Slovakia). The group developed a model called the “Third Way”, which is based on a medical and capitalistic partnership.²⁷ Our first partner, the *Hôpital Privé de la Baie* (HPB), situated in Avranches, France is part of this group. HPB welcomes 18500 patients per year and hires 70 doctors and 200 paramedical staff. 78% (8054) of its patients admitted for surgery are outpatients.²⁸

Our second partner, the *Centre Hospitalier d’Albi* (CHA), situated in Albi, France, is part of the “Coeur d’Occitanie” regional hospital group, which regroups 7 healthcare facilities and serves a 330,000 inhabitants’ population. Each year, the CHA realizes 1,400 births, 25,000 inpatient admission, 120,000 consultations and 4,000 surgeries. The staff consists of 2000 professionals and includes 200 doctors. On top of that, the CHA is the headquarters of the emergency medical service of the Tarn department.²⁹

Lastly, our third partner is the *Centre Hospitalier Intercommunal de Créteil* (CHIC), situated in Créteil, France. It is a supporting facility of the “Hôpitaux Confluence” regional hospital group. The CHIC is approved as a university hospital for 9 disciplines. The CHIC’s staff consists in 2587 professionals (405 medical staff and 2182 non-medical staff). Each year, the CHIC realizes 3,000 births and 14,000 surgeries.³⁰

We present key information on these 3 healthcare facilities in numbers in Table 37. It is interesting to note that, these partners allow us to have access to facilities:

- From both the public and private sectors.
- From both regional and university hospitals.
- With different activity volumes.
- With outpatient surgery services.
- With maternity, Intensive care unit and emergency services.
- With different surgical suite sizes.
- With different emergency services patient population.

²⁷ <https://www.vivalto-sante.com/le-groupe/>

²⁸ <https://hopitalprivedelabaie.vivalto-sante.com/>

²⁹ <https://www.gh-tarn-nord.fr/albi-centre-hospitalier>

³⁰ <https://www.chicreteil.fr/>

Table 37 – Brief presentation of the facilities of our partners.

Facility	Hôpital privé de La Baie (HPB)	Centre Hospitalier d'Albi (CHA)	Centre Hospitalier Intercommunal de Créteil (CHIC)
Location	Avranches, Manche (50)	Albi, Tarn (81)	Créteil, Val-de-Marne (94)
Sector	Private	Public	Public
Staff	Total: <i>unknown</i> Medical: 70 doctors Paramedical: 200ppl	Total: 2000 people Medical: 200 doctors Paramedical: <i>unknown</i>	Total: 2587 people Medical: 405 doctors Paramedical: <i>unknown</i>
Accommodations	172 beds including 33 outpatient surgery places and 16 chemotherapy places	616 beds and places, including 12 outpatient surgery places	563 beds
Activity	18,500 patients/year 6,500 emergency visits 3,504 medicine admissions 10,342 surgery admissions 8,054 outpatient surgery admissions 1106 follow-up and rehabilitation care admissions	25, 000 hospitalizations, 120,000 consultations 4,000 surgeries 1 400 births	146,000 hospitalized days 336,000 consultations 104,000 emergency visits 14,000 surgeries 73,000 imaging acts 3,000 births
Emergency Service	Monday to Friday (8:30am-7pm)	24/7	24/7
Maternity Service	No	Yes	Yes
Intensive Care Unit	No	Yes ³¹	Yes
Surgical suites	1 suite with 10 ORs 6 – surgery 2 – ophthalmology 2 – endoscopy	1 suite with 8 ORs: 6 – surgery 1 – endoscopy 1 – C-section	3 suites with several ORs each.

³¹ <https://www.gh-tarn-nord.fr/albi-centre-hospitalier>

2. Proposed method for choosing a study case

The database provided by our partners were descriptions of the performed schedule. HPB and CHIC have an OR software while CHA does not. The databases are organized as follows: each row corresponds to a surgical case and each column corresponds to an information about that surgical case. In Table 38, we briefly present these databases.

Table 38 – Brief presentation of the OR software database provided by our partners.

Facility	HPB	CHA	CHIC
Number of cases	75,253	147	26,213
Extraction dates	January 2016 to December 2021	2021	Nov 2018 to June 2019
Extraction duration	6 years	1 week	8 months

We focus on the HPB database because it is the first we got access to and because that it is a rather rich database. We use the other databases afterwards to understand better what we could expect to extract from another type of database or OR software, and if our data needs could be aligned with regular OR software functionalities.

The initial HPB database contains 75,253 cases that were performed over 6 years. Our objective is to extract data from *one* relevant day for which we can apply our prospective and retrospective methodology using our DT-DSS. In Figure 58, we describe the macro-steps we followed to structure and correct the initial database before extracting a study case. Step #2 is detailed in Figure 59 and in Chapter V. The schedule of potential study cases must respect conditions described in Table 39.

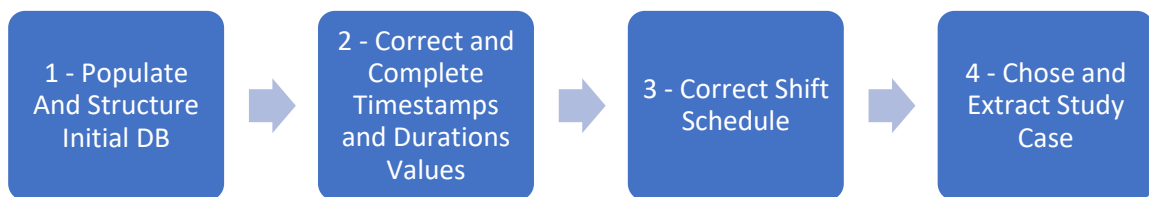


Figure 58 – Database Treatment Steps.

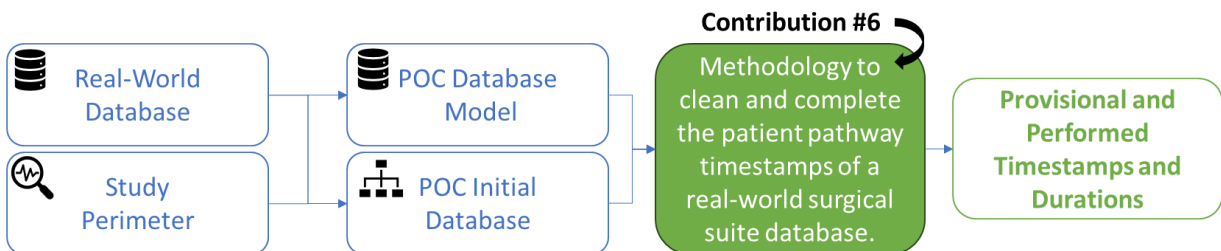


Figure 59 – Steps to Correct and Complete Timestamps and Durations Values from the Database.

Table 39 – Schedule constraints that must be respected in to be able to reach our study objectives

#	Objective	Constraint
1	Simulate the execution of the provisional and the performed schedules for an entire day.	All performed and provisional timestamps must be available, whether initially or after correction (see Chapter V).
2	Test the robustness of the schedule by simulating its execution in an environment where durations are stochastic.	Not relevant.
3	Test the resilience of the schedule by simulating its execution in an environment where there are stochastic arrivals of non-elective cases.	There must be at least one urgent case in the performed schedule.
5	Be representative of a regular operating day.	The day must be a weekday.

3. Description of the study case

3.1. Overview

In Table 40, we provide an overview of the characteristics of the provisional and the performed schedule.

Table 40 – Overview of the Provisional Schedule and the Performed Schedule.

	Provisional Schedule	Performed Schedule	Difference
# Surgeons	9	9	0
# Anesthesiologist	5	5	0
# Open Operating Room	6	6	0
# Bed in the Waiting Area	5	5	0
# Bed for LRA	3	3	0
# Bed for OIP	3	3	0
# Bed in PACU	14	14	0
# Case	51	53	0
# Elective Case	51	51	0
# Semi-urgent Case	0	0	0
# Urgent Case	0	2	+2
# Surgery Type	27	29	+2
# Represented Specialty	6	6	0
# Inpatient	9	10	+1
# Outpatient	42	43	+1
# Cases with LRA	3	4	+1
# Cases with OIP	19	19	0

To display and analyze both schedules, we simulate their execution in a deterministic environment with flexible resource constraints and aggregated processes. This means that the surgical suite process consists only in the patient pathway (1-step preoperative care, 3-step perioperative care, and 2-step post-operative care) without including the OR cleanup, and that the only resources we consider are the nominative ORs.

3.2. Provisional schedule

3.2.1. Provisional master surgery schedule

We display the provisional master surgery schedule (MSS) in Figure 60.

Each row corresponds to one of the nine ORs. The waiting line is a fictional OR that we do not use in the prospective analysis. The color code is the following: OR shift (green), OR off schedule (blue), and OR off schedule but if a case scheduled during this time window would be considered overtime (yellow and red).

The provisional MSS has 6 ORs opened throughout the day; there are 4 morning shifts from 8am to 1pm (OR#1, OR#2, OR#6, and OR#8) and 5 afternoon shifts from 2pm to 6pm (OR#1, OR#5, OR#6, OR#7, and OR#8).

Note that: (1) an OR cannot be preempted before it opens for its first shift, but it can perform overtime during the lunch break and after the provisional end of the last shift, (2) we consider the staff schedule to be the same as the MSS. This is also true for the performed schedule execution.

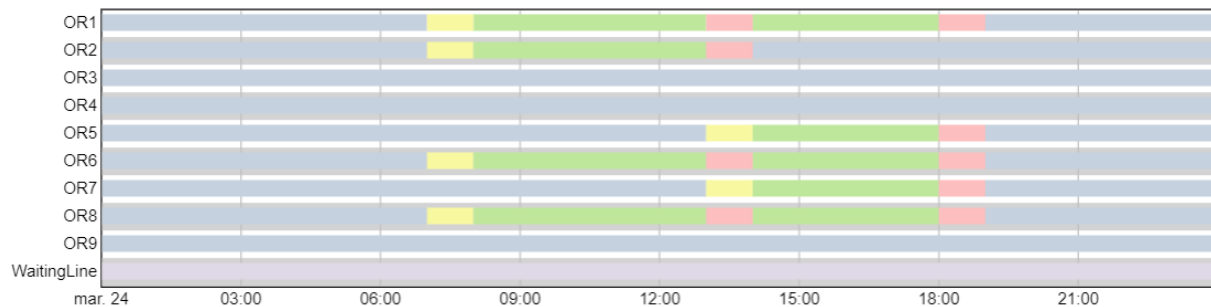


Figure 60 –Provisional Master Surgery Schedule.

3.2.2. Surgery schedule

We display the provisional schedule in Figure 61. The color code is the following: setup with anesthesiologist (yellow), setup without anesthesiologist (blue), surgical procedure (green), reversal (purple), idle time (light gray), and off schedule (dark gray). We keep the same color code for the rest of this Chapter.

We highlight in black the window time during which there is at least one OR in overtime: it happens during the lunch break from 1pm to 2pm (OR#1 and OR#6 and OR#8) and until 7:20pm (OR#4 and OR#5).

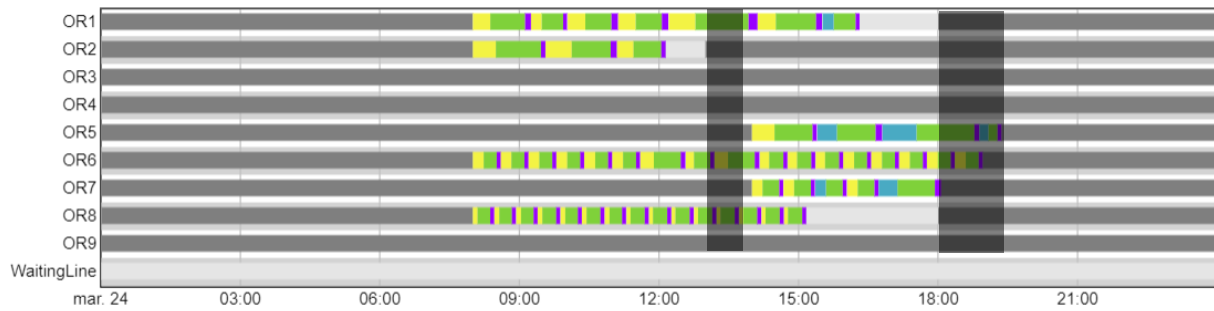


Figure 61 - Simulation of the Provisional Schedule Execution in a Deterministic Environment with Aggregated Processes and Flexible Constraints.

3.2.3. KPI analysis

We display in Table 41 the KPI related to the OR utilization, and in Table 42 the ones related to patient waiting time (PWT).

In Table 41, the column “duration” is in minutes (rounded to the closest value), and the column “rate” is a percentage (rounded to the closest value) which is calculated according to the following formula:

$$KPI_{rate} = KPI_{duration} / \text{Sum of All OR Shifts}$$

The utilization rate is 781%, and the overtime is 145%. This can be explained by the fact that some OR are overutilized (5, 6 and 7) and others are underutilized (1, 2 and 8). We note that none of the KPIs reach their target (except the global overutilization rate, since the suite is underutilized).

Based on this provisional schedule, we can suggest that the activity is not well distributed between the different rooms. If the constraints imposed by specialties allow it (each OR can only welcome a certain range of specialties), it might be interesting during the schedule execution to move cases from overutilized ORs to underutilized ones. Plus, since the suite is underutilized, it could be interesting to schedule more cases (elective add-ons, semi-urgent cases, urgent cases).

Table 41 - KPIs Related to the Operating Room Utilization.

KPI	Duration (minutes)	Rate (%)	Rate Target
Utilization	1874.3	78,1%	~85%
Overtime	353.6	14,7%	≤ 5%
Idle	525.7	21,9%	≤ 5%
Overutilization	0.0	0,0%	≤ 5%
Underutilization	172.6	7,2%	≤ 5%

In Table 42, the KPIs are all in minutes. The KPIs show that there is **no patient waiting time**. This is because the arrival times are computed so that the patients are available for surgery when

the staff and the OR are themselves available for the surgery. Moreover, this simulation considers flexible constraints on resources, so the ORs are the only limiting resources.

Table 42 - KPIs Related to the Patient Waiting Time.

Patient Waiting Time	Minimum	Maximum	Average
Total	0.0°	0.0°	0.0°
Material Resources	0.0°	0.0°	0.0°

3.3. Performed schedule

3.3.1. Master surgery scheduling

We display the performed master surgery schedule (MSS) in Figure 62. Each row corresponds to one of the nine ORs. The color code is the following: OR shift (green), OR off schedule (blue), and OR off schedule but if a case scheduled during this time window would be considered overtime (yellow and red). We keep the same code for all the MSS displayed in this manuscript.

The performed MSS has 6 ORs opened throughout the day; there are 5 morning shifts from 8am to 1pm (OR#1, #2, #6, #7 and #8) and 5 afternoon shifts from 2pm to 6pm (OR#1, #5 #6, #7, and #8). **All these shifts were present in the provisional MSS (Figure 60) except the OR#7 morning shift from 8am to 1pm.**

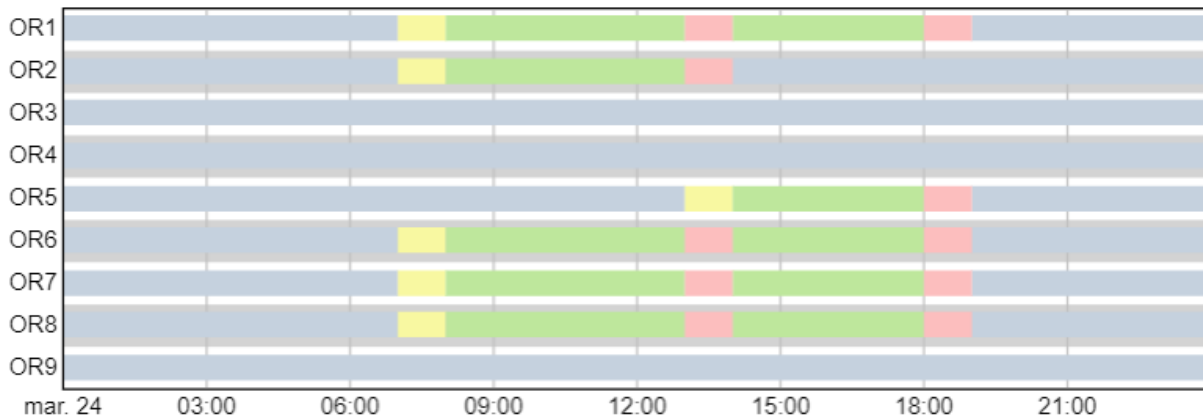


Figure 62 – Retrospective Analysis (step #1): Performed Master Surgery Schedule.

3.3.2. Surgery Schedule

We display the performed schedule in Figure 63; we obtained it by running a single-replication scenario of the performed schedule execution in the DT deterministic environment. The color code is the following: setup with anesthesiologist (yellow), setup without anesthesiologist (blue), surgical procedure (green), reversal (purple), idle time (light gray), and off schedule (dark grey). Note that the patient pathway steps are opaque for the elective cases and see-through for the non-elective ones, and that we used a **red line** to indicate the non-electives for better readability. We keep the same color code for the rest of the Chapter.

We highlighted in black the window time during which there is at least one OR is in overtime: it happens during the lunch break from 1pm to 2pm (OR #1) and until 8:03pm (OR #1, #5, #6 and #7). The only resources considered are the nominative operating rooms (flexible resource constraints).

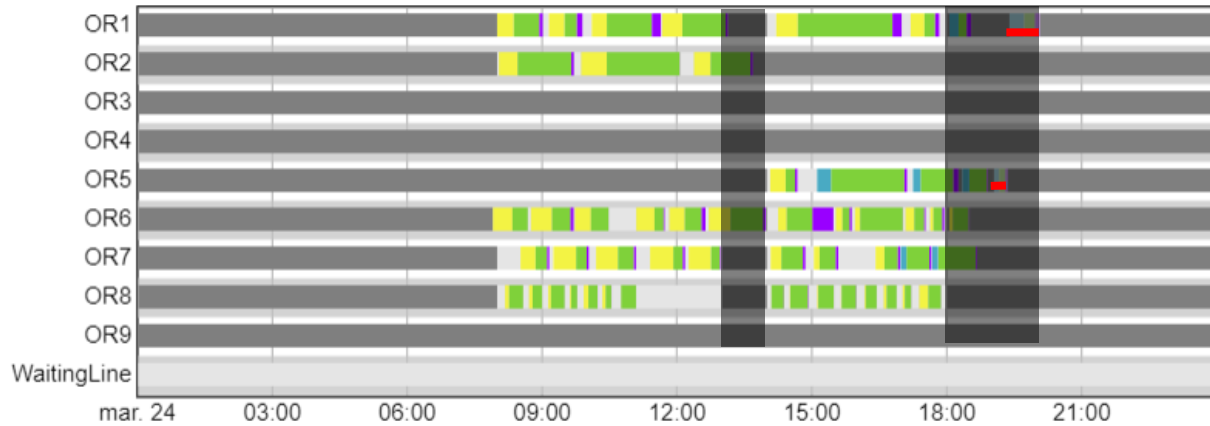


Figure 63 - Retrospective Analysis (step #1): Performed Surgery Schedule.

There are two urgent cases in the performed schedule that were not in the provisional schedule. We describe them in Table 43, show their surgeon and room allowed in Table 44, and display their steps durations in Table 45.

Case#1 arrived at 7:08pm, had a 14-minute preoperative step and entered OR#1 at 7:23pm. Case#2 arrived at 5:15pm, had a 1-hour 45-minute long preoperative step and entered OR#5 at 7:03pm. Both cases entered at the earliest time possible and were the last case in their respective OR.

We do not know why the OR manager decided to schedule the cases in these ORs, but we can try to logically backtrack the reasons behind those choices. We know that (1) the cases can be scheduled in OR#1 to 5, (2) OR#2 has been closed for several hours, (3) OR#3 and #4 were not open at all throughout the day. Consequently OR#1 and OR#5 seem like the best choice. Case #2 was scheduled in OR#5 because it was the last room with the latest end shift. Case #1 was scheduled in OR#1 because it was the last before one room that had been opened and continuing in OR#5 would have meant needing to wait for the cleanup to be over.

Table 43 - Description of the Urgent Cases in the Performed Schedule.

#	Suite Arrival Time	OR Entry Time	#OR	Preoperative Care Location	OR allowed	Rank	Max Rank in the OR
1	19:08:39	19:23:44	1	Waiting Area	1, 2, 3, 4, 5	8	8
2	17:15:27	19:03:06	5	LRA	1, 2, 3, 4, 5	5	5

Table 44 - Study Case Description: OR and Surgeons Allowed for the Urgent Cases

Case ID	OR ID Allowed	Surgeons ID Allowed
1	[1, 2, 3, 4, 5]	[17, 18, 19]
2	[1, 2, 3, 4, 5]	[48, 49, 50]

Table 45 - Description of the Urgent Cases Durations in the Performed Schedule (in minutes).

#	Preoperative Care	Setup	Surgical Procedure	Reversal	Move To PACU	PACU Monitoring
1	14.08	19.6	14.3	5.9	5.8	61.9
2	106.7	6.9	8.4	2.8	0.3	10.8

3.3.3. KPI Analysis

During the performed schedule execution, the utilization, the overtime, the idle time, and underutilization rates did not reach their targets (see Table 46). The utilization and idle time rate values can partly be explained by the fact that the OR cleanup is included in the utilization rate in the prospective analysis, but not in the retrospective analysis. This is because the performed cleanup timestamps are not recorded in the original database.

Table 46 - KPI Related to the Operating Room Utilization.

KPI	Duration (minutes)	Rate (%)	Rate Target
Utilization	2087	77%	~85%
Overtime	259	10%	≤ 5%
Idle	613	23%	≤ 5%
Overutilization	0	0%	≤ 5%
Underutilization	355	13%	≤ 5%

Regarding PWT, the total PWT is null because the arrival time of the patients in the surgical suite in the performed schedule is computed so that the is ready for entering the OR only when the OR is available itself. Note that we do not consider human resources since we are simulating the performed schedule execution (flexible resource constraints).

Table 47 - KPI Related to the Patient Waiting Time.

Patient Waiting Time	Minimum	Maximum	Average
Total	0.0	0.0	0.0
Material Resources	0.0	0.0	0.0

3.4. Comparison of KPIs for both schedules (provisional and performed ones)

In Table 48, we display the utilization related KPIs for both schedules as well as the gap between them. The **utilization** and **idle time** barely change and stay under the performance target. The **overtime** decreases by 5%, which is good. The **underutilization** increases by 6%. The capacity required for performing all the surgeries (utilization + overtime) decreases from 93% to 87%. Since there are no cancelled cases from the provisional schedule (on the contrary there are 2 more urgent cases), this could mean that the stochastic durations are overestimated.

Table 48 - Comparison of KPIs for both schedules.

KPI	Provisional Rate	Performed Rate	Rate Target	Gap
Utilization	78%	77%	~85%	- 1%
Overtime	15%	10%	≤ 5%	-5%
Idle	22%	23%	≤ 5%	+1%
Overutilization	0%	0%	≤ 5%	/
Underutilization	7%	13%	≤ 5%	+6%

4. Chapter synthesis

In this Chapter, we have described how we obtained the data for our study case. In the remaining of this manuscript, we will use this study case to provide a proof of concept for the use of a DT-DSS to apply our prospective and retrospective analysis.

CHAPTER VIII. PROSPECTIVE ANALYSIS AND RETROSPECTIVE ANALYSIS

In Chapter VII, we have first presented the facilities of our three partners: HPB, CHA and CHIC. Then, we have proposed a method to choose a study case from the surgical suite' databases we had access to. Finally, we have applied this method to extract a one-day study case from HPB's database. We described both the provisional and the performed schedules of our study case in terms of master surgery schedule, surgery schedule and KPIs.

This Chapter is structured into four sections, aimed at showcasing the application of both retrospective and prospective analyses on our selected case study. Firstly, we delve into the experimental setup necessary to conduct both analyses, with a detailed exposition of parameter configurations (Section 1). Following this, we present the findings of the prospective analysis (Section 2) alongside those of the retrospective analysis (Section 3). In concluding this manuscript, we offer a synthesis of the chapter, highlighting the interconnection between the analyses and elucidating how they provides insights to take tangible real-world actions (Section 4).

1. Experimentations design

1.1. Table with all the experimentations

Table 49 presents how to configure the DT-DSS to be able to run the prospective analysis (rows 1 to 5), and the retrospective analysis (rows 6 to 10). Each step (rows) is described in Chapter 3, and each parameter are defined in Appendix #4. Our simulations were run on a machine with an Intel(R) Core(TM) i7 – 9750H processor running at 2.6 GHz, with 32 GB of RAM and an integrated graphics card. All simulations are from midnight to midnight ($t = 0, t = 11:59 pm$). A run takes about 1 minute.

1.1.1. A note on the number of possible scenarios and the studied KPI

Number of possible scenarios. In the last column of Table 49, we indicated the number of scenarios to be run for each experimentation; it is either 1 or 60. The 60 scenarios allow to represent the arrival and scheduling of non-elective cases that were either in the initial schedule or not (see Chapter 6). These scenarios are determined by the number of arrivals and the arrival time window:

$$\begin{aligned} \# \text{ possible scenarios} &= (\# \text{ arrival windows}) * (\# \text{ NE arrivals}) * \\ &(\# \text{ scheduling strategies}) = 5 * 4 * 3 = 60 \text{ scenarios} \end{aligned}$$

The options for each of these parameters are the following:

- **Arrival time window (5 options):** midnight - midnight, 7am - 7pm, 7am - noon, noon - 2pm, 2pm - 7pm.
- **Number of NE arrivals (4 options).** The number of arrivals is randomly selected from a set of number of arrivals per day that consists in all days with NE cases, 25% of the days with the least number of arrival (Q1: lower quartile), 25% of the days with the maximum number of arrivals (Q4: upper quartile) and the rest of the days (Q2 and Q3)
- **Scheduling strategies (3 options):** FIFO, BF, WF

KPI studied. Throughout the experimentations, we consider performance indicators related to OR usage (utilization, idle time, overtime, overutilization, and underutilization). We compute both their duration in minutes and their percentages (duration divided by the sum of OR shift length). Note that: (1) the surgical suite utilization is the sum of all the ORs utilization, (2) the surgical suite utilization *rate* is the sum of all ORs utilization divided by the sum of all of the ORs shifts, and (3) a similar computation can be made for each OR utilization related KPI.

For 1-replication scenarios, we display the discrete value of each indicator. For n-replication scenarios, we display the mean rate value (95% confidence interval), the sample standard deviation, the minimum and the maximum values. The OR usage KPIs are described in Chapter I.

We also consider different indicators related to patient waiting time (PWT) in minutes such as total PWT, total PWT for human resources, total PWT for material resources, etc. For both 1-replication and n-replication scenarios, we display the average, minimum and maximum values of each indicator.

1.1.2. Description of the Prospective Analysis

The prospective analysis consists of 5 steps. To begin with, we simulate the provisional schedule execution in a deterministic environment to assess resource synchronization (step #1) and schedule performance (step #2). Then we consider the impact of stochastic durations on the performance to assess schedule robustness (step #3). After, we add additional non-elective arrivals, and we compute the schedule performance for different scheduling strategies (step #4). Finally, we simulate the provisional schedule execution in a stochastic environment that has both stochastic durations and stochastic non-elective arrivals to assess both the robustness and resilience of the provisional schedule at the same time (step #5).

Throughout the prospective analysis, we use detailed surgical processes and apply strict resource constraints. First, we consider a detailed patient pathway, meaning that the preoperative care phase is different depending on which anesthesia the patient requires. Second, regarding human resources, we consider the surgeons, the anesthesiologists, and the OR nurses to be nominative. Third and finally, on top of keeping the nominative operating rooms, we add non-nominative limited preoperative beds (dedicated to the waiting area, the LRA and the OIP), and non-nominative post-operative beds in the PACU. Note that nominative resources are necessarily limiting and can provoke PWT (Chapter 4).

It should be noted that as there are many scenarios simulated at each step, we will not present the results of each of them, but only present the ones that seem the most important to use.

1.1.3. Description of the retrospective Analysis

The retrospective analysis (described in Chapter III) consists in 3 different steps: simulate the performed schedule execution in a determinist environment and compute its performance (step #1), try different scheduling solutions for the urgent cases that arrived during schedule execution (step #2), and identify the performance gap between the performed and the provisional schedules and assess whether they are a consequence of offline or online operational decisions (step #3).

The simulation of the performed schedule is systematically realized in a deterministic environment with an aggregated surgical suite process and flexible constraints on resources (justified in Chapter IV). This means that the patient pathway is modeled based on the existing timestamps of the database (suite arrival, OR entry, incision...), and that the resources modeled consist in nominative ORs. All simulations are from midnight to midnight ($t=0$, $t=11:59\text{pm}$). A run takes about 1 minute.

We have already displayed the results of step #1 in Chapter VII. As for step #3, we refer the reader to other papers we have previously worked on (Rifi, Fontanili, and Jeanney 2020; Rifi, Martinez, et al. 2022; Rifi, Fontanili, and Jeanney 2022). **Consequently, we only present step #2.**

Table 49 - Experimentations performed by the DT-DSS

#	Objective	Initial Schedule	Process Type	Constraints on Resources	Duration Type	Keep NE Cases of Initial Schedule	Add NE Arrivals to Initial Schedule	# Replications	# Possible Scenarios
1	Assess Resource Synchronization	Provisional	Detailed	Strict	Deterministic	No	No	1	1
2	Assess Performance				Deterministic	No	No	1	1
3	Assess Robustness				Stochastic	No	No	30	1
4	Assess Resilience				Deterministic	No	Yes	30	60
5	Simulate Provisional Schedule Execution				Stochastic	No	Yes	30	60
6	Assess Performance	Performed	Aggregated	Flexible	Deterministic	No	No	1	1
7	Assess other Scheduling Strategy	Performed	Aggregated	Flexible	Deterministic	Yes	No	1	1
8	Identify the Root Cause of Performance Gaps	Provisional	Detailed	Strict	Stochastic	No	Yes	30	60
9		Performed	Aggregated	Flexible	Deterministic	No	No	1	1
10		Performed	Aggregated	Flexible	Deterministic	Yes	No	30	60

2. Prospective analysis experimentations

2.1. Steps #1 and #2. Assess resource synchronization and schedule performance

2.1.1. Introduction

In Chapter VII, we have displayed and analyzed the provisional schedule as validated by the staff. Our next goal is to assess the resource synchronization (step #1) and to analyze the schedule performance (step #2).

2.1.2. Simulation of the provisional schedule execution

In Figure 64 we display the results of the provisional schedule execution. The color code remains the same as for Figure 61, except that we add waiting for anesthesiologist (red) and waiting for surgeon (orange). Note that on the figure, we cannot see any orange color as the duration during which patients wait for their surgeon is non-existent in the simulation. However, we can notice several times where the patient is waiting in the OR for the anesthesiologist. This is because one anesthesiologist is responsible for several rooms. We highlighted in black the window time during which there is at least one OR in overtime: it happens during the lunch break from 1pm to 2pm (OR#1, #2, #6) and until 10:20pm (OR #1, #4, #5 and #7).

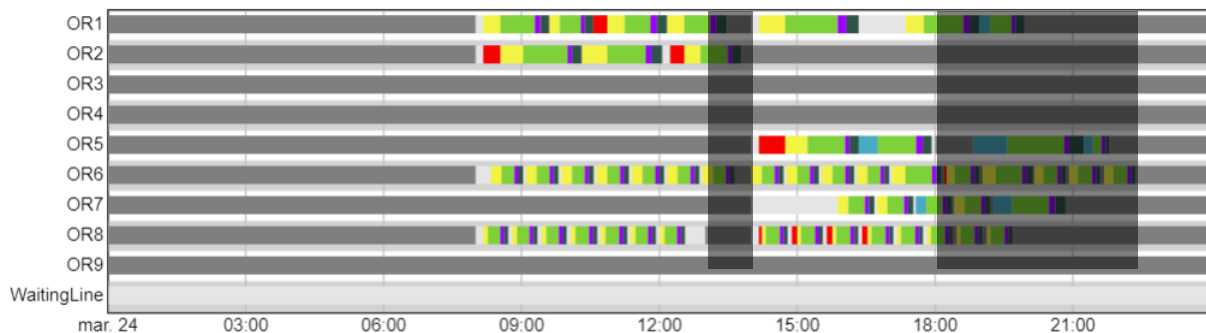


Figure 64 – Prospective Analysis (steps #1 and #2): Simulation of the Provisional Schedule Execution in a deterministic environment with detailed processes and strict constraints on resources.

2.1.3. KPI analysis

2.1.3.1. Assess resource synchronization using patient waiting time

We assess **resource synchronization** thanks to the indicators related to PWT (i.e. patient idle time) that we display in Table 50 – Prospective Analysis (steps #1 and #2): Global patient waiting time., (global PWT), Table 51 (PWT for material resources) and Table 52 (PWT for human resources). All waiting times are in minutes.

Note that in Table 50, the first row corresponds to the PWT for the right rank. This is since each case in the schedule has a specific rank. Thus, if a patient arrives too early at the surgical suite, they will receive preoperative care and then wait for their turn to be received by their OR nurse. In a nutshell: the PWT for the right rank is a PWT for the OR nurse that is due to the patient arriving early; this explains why we put it in the PWT for the human resources dashboard.

We highlight the cells that we discuss in our analysis. On average, each patient waits 74 minutes (minimum 0 minutes, maximum 212 minutes). We note that the PWT is mainly for human resources (minimum 0 minutes, maximum 175 minutes, average 61 minutes). This PWT is divided between the anesthesiologist (min 0 minutes, max 34 minutes, average 3 minutes) and the OR nurse (minimum 0 minutes, maximum 175 minutes, average 74 minutes) (right rank). In other words, patients are scheduled to arrive in the suite about 1-hour 15-minutes too early. Please note that this is not an observation that holds for all patients, since there is also OR idle time – meaning that some patients are scheduled to arrive in the suite too late.

Consequently, resource synchronization improvements could be made by adapting patient arrival times in the surgical suite.

Table 50 – Prospective Analysis (steps #1 and #2): Global patient waiting time.

#	Patient Waiting Time Indicators	Minimum	Maximum	Average
1	All resources	0	212	74
2	Human Resources	0	175	61
3	Material Resources	0	95	13

Table 51 - Prospective Analysis (steps #1 and #2): Patient waiting time for material resources.

#	Patient Waiting Time Indicators	Minimum	Maximum	Average
1	Preoperative Beds	0	95	13
2	Operating Room	0	18	1
3	Postoperative Beds	0	0	0

Table 52 - Prospective Analysis (steps #1 and #2): Patient waiting time for human resources.

#	Patient Waiting Time Indicators	Minimum	Maximum	Average
1	OR Nurse (Right Rank)	0	175	57
s	OR Nurse (Other)	0	0	0
3	Anesthesiologist	0	34	3
4	Surgeon	0	0	0

2.1.3.2. Schedule performance

We assess **schedule performance** thanks to the KPI displayed in Table 53. The utilization, the underutilization and the overutilization rates respect the targets.

Table 53 - Prospective Analysis (Step #1 and #2): KPI Related to the Operating Room Utilization.

KPI	Initial Provisional Schedule		Step #1 & #2		Rate Target
	Duration (minutes)	Rate (duration/ planned open)	Duration (minutes)	Rate (duration/ planned open)	
Utilization	1874.3	78.1	2022.4	84.3	~85%
Overtime	353.2	14.7	369,1	15.4	≤ 5%
Idle	525.7	21.9	377.6	15.7	≤ 5%
Overutilization	0	0	0	0	≤ 5%
Underutilization	172.6	7.2	8.5	0.3	≤ 5%

Now that we have computed the provisional schedule performance in a determinist environment, we are going to assess whether the surgical suite organization is able to maintain this level of performance in a stochastic environment with stochastic durations, non-elective arrivals, or both.

2.2. Step #3. Robustness analysis

2.2.1. Introduction

In the previous steps we have studied the provisional schedule execution in a determinist environment with either aggregated processes and flexible resource constraints (Chapter 7), or detailed processes and strict resource constraints (previous section).

For this third step, we keep the last configuration and add stochastic durations. Our goal is to assess whether the schedule is robust, meaning, whether it stays performant in case of variable durations. We proceed to run 30 replications.

In this section, we present an analysis of the aggregated KPIs for all replications of the scenario and display two examples of surgical schedules.

2.2.2. KPI analysis

We display the summary of the KPI values across all the replications in Table 54. We compare the average values of this scenario (second column) with the values from the previous step (last column):

- The **utilization rate** and the underutilization time both drop by almost 15%.
- The **overtime rate** increases by 2%, and the **idle rate** by almost 15%.
- The **total PWT** decreases by about 5 minutes.

At first glance, we could say that the organization does not maintain its performance when dealing with duration variability. However, the 15% underutilization drop can probably explain the utilization drop, and the idle rate rise of the same value. Indeed, it seems like the duration stochasticity provoked a drop of 15% in the volume of required OR time.

Table 54 - Prospective Analysis (Step #3): Summary of the KPI values across all the replications. The PWT are in minutes and the PWT results from steps #1 and #2 are the average value.

KPI	Rate	STD	Min	Max	Target	Step #1-2
Utilization	70.6 ± 1.1	3	65.5	78.2	~85%	84.3
Overtime	13.5 ± 0.6	1.6	11.5	17.3	≤ 5%	15.4
Idle	29.4 ± 1.1	3	21.8	34.5	≤ 5%	15.7
Overutilization	0.00 ± N/A	0.0	0.0	0.0	≤ 5%	0.0
Underutilization	15.9 ± 1.5	3.9	7.2	21.9	≤ 5%	0.4
Total PWT	68.6 ± 4.2	11.3	51	95.1	≤ 20 minutes	74*
PWT for human resources	55.5 ± 1.9	5.1	46.1	65.3	/	61*
PWT for material resources	13.1 ± 2.6	7.00	3.1	32.5	/	13*

2.2.3. Surgical schedules

In Figure 65, we display the box plot of the utilization rate across the 30 replications we ran. We display two examples of provisional schedule executions in Figure 66 (replication with the highest utilization rate), and in Figure 67 (replication with the lowest utilization rate). It seems like the high utilization comes from: (1) the duration of the first case of OR#5, and (2) the PWT for an anesthesiologist that resulted from it in OR#1.

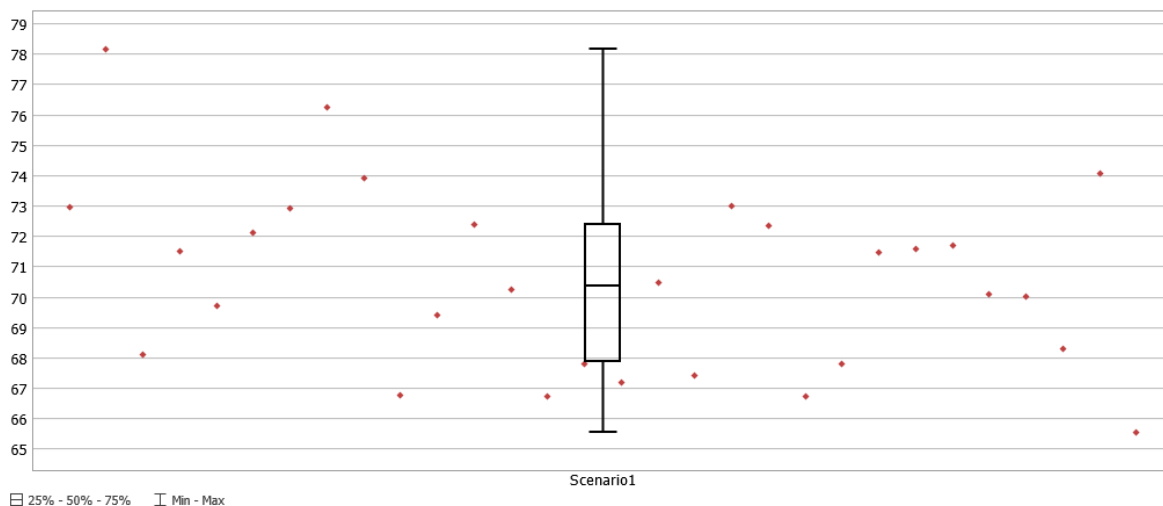


Figure 65 - Prospective Analysis (Step #4): Utilization Box Plot.

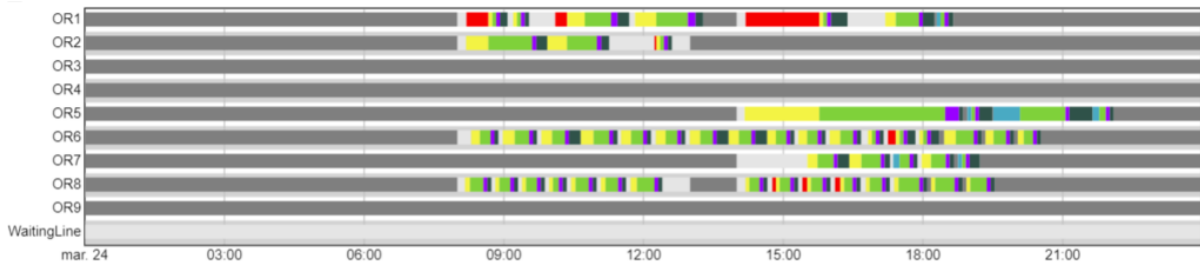


Figure 66 - Prospective Analysis (Step #4): Provisional Schedule Execution with detailed pathway, strict constraints, and stochastic durations, of the replication with the **highest utilization rate**.

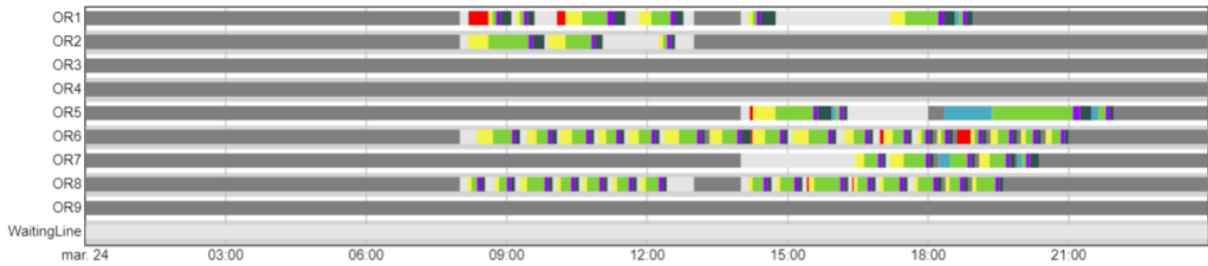


Figure 67 - Provisional Schedule Execution with detailed pathway, strict constraints, and stochastic durations, of the replication with the **lowest utilization rate**.

2.3. Step #4. Resilience analysis

2.3.1. Introduction

In the previous steps we have studied the provisional schedule execution in a determinist environment (Chapter 7 and this Chapter), and in a stochastic environment where durations are variable. We now want to assess the resilience of the provisional schedule. To do so, we simulate its execution with different non-elective arrival scenarios, and different non-elective scheduling strategy scenarios.

For a better readability, we present a single non-elective schedule arrival scenario. The number of arrivals is randomly extracted from a histogram with the number of non-elective arrivals per day, and the time window of arrival is set from midnight to midnight (i.e. the entire day).

2.3.2. All scenario: KPI analysis

Upon simulation the provisional schedule execution degraded upon the introduction of non-elective arrivals. We note that the BF and WF strategies proposed the same solutions. This is because these scheduling strategies shift to “schedule non-elective case at the end of the provisional schedule while minimizing overtime” when there is not enough room at the end of any allowed OR for scheduling the non-elective case which is our case here. Therefore, from now on we only present the FF and the BF solutions. We display them in Table 55. We note that the utilization and the overtime are slightly higher for the FF solution than for the BF one. The patient waiting time confidence interval for FF is larger than that for BF.

In Table 56, we compare the performance of the schedule execution in a determinist environment (step #1-2) with the schedule execution disrupted by non-elective arrivals (step #4). Except for the PWT that increases by about 10 minutes (no matter the scheduling solution), the performance gap between step #1-2 and step #4 is small.

Table 55 –Prospective Analysis (step #4): Resilience FF VS BF

KPI	Scenario #1 - FF				Scenario #2 - BF				Target
	Mean	STD	Min	Max	Mean	STD	Min	Max	
Utilization	84.4 ± 0.8	2.1	77.4	88	83.1 ± 0.5	1.4	78.4	84.3	~85%
Overtime	16.5 ± 0.6	1.5	11.6	20.7	15.7 ± 0.2	0.7	13.7	16.5	≤ 5%
Idle	15.6 ± 0.8	2.1	12	22.6	16.9 ± 0.5	1.4	15.7	21.6	≤ 5%
Overutilization	1.5 ± 0.6	1.6	0	5.5	0.0 ± 0.0	0	0	0.1	≤ 5%
Underutilization	0.6 ± 0.8	2.1	0	11	1.2 ± 0.6	1.7	0	6.5	≤ 5%
Total PWT	86.9 ± 14.2	37.9	64.4	247.5	85.6 ± 4.9	13	65.9	125.9	≤ 20 minutes
PWT for human resources	65.0 ± 4.6	12.4	52.3	107.7	72 ± 3.6	9.7	55.1	92.1	/
PWT for material resources	21.9 ± 10	26.7	9	139.8	13.6 ± 2.6	6.9	9	34	/

Table 56 - Prospective Analysis (step #4). Comparison of the performance of schedule execution in a determinist environment with schedule execution disrupted by non-elective arrivals.

KPI	Step #1-2	Step #4 + FF	Gap	Step #4 + BF	Gap	Target
Utilization	84.3	84.4 ± 0.8	+ 0.1	83.1 ± 0.5	- 1.1	~85%
Overtime	15.4	16.5 ± 0.6	+ 1.2	15.7 ± 0.2	+ 0.3	≤ 5%
Idle	15.7	15.6 ± 0.8	- 0.1	16.9 ± 0.5	+ 1.1	≤ 5%
Overutilization	0	1.5 ± 0.6	+ 1.5	0 ± 0	+ 0.0	≤ 5%
Underutilization	0.4	0.6 ± 0.8	+ 0.3	1.2 ± 0.6	+ 0.8	≤ 5%
Total PWT	74	86.9 ± 14.1	+ 12.9	85.6 ± 4.9	+ 11.6	≤ 20 minutes
PWT for human resources	61	65 ± 4.6	+4.0	72 ± 3.6	+ 11.0	/
PWT for material resources	13	21.9 ± 10	+8.9	13.6 ± 2.6	+ 0.6	/

2.3.3. Example of surgical schedule.

In Figure 68 and Figure 69, we display the surgical schedule for the replication where the FF strategy led to the maximum utilization rate of the scenario (88%). The random disruptions are the same so this allows to compare two scheduling strategies for the same schedule execution.

The color code remains the same as for Figure 61, except that we add PWT for anesthesiologists (red for elective cases, pink for non-elective cases) and PWT for surgeons (orange). In this replication, there are three additional non-elective arrivals.

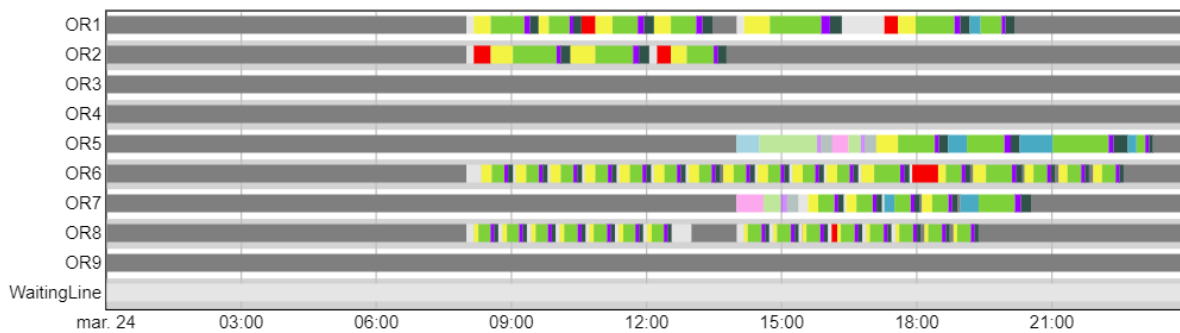


Figure 68 - Prospective Analysis (step #4). Example of a surgical schedule with the FF strategy.

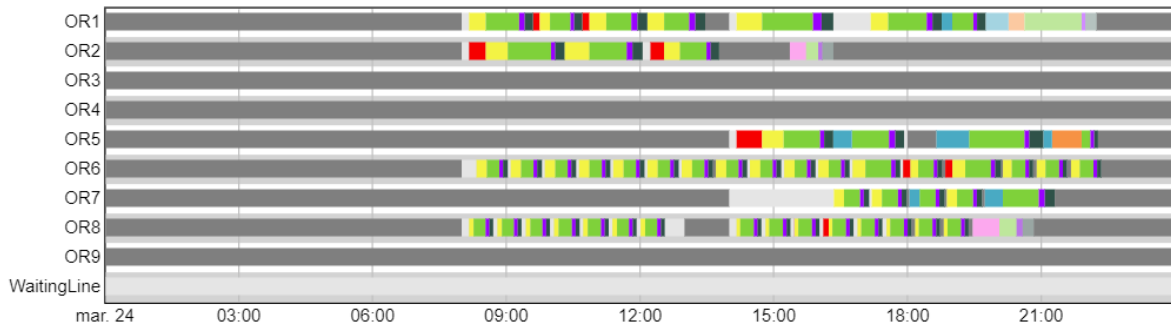


Figure 69 - Prospective Analysis (step #4). Example of a surgical schedule with the WF strategy.

2.4. Step #5. Simulate the provisional schedule execution in a stochastic environment

To conclude our prospective analysis, we simulate the prospective schedule execution in a stochastic environment with both variable durations and non-elective arrivals. For a better readability, we present a single non-elective schedule arrival scenario. The number of arrivals is randomly extracted from a histogram with the number of non-elective arrivals per days, and the time window of arrival is set from midnight to midnight (i.e. the entire day).

2.4.1. KPI analysis

We display the KPI related to the FF scheduling strategy and the BF one in Table 57. Neither the FF scheduling strategy nor the BF scheduling strategy allows to reach the KPI targets. The utilization rate drop probably comes from the way the stochastic durations are computed.

Table 57 –Prospective Analysis (step #5): All

KPI	Scenario #1 - FF				Scenario #2 - BF				Target
	Mean	STD	Min	Max	Mean	STD	Min	Max	
Utilization	73.7 ± 1.6	4.2	66.14	81.8	69.2 ± 1.3	3.5	61.2	78	~85%
Overtime	14.4 ± 0.9	2.3	11.8	19.7	14.2 ± 0.8	2.1	10.9	18.5	≤ 5%
Idle	26.3 ± 1.6	4.2	18.2	33.9	30.8 ± 1.3	3.5	22	38.8	≤ 5%
Overutilization	0 ± 0	0.1	0	0.4	0 ± N/A	0	0	0	≤ 5%
Underutilization	12 ± 2.1	5.6	0	21.5	16.6 ± 1.7	4.6	5.1	25.3	≤ 5%
Total PWT	86.9 ± 14.5	38.7	55.9	255.7	86.6 ± 6.5	17.4	62.5	151	≤ 20 minutes
PWT for human resources	61.9 ± 5.1	13.6	46.6	112.9	69.1 ± 4	10.7	49.1	98.4	/
PWT for material resources	25 ± 9.7	26	9.2	142.8	17.6 ± 3.6	9.8	4.2	52.6	/

2.4.2. Example of surgery schedules

In Figure 70 and Figure 71, we display the surgical schedule for the replication where the FF strategy led to the maximum utilization rate of the scenario (81.8%). The random disruptions are the same, so this allows to compare two scheduling strategies for the same schedule execution. The color code remains the same as for Figure 61, except that we add PWT for anesthesiologist (red for elective cases, pink for non-elective cases) and PWT for surgeon (orange). In this replication, there are three additional non-elective arrivals.

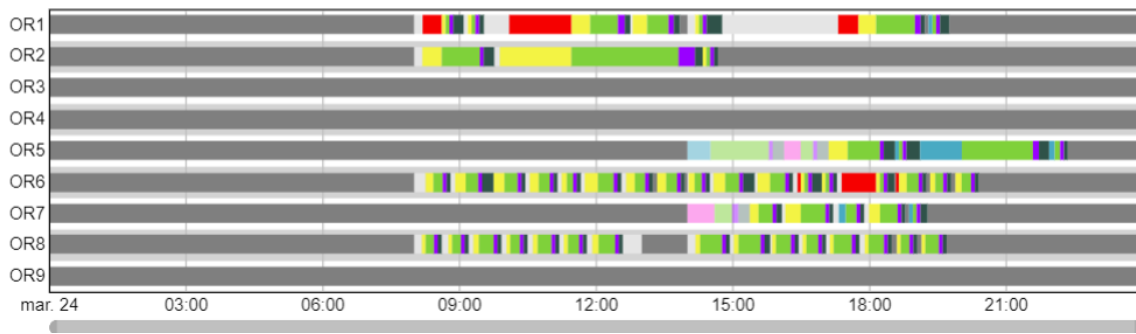


Figure 70 - Prospective Analysis (step #5). Example #1 of a surgical schedule with the FF strategy.

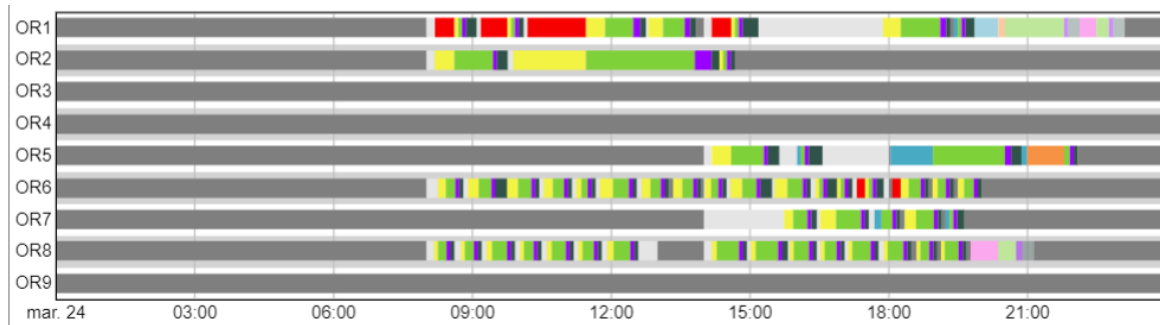


Figure 71 - Prospective Analysis (step #5). Example #1 of a surgical schedule with the WF strategy.

In this second example, we display a replication where both the FF (Figure 72) and the BF (Figure 73) strategy scheduling lead to the same utilization. We notice that the case durations in OR#1 are quite short. The utilization is the same because the non-elective case arrives late during the day and can only be scheduled after the end of the last OR shift.

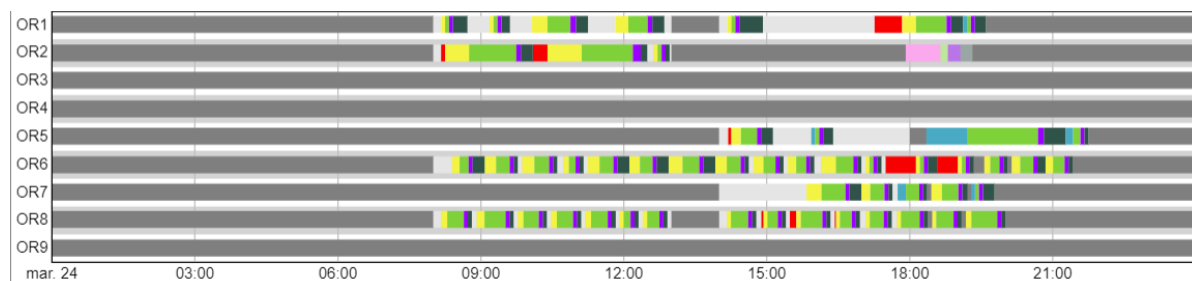


Figure 72 - Prospective Analysis (step #5). Example #2 of a surgical schedule with the FF strategy.

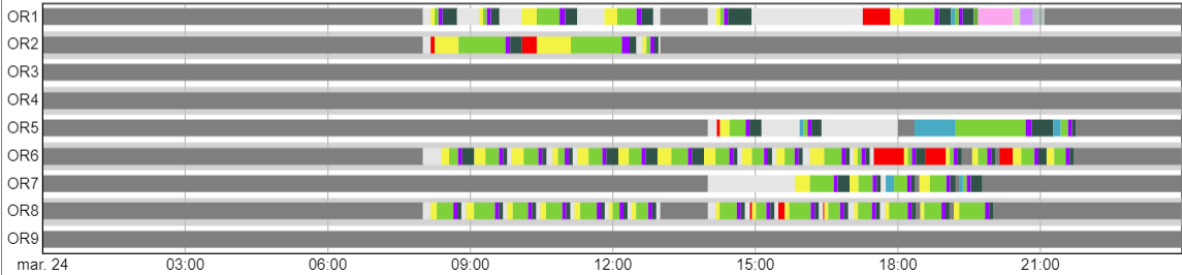


Figure 73 - Prospective Analysis (step #5). Example #2 of a surgical schedule with the WF strategy.

3. Retrospective analysis - step#2. Test other scheduling strategies on the performed schedule non-elective cases

3.1. Display surgical schedule

During the real performed schedule execution, the OR manager dealt with two urgent cases and scheduled them in OR#1 and #2. In this step, we simulate the performed schedule execution as it happened in real-life, but we change the urgent case scheduling solution. We test FF, BF and WF strategies. BF and WF strategies give the same scheduling solution because there are no shift end durations available for any of the urgent cases.

In Table 58, we display the Suite Arrival Time and the OR Entry time for each strategy. In Figure 74 and Figure 75, we display visually the performed schedule with respectively the FF strategy and the WF strategy. We note that the FF strategy leads to scheduling the case in an OR#2 that has been closed for several hours, and that the BF strategy leads to scheduling both cases one after the other.

Table 58 - Retrospective Analysis (step #1 & 2): Comparison of the scheduling strategy

#	Suite Arrival Time	Real NE Scheduling		FF NE scheduling		BF NE scheduling	
		OR Entry Time	OR	OR Entry Time	#OR	OR Entry Time	#OR
1	19:08:39	19:23:44	1	19:23:44	1	19:23:44	1
2	17:15:27	19:03:06	5	19:03:06	2	19:03:06	1

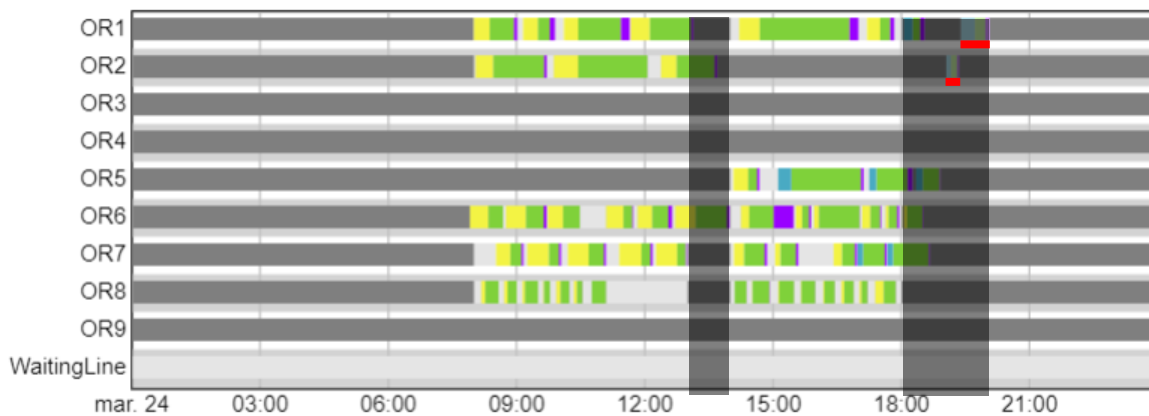


Figure 74 – Retrospective Analysis (step #2): First Fit Scheduling

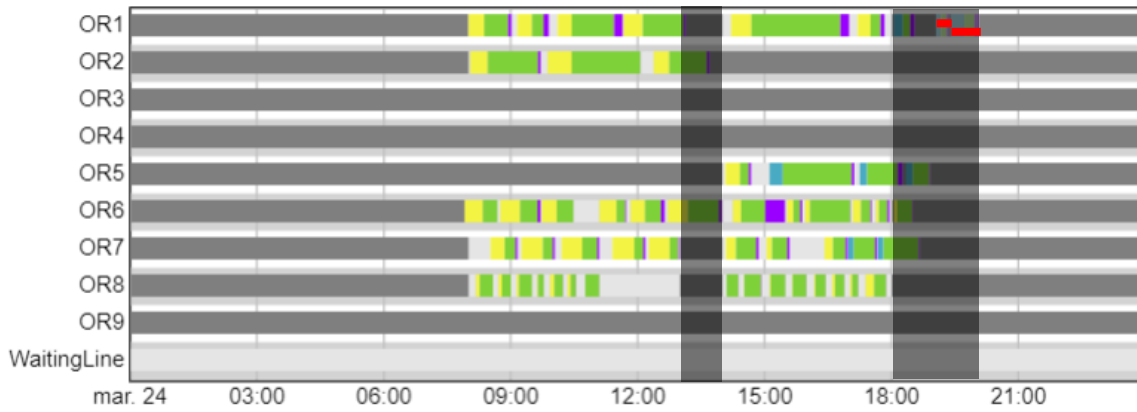


Figure 75 – Retrospective Analysis (step #2): Best Fit Scheduling

3.2. Result analysis

In Table 59, we display side to side the KPI related to OR usage for the execution in a determinist environment for the performed schedule (column 2), the performed schedule with an FF scheduling strategy (column 3), and the performed schedule with a WF scheduling strategy (column 4).

The KPI values related to the OR usage are the same no matter the scheduling strategy (OR manager, FF, WF). This is due to the fact that the urgent cases had arrival times and preoperative durations such that they could only be scheduled in overtime, after the last OR shift end. Consequently, the FF strategy and the WF strategy analysis are the same as the step #1 of the prospective analysis (Chapter V).

Table 59 – Retrospective Analysis (step #2). KPIs Related to the Operating Room Utilization.

KPI	Rate (%) – Performed schedule (step#1)	Rate (%) – Performed schedule + FF (step #2)	Rate (%) – Performed schedule + Bf (step #2)	Rate Target
Utilization	77.3	77.3	77.3	~85%
Overtime	9.6	9.6	9.6	≤ 5%
Idle	22.7	22.7	22.7	≤ 5%
Overutilization	0.0	0.0	0.0	≤ 5%
Underutilization	13.1	13.1	13.1	≤ 5%

4. Chapter synthesis

In this chapter we have presented how we can use the DT-DSS to provide a prospective analysis on the provisional schedule, and a retrospective analysis on the retrospective schedule in order to improve OR management. In this synthesis, we would like to give the reader an idea of how these analyses could be implemented in the daily life of the suite. In Table 60, we take the example of a surgical suite which scheduling meeting is on Thursday.

The second column describes what the user does with the DT-DSS. At every scheduling meeting, we especially suggest running a retrospective analysis on the days that passed since the last meeting (row #1), and to run a prospective analysis on the future week (row #3). The third column describes the information acquired after each step of the analyses. The fourth and last column gives examples of decisions / actions to take based on this information.

Table 60 – How does the DT-DSS can be used during the weekly scheduling meeting in order to facilitate schedule execution?

#	Actions in the DT-DSS	Allows to get the following information (see C3)	And take the following decisions/actions in the real world
1	Run a retrospective analysis of: Thursday and Friday of week(i-1), and Monday, Tuesday and Wednesday of week(i)	Step 1. Compute Performed Schedule Performance	The information related to the suite performance can help when taking decisions related to opening more OR shifts or closing existing ones (punctually or regularly).
		Step 2. Assess the impact of implementing other decisions to tackle the disruptions.	The information related to the impact of different non-elective case scheduling strategies can either serve to encourage or discourage OR managers to implement specific strategies.
		Step 3. Identify performance gap root causes	Performance gap root causes can either be from the tactical and offline operational level, or from the online operational level. Identifying the root causes can help target the efforts of the staff
2	Compare the results of the retrospective and the prospective analyses of week(i-1) and week(i)	Update the prospective analysis parameters.	Update the activity duration modeling and the non-elective patient arrival modeling and add new disruptions modeling.
3	Run a prospective analysis of week(i+1)	Step 1 to 4. Assess feasibility, performance, robustness, and resilience	Provide to the OR manager and the rest of the stakeholders' information on the relevance of the current provisional schedule. They can then modify the schedule (add or remove case, change case sequence, etc.) and run the prospective analysis again.
		Step 5. Assess the best non-elective case scheduling strategy based on the provisional schedule	Provide to the OR manager information as to what NE case scheduling strategy might be the most relevant to use during schedule execution.

CONCLUSION

1. Reminder of the problematic

As we demonstrated in Part 1 of this PhD Thesis, the surgical suite is an inherently complex environment subject to uncertainties. This is due to numerous human and technical resources that are involved and must be synchronized for each operating case (Figure 1 and Figure 6). This complexity implies mastering the surgical cases' planning and scheduling problem. The planning and scheduling problem is divided into 4 decision levels: (1) strategic (capacity planning problem), (2) tactical (master surgery scheduling problem), (3) offline operational (surgery scheduling problem) and (4) online operational (schedule execution management problem). In the State of the Art Chapter (Chapter II), we show that there are few research works for treating the problems occurring at the operational level compared to all the contributions at the 2 top levels. Despite this, observations, and interviews in 5 hospital surgical suites allowed us to highlight that there is not any decision-support tool for helping the surgical suite staff each time a disruption occurs. This is the starting point of this PhD that focuses on the operational level.

At the end of the offline operational level, a provisional schedule is created. This schedule is used by the OR manager as a guide during the online operational level (schedule execution), although it is known from the start of the day that it will not be fully respected. Indeed, part of the complexity of the surgical suite lies in the stochastic nature of its activity. We focus on two types of uncertainties: (1) duration variability and (2) non-elective arrivals. These uncertainties can disrupt the schedule execution; consequently, the operational levels are strongly linked to the disruption management problem.

In Chapter II, we show that the *predictive disruption management* can take place during both offline and online levels; its goal is to anticipate and account for the disruptions before they even occur. On the other hand, the *reactive disruption management* is related to the online level only, during which the OR manager provides a remedy for a disruption only after it has happened. Disruption management aims at maintaining – or even improving – the performance of the provisional schedule throughout its execution. In this work, we assess the surgical suite performance based on three KPIs: (1) the OR utilization, (2) the staff overtime and (3) the average patient waiting time.

This leads us to our general research question: “How can we promote and maintain the performance of a surgical suite’s organization under uncertainties?”. We focus on the disruption management issue at the operational levels.

In the remainder of this conclusion, we discuss our contributions, the limits of our study, and our future research perspectives.

2. Contributions

2.1. Prospective and retrospective methodologies to analyze the operating schedule (contributions #1 and #2)

The disruption management is mostly handled by the OR manager. We make three observations:

1. The day-to-day regulation is dependent on the quality of the surgery scheduling: a non-performant provisional schedule is likely to lead to a non-performant performed schedule.
2. Feedback on schedule execution is only provided in case of a serious undesirable event. Most of the days, disruption management strategies are never revisited.
3. The disruption management strategies are usually empirical and can vary depending on the OR manager personality. To our knowledge, there is no specific training designed for OR managers, which could be a partial explanation for the previously mentioned statement.

Based on these observations; we propose 5 sub-research questions:

- Q1. How can we anticipate disruptions before schedule execution?
- Q2. How can we assess the quality of the predictive disruption management?
- Q3. How can we assess the quality of the reactive disruptions management?
- Q4. How can we identify whether performance lack stems from offline or online decisions?
- Q5. How can we train OR managers on disruption management?

To answer these research questions, we propose three methodologies:

1. A prospective methodology to assess the quality of the predictive disruption management (contribution #1).
2. A retrospective methodology to assess the quality of the reactive management (contribution #2).
3. A methodology to train the OR manager on disruption management in a virtual environment (contribution #3).

2.2. Prospective analysis: assessing schedule robustness using a digital twin (contribution #2)

To assess the robustness of the provisional schedule, we simulated the provisional schedule while considering duration stochasticity.

We faced two main issues: neither the provisional schedule durations nor the standardized surgery types were recorded in the database. This issue was addressed through our contribution #2. We estimated stochastic durations for our specific case study only. We manually assigned a standardized surgery label to each type of surgery performed during our case study. Subsequently, we attempted to categorize the remaining historical data based on these standardized labels.

For each duration type (ex: preoperative care duration, setup duration, etc.), we proposed a computation method based on the number of available datapoints with (1) the same surgery type

and the same surgeon $n_{same\ surgeon}$, or (2) the same surgery type only $n_{all\ surgeons}$. If $n_{same\ surgeon} > 100$, the duration is based on the historical durations of cases with the same surgeon and the same surgery type. Else, if $n_{all\ surgeons} > 100$ the duration was based on the historical durations of cases with the same surgery type only. Otherwise, we employed a uniform distribution spanning from the minimum to the maximum duration of historical duration cases with the same surgery type only. By adhering to this approach, we successfully obtained discrete and stochastic provisional durations to simulate the provisional schedule execution in our digital twin.

2.3. Prospective analysis: assessing schedule resilience using a digital twin (contribution #2)

To assess the robustness of the provisional schedule, we wanted to simulate the provisional schedule while considering non elective arrivals. To do so, we needed to create non-elective arrival scenarios and provide plausible scheduling solutions. **We had already proposed some contribution related to that subject in** (Abdoune et al. 2023; Rifi et al. 2023).

The main issues we faced while trying to create our non-elective arrival scenarios was that our database did not specify (1) the cases' urgency levels, (2) the maximum delay allowed for a case to be scheduled, (3) the surgeons allowed to perform the surgery, (4) the OR in which the case could be performed.

Consequently, we hypothesized that the maximum delay allowed was always respected and specified the case urgency level based on the time difference between the patient admission in the hospital and the patient arrival in the surgical suite. Surgeries performed on their admission day were considered urgent, surgeries performed 4 days or more after their admission day were considered elective, and the rest were considered semi-urgent. We created arrival scenarios based on the number of arrivals per day and the time window during which the arrival happened.

Regarding the surgeons and the OR assignment to non-elective cases, we studied the historical database and proposed rules based on the number of times a surgeon had practice a surgery within a certain specialty, or an OR had welcome a case from a certain specialty.

2.4. Methodology to train the OR manager to disruption management in a virtual environment (contribution #3)

Our contributions #3 is a methodology to train the OR manager on disruption management in a virtual environment. **We previously worked on this topic in** (Rifi, Fontanili, and Jeanney 2020; Rifi, Martinez, et al. 2022; Rifi, Fontanili, and Jeanney 2022; Rifi, Fontanili, et al. 2022)

Although our DT-DSS can be used offline to support both our prospective and retrospective analysis, it can also be used *as if* it was an online tool to support schedule execution. The principle is the following: the OR manager (1) simulates the schedule execution in the DT-DSS and pretends the tool is synchronized with a real surgical suite – meaning that what happens in the tool happens in real life, (2) tests different scheduling strategies – including their own – in case of an urgent case

arrival, (3) implements the strategy of their choice, (4) continues until there are no more urgent cases to schedule, and (5) studies the organization performance based on the choice they have made throughout the simulation.

We developed our DT-DSS so that the training can take place on a performed schedule or a provisional schedule. In the first case (performed schedule), the processes' durations and the urgent cases are identical to what happened in real life; in other words, the virtual environment is determinist. In the second case, the processes' durations and the urgent case arrivals are stochastic; they can be configured and can vary from one training session to another. While training on a performed schedule, the goal is to assess whether or not the schedule execution could have been better. While training on a provisional schedule, the goal is to anticipate before the schedule execution, what could be the best way to deal with disruptions based on that specific provisional schedule. Either way, these training sessions can be used to help OR managers assess the impact of disruptions and their decisions on the surgical suite, as well as promote a common approach to disruption management in a facility.

2.5. Building a digital twin of the surgical suite (contributions #4, #5, #6 and #7)

We proposed and applied a standardized methodology to build a DT-DSS for any specific surgical suite. To do so we used our methodology to conceive and build a digital twin-based decision support system of a surgical suite (contribution #4). In this sub-section, we discuss how we concretely built our DT of a surgical suite.

2.5.1. Modeling and simulation of the schedule execution (contribution #5)

In Chapter IV, we describe how we model and simulate the schedule execution using discrete event simulation in our surgical suite DT. This is quite a complex task as the surgical suite processes gather multiple human resources and material resources that must be synchronized for a smooth schedule execution. Since the OR database does not have all the data required to model such a heavy process, we combined our on-site observations, staff interviews and the OR database. We propose different approaches for the provisional and the performed schedule due to the fact that their simulations have different goals.

2.5.1.1. Modeling and simulation of the performed schedule execution

When simulating the performed schedule execution, the objective is to have a simulated schedule execution that is as close to the performed schedule execution as possible (i.e. the performed and the real patient room entry time are identical), *then* to exhaustively model the activity (i.e. model the different steps of the preoperative patient pathway). The objective of this simulation is to replay the execution of a past schedule and to be able to have feedback on the decisions that have been taken after each disruption. Then, we would like to analyze if another decision should have been taken, to keep the target performance.

Consequently, we model the performed surgical suite processes based on the timestamps available in the database. We obtain an "aggregated" surgical suite process with a one-step preoperative phase, a 3-step perioperative phase, a 2-step post-operative phase, and no OR cleanup. Regarding resources, we only model nominative ORs (we call this "flexible" constraints on resources).

The reasons are the following:

1. **Material resources:** there are no information regarding material resources different than the OR in the database.
2. **Human resources:** the only IDs recorded are those of the surgeons and the anesthesiologists.
3. **Human resources:** the anesthesiologist ID is not always recorded, even in case of an induction in the OR.
4. **Human resources.** The times during which the human resources are present in the OR are not recorded – even the anesthesiologist and the surgeon. When simulating their presence according to best practices (from room entry to room exit), or according to our observations (room entry to incision for the anesthesiologist, room entry to the suture for the surgeon), the simulated patient pathway does not match the reality anymore.

2.5.1.2. Modeling and simulation of the provisional schedule execution

On the other hand, the provisional schedule is naturally based on estimations and hypotheses. For instance, timestamps and durations are estimated as they are not known in advance and the resource synchronization is assessed in an empirical manner. While executing the provisional schedule, we want to get a good idea of all the disruptions that could happen.

Consequently, for the provisional schedule execution, we used both timestamps available in the database *and* timestamps estimated based on our observations and staff interviews (see Chapter VIII). This allows us to propose a richer patient pathway with three preoperative care options (no induction, LRA and OIP), and to add an OR cleanup step at the end of every reversal. By opposition to the previous term “aggregated”, we call this process “detailed”. Concerning human resources, we model nominative surgeons (from incision to suture), anesthesiologists (from room entry to induction) and OR nurses (from at least room entry to PACU entry). This can cause patient waiting times during schedule execution. As for material resources, we keep nominative ORs and add beds for preoperative care and post-operative care. Since the number of beds has probably evolved throughout the 6-year database we work with, we cannot know exactly how many beds were available. We decide to choose a number that does not provoke irrational patient waiting times during provisional schedule execution. By opposition to the previous term “flexible”, we call this resource constraint type “strict”.

Our contribution here lies in the fact that we use different approach for the provisional and the performed schedule execution, and that the provisional schedule execution relies on a very detailed surgical suite process and that we consider resources throughout the entire surgical suite patient pathway – which as far as we know is quite rare.

2.5.2. Methodology to clean and complete the patient pathway timestamps of a real-world surgical suite database (contribution #6)

To build a surgical suite digital twin, we must have access to a reliable OR software database. This raises several issues. First, recording timestamps of each surgical case in the operating room software (suite arrival, OR entry, incision start, suture start, OR exit, PACU entry, PACU exit) is usually done manually by the suite staff. Not only is it not the priority as they are more preoccupied by providing care to the patient, but they also have little to no interest in the data once the surgery

day is over. Second, the OR software is catered for the hospital staff. Consequently, information that are interesting to us, but that are not required by the staff might not even be available in the database. Third, some surgical suites still record part of all their data on paper, which make the use of their data impossible. This is notably the case of induction related timestamps and anesthesia details.

Multiple issues are encountered when dealing with our data: canceled cases do not appear in the database, the urgency level is never specified, performed timestamps can be either incorrect or missing, and the only information available for the provisional database are the patient provisional room entry time, their provisional room, and their provisional rank in the room.

Based the data available in the database, and the study perimeter, we propose a standardized methodology to clean and structure an OR database. This global methodology includes our contribution #6: “Methodology to clean and complete the patient pathway timestamps of a real-world surgical suite database”. This methodology includes defining rules to: (1) identify performed incorrect timestamps, (2) compute missing performed timestamps based on existing ones, and (3) compute discrete and stochastic provisional durations based on historical performed durations. We discuss this methodology and its results in detail in Chapter V.

2.5.3. Prototype of a digital twin-based decision support system applied to a real-world case study (contribution #7)

After applying our standardized methodology to build the digital twin of a surgical suite, we obtained our own DT-DSS curated to the HPB surgical suite. We used it in Part 3 to provide a proof of concept for the potential use of our prospective and retrospective analysis, and it consists in itself as the POC of contribution #5.

3. Limits and possible improvements

In this section we draw a parallel between our study's limits and the possible improvements that we could implement in future research. We discuss our need for a richer and more reliable database, our surgical suite DT, the functionalities of the decision support system, and the choice of our study case.

3.1. Data

The input data we used to feed our digital twin included the description of the provisional and the performed operating and resource schedules. We did not have access to the full provisional data, so we had to make modelling hypothesis. Consequently, we can never know what the real initial provisional schedule was. Plus, there are probably methods that provide better results to estimate discrete and stochastic provisional durations for the surgical suite activities than the ones we obtained.

3.2. Surgical suite DT

We discuss potential improvements in our digital twin in terms of resources, uncertainties, and perimeter.

Resources. In Table 61, we display a synthesis of how each surgical suite human resource is modeled in our DT for the provisional schedule execution. The columns indicate: whether or not the resource appears in the model (column 2), whether or not the resource is limited and can thus provoke patient waiting times (column 3), whether or not the resource is nominative (column 4), and whether or not the simulated resource is on the same schedule as in real-life (column 5). We do the same for material resources in Table 62. These two tables clearly highlight both the limits and the improvement possibilities for the modeling and simulation of resources in our surgical suite DT. Note that for the performed schedule, even more work is needed as we only model nominative ORs.

Table 61 - Human resources modeled in our DT during the provisional schedule execution.

Staff Profession	Modeled?	Limited?	Nominative?	Real Schedule?
Surgeon	X	X	X	
Anesthesiologist	X	X	X	
OR Nurse	X	X		
Anesthesiologist Nurse				
PACU Nurse	X			
Radiologist Operators				
Nurse Assistants	X			

Table 62 - Human resources modeled in our DT during the provisional schedule execution.

Type of Material Resources	Modeled?	Limited?	Nominative?	Real Schedule?
Operating Rooms	X	X	X	X
Preoperative Beds	X	X		
Post-Operative Beds	X	X		
Surgical Supplies (disposable)				
Surgical Instruments (reusable)				
Imaging and Visualization Equipment				
Surgical Support Equipment				

We complete these two tables with a word on the anesthetist nurse which was not modeled in our study. Although it is not a common practice, anesthetist nurses are legally allowed to perform the induction in the OR instead of the anesthesiologist. In our study we have considered only nominative anesthesiologists, which created patient waiting times (PWT) when the anesthesiologist was working in two parallel ORs. However, in real life, it is possible that there were no PWT if the anesthetist nurse performed the induction themselves. Modeling the dynamics between the anesthesiologist and the anesthetist nurse could be interesting but would require having access to their presence time in the OR, which is data hard to come by.

Uncertainty. Another limit of our model is that we only focus on two types of uncertainties: non-elective arrivals and duration variability. It would be interesting to include uncertainties on patient cancellation, patient no-show, patient suite arrival time, human resource unavailability (ex: sick leave), and material resource unavailability (ex: equipment breakdown).

Perimeter. Our DT focus on the surgical suite process from the patient suite entry to the patient suite exit. However, the surgical suite activity is strongly impacted by the activity of external services – and vice-versa. It would be interesting to extend the surgical suite DT to the other services that interact with the surgical suite. This includes the inpatient wards, the outpatient wards, the ICU, and the stretcher-bearer services.

3.3. Decision support system

Our DSS has an interesting margin of improvement in terms of KPI range and in terms of disruption management strategy options. Although in this study we mostly focused on OR utilization, staff overtime and patient waiting time, more indicators could be computed.

Prospective analysis indicators. First, we could include more indicators catered to assessing the quality of the predictive disruption management. We could develop a set of indicators dedicated to assessing a provisional schedule's robustness and resilience instead of using the performance gap only, and it could also be interesting to study the stability of the operating schedule (i.e. its ability to remain despite disruptions) during the prospective analysis.

Resource utilization indicators. Today, we only focus on the OR utilization. However, it would be interesting to add indicators related to the staff utilization or to the PACU and preoperative beds' utilization.

Reactive disruption management strategy. Our current DSS allows three strategies for scheduling non-elective cases. However, as we have seen in Chapter II, the scope of schedule disruptions and online decisions to tackle them is broader than that. We discussed adding more uncertainties (and thus disruptions) in the previous section. As for the decisions, it would be interesting to:

- Add more options for non-elective case scheduling:
 - model block, open and mixed strategy.
 - Arbitrate between scheduling a case in overtime or postponing it.
- Add decisions such as online rescheduling resources (human or material) to deal with the evolution of the demand throughout the day (case cancelling, new case arrivals, shift early end, etc.).

Predictive disruption management strategy. Today, we only assess the quality of the predictive disruption management by evaluating the robustness and the resilience of the provisional schedule. This means that if the provisional schedule performance is low, it will most likely impact the performed schedule performance. Consequently, a future improvement could be to give the user insight as to how to improve an already built provisional schedule.

User Point of View. One of the weaknesses of our study is that, although we performed many on-site observations and staff interviews, as well as discussed at length the goals of our research with an expert committee, we did not have the opportunity to let a OR manager test our DT-DSS.

3.4. Study cases

In our current study case, urgent cases arrive at the end of the day: their earliest possible room entry time is after the last OR shift end. This strongly reduces the diversity of potential scheduling solutions proposed by our tool.

It would be interesting to have a panel of different one-day schedules to have a more exhaustive view of what insights our DT-DSS can provide depending on the situation.

1-day study case VS 1-week study case. In our study we use a one-day study case. However, real-life OR managers dealing with scheduling and rescheduling decisions consider more than a one-day horizon. For instance, an elective case can be postponed to the next day, or to the next week. Same could be said for semi-urgent cases. A strong improvement would be to consider several day study cases (for instance, a 1-week study case) and to develop decisions such as scheduling or rescheduling a case on a one-week horizon.

Throughout our research, we had to address the issue of the lack of data in the database (partial recording of the provisional schedule, no recordings of the staff presence in the OR, etc.). It would open more modeling and simulation opportunities if we had access to a richer database. This would allow us to describe more accurately the activity within the surgical suite:

- Material resources: nominative
- Human resources: nominative staff with specific processes.

4. Future research perspectives

Throughout this research project, we have developed a surgical suite digital twin based on discrete event simulation, and we have used it as an offline decision support system to improve predictive and reactive disruption management. In this section, we discuss future research perspectives.

4.1. An online DT-DSS

We propose to transform our offline DT-DSS into an online DT-DSS. This would allow us to cover both the offline *and* the online sides of the operational decision-level. The objective would then be to apply the OR manager training methodology to online management. This would allow us to have: (1) a DT for monitoring (DTM), (2) a DT for predicting (DTP), and (3) a DT for optimizing (DTO). This future work perspective is closely related to the work done by (Abdallah Karakra 2021). We describe these below.

The requirements to develop an online tool include sensors to update the locations of patients, staff, and material resources in real-time. Although several methods exist (geolocation, RFID chips...), their implementation is technically complex and could be slowed down – and even prevented – by staff reluctant to be monitored. The offline analysis is similar to the one we could perform online. Thus we have decided to first develop a functional offline tool, before transforming it into an online tool in a future project.

First, we propose to create a **DT for monitoring the surgical suite activity (DTM)**. To do so, we would develop an **online connection between our current DT and the surgical suite**. This would allow to simulate the schedule execution in the DT at the same time as it is happening in real life; at any time the DT would be a virtual replication of the real-life surgical suite.

Second, we suggest developing a **DT for predicting the surgical suite activity (DTP)**. To do so, we propose to use the DTM and to couple it with the decision-support system present in our current tool. By applying our third methodology (methodology to train an OR manager), we would provide the OR manager with an online tool that could help them to anticipate future disruptions (predictive disruption management), or to assess the impact of disruptions that have already occurred and to test the impact of different solutions to deal with them (reactive disruption management).

Third, we submit the idea of capitalizing on both the DTM and the DTP to create a **DT to optimize the disruption management (DTO)**. This would require modeling and simulating more types of disruptions and more types of disruption management solutions. Instead of just displaying possible disruption management solutions like in the DTP, the tool would suggest the best solution for a specific set of KPIs.

4.2. A surgical suite DT generator

One perspective could be to work on how to automatically generate a surgical suite DT. This is a part that took a long time in our research. This would require to: (1) Propose an ideal surgical suite DT database, and (2) Identify which parameters would be necessary.

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APPENDICES

1. Appendix #1 – description of the study case

Table 63 - Case Study Description: Pathway and Resources.

Case ID	Admission	Surgey	Urgency Level	Preoperative Care Type	OR Induction	Surgeon ID	Anesthesiologist ID
1	OUT	0	Elective	WA	1	60	12
2	IN	1	Elective	WA	1	60	12
3	IN	2	Elective	WA	1	60	12
4	IN	3	Elective	WA	1	60	12
5	OUT	4	Elective	WA	1	40	4
6	IN	5	Elective	WA	1	40	4
7	OUT	6	Elective	WA	0	40	4
8	IN	7	Urgent	WA	0	18	4
9	OUT	8	Elective	WA	1	18	12
10	IN	9	Elective	WA	1	18	12
11	IN	10	Elective	WA	1	18	12
12	OUT	11	Elective	WA	1	48	4
13	IN	12	Elective	LRA	0	48	4
14	OUT	13	Elective	LRA	0	48	4
15	OUT	14	Elective	LRA	0	48	4
16	OUT	15	Urgent	LRA	0	48	4
17	OUT	16	Elective	OIP	1	34	5
18	OUT	16	Elective	OIP	1	34	5
19	OUT	16	Elective	OIP	1	34	5
20	OUT	16	Elective	OIP	1	34	5
21	OUT	16	Elective	OIP	1	34	5
22	OUT	16	Elective	OIP	1	34	5
23	OUT	17	Elective	OIP	1	32	4
24	OUT	18	Elective	OIP	1	32	4
25	OUT	19	Elective	OIP	1	32	4
26	OUT	20	Elective	WA	1	32	4
27	OUT	20	Elective	OIP	1	32	4
28	OUT	20	Elective	OIP	1	32	4
29	OUT	16	Elective	OIP	1	34	5
30	OUT	16	Elective	OIP	1	34	5
31	OUT	16	Elective	OIP	1	34	5
32	OUT	16	Elective	OIP	1	34	5
33	OUT	16	Elective	OIP	1	34	5
34	OUT	21	Elective	OIP	1	37	42
35	OUT	22	Elective	OIP	1	37	42
36	OUT	22	Elective	WA	0	37	42
37	OUT	23	Elective	OIP	1	37	42
38	OUT	24	Elective	WA	0	37	42
39	OUT	25	Elective	WA	1	23	3
40	OUT	26	Elective	WA	1	23	3
41	OUT	25	Elective	WA	1	23	3

42	OUT	27	Elective	WA	1	23	3
43	IN	26	Elective	WA	1	23	3
44	OUT	27	Elective	WA	1	23	3
45	IN	25	Elective	WA	1	23	3
46	OUT	28	Elective	WA	1	22	5
47	OUT	28	Elective	WA	1	22	5
48	OUT	29	Elective	WA	1	22	5
49	OUT	28	Elective	WA	1	22	5
50	OUT	28	Elective	WA	1	22	5
51	OUT	29	Elective	WA	1	22	5
52	OUT	28	Elective	WA	1	22	5
53	OUT	28	Elective	WA	1	22	5

Table 64 - Case Study Description: Provisional and Performed Arrival Time, OR ID, Case Rank and Maximum Rank.

Case ID	Performed Suite Arrival Time	Provisional Suite Arrival Time	Performed OR ID	Provisional OR ID	Performed Case Rank	Performed Maximum Rank	Provisional Case Rank	Provisional Maximum Rank
1	7:49 AM	7:59 AM	1	1	1	8	1	7
2	8:43 AM	8:59 AM	1	1	2	8	2	7
3	9:42 AM	9:53 AM	1	1	3	8	3	7
4	10:58 AM	11:38 AM	1	1	4	8	4	7
5	1:25 PM	1:59 PM	1	1	5	8	5	7
6	3:59 PM	4:59 PM	1	1	6	8	6	7
7	5:53 PM	5:57 PM	1	1	7	8	7	7
8	7:08 PM	7:29 PM	1	0	8	8	2	2
9	7:48 AM	7:59 AM	2	2	1	3	1	3
10	9:29 AM	9:41 AM	2	2	2	3	2	3
11	11:32 AM	12:03 PM	2	2	3	3	3	3
12	1:30 PM	1:59 PM	5	5	1	5	1	4
13	1:54 PM	2:40 PM	5	5	2	5	2	4
14	4:28 PM	5:06 PM	5	5	3	5	3	4
15	4:28 PM	6:14 PM	5	5	4	5	4	4
16	5:15 PM	5:29 PM	5	0	5	5	1	2
17	7:37 AM	7:59 AM	6	6	1	12	1	17
18	8:14 AM	8:39 AM	6	6	2	12	3	17
19	8:58 AM	9:19 AM	6	6	3	12	5	17
20	9:58 AM	11:05 AM	6	6	4	12	7	17
21	10:36 AM	11:45 AM	6	6	5	12	9	17
22	11:41 AM	12:25 PM	6	6	6	12	11	17
23	2:06 PM	1:59 PM	6	6	7	12	12	17
24	2:08 PM	3:28 PM	6	6	8	12	13	17
25	3:48 PM	3:56 PM	6	6	9	12	14	17
26	4:09 PM	5:00 PM	6	6	10	12	15	17

27	5:15 PM	5:30 PM	6	6	11	12	16	17
28	5:41 PM	5:56 PM	6	6	12	12	17	17
29	7:41 AM	8:19 AM	7	6	1	10	2	17
30	8:33 AM	8:59 AM	7	6	2	10	4	17
31	9:26 AM	9:39 AM	7	6	3	10	6	17
32	10:08 AM	11:25 AM	7	6	4	10	8	17
33	11:27 AM	12:05 PM	7	6	5	10	10	17
34	1:30 PM	1:59 PM	7	7	6	10	1	5
35	2:08 PM	2:51 PM	7	7	7	10	2	5
36	3:37 PM	3:34 PM	7	7	8	10	3	5
37	3:37 PM	4:20 PM	7	7	9	10	4	5
38	4:24 PM	4:57 PM	7	7	10	10	5	5
39	7:43 AM	7:59 AM	8	8	1	15	1	15
40	8:21 AM	8:34 AM	8	8	2	15	2	15
41	8:54 AM	8:59 AM	8	8	3	15	3	15
42	9:07 AM	9:29 AM	8	8	4	15	4	15
43	9:43 AM	10:15 AM	8	8	5	15	6	15
44	9:55 AM	10:13 AM	8	8	6	15	5	15
45	10:12 AM	10:31 AM	8	8	7	15	7	15
46	1:32 PM	1:59 PM	8	8	8	15	8	15
47	2:04 PM	2:22 PM	8	8	9	15	9	15
48	2:55 PM	2:54 PM	8	8	10	15	10	15
49	3:37 PM	3:28 PM	8	8	11	15	11	15
50	3:37 PM	3:58 PM	8	8	12	15	12	15
51	4:24 PM	4:25 PM	8	8	13	15	13	15
52	4:44 PM	4:52 PM	8	8	14	15	14	15
53	5:05 PM	5:11 PM	8	8	15	15	15	15

2. Appendix #2 – visual illustration of our surgical suite digital twin

2.1. Introduction

This appendix clarifies both part II and part III of our manuscript. Part II describes how we have built our surgical suite digital twin (SS-DT), and part III discusses how we have used this digital twin as a proof of concept for our prospective and retrospective analysis of the operating schedule execution. **In this annex, we provide videos and screenshots of our digital twin decision support system.** We hope this will help the reader to better visualize what our tool looks like and how it can be used.

The first video is a slow recording of a schedule execution in our SS-DT 3D view. It displays the different virtual rooms, patients and resources modeled in the SS-DT; one can see the patients moving around the surgical suite, the human resources caring for them, and the material resources being used. The link for the video is the following: <https://www.youtube.com/watch?v=qBLwxW6RZKY>.

The second video displays a fast recording of a schedule execution in our SS-DT 3D view and the real-time computation of a part of the dashboard. This video highlights how the KPI are computed while the simulation is running. This could be especially useful for an online implementation of the SS-DT. This link for the video is the following: <https://www.youtube.com/watch?v=GzTiVgyYNV8>.

Finally, we describe the **screenshot of an example of a dashboard** that can be found in the simulation model.

2.2. Illustration of The Schedule Execution in our Surgical Suite Digital Twin

2.2.1. Brief description of the 3D Model

For this research, we have worked with a specific surgical suite (Hôpital Privé de La Baie for the French group Vivalto Santé). Thus, we have based our digital twin on the real layout of their service.

In Figure 76, we display the real-world surgical layout we have used to create our digital twin, and in Figure 77, we display the 3D view of our model. In our model, we have only represented the parts of the real-world surgical suite related to our study (the operating rooms, the patient waiting area, etc.).

For an easier visualization, each operating room (OR) has a specific color, and patients' shirts match their assigned OR. Each staff has a specific shirt color too: green for surgeons, grey for anesthesiologists, clear blue for the OR nurses, purple for the anesthesiologist nurses, yellow for the PACU nurses and the OIP nurses, dark blue for the nurse assistants, and white for the stretcher-bearers. This is particularly helpful when we perform visual verification to ensure that the patient pathway is properly executed.

Note that visual changes can be done to make the model more user-friendly. This includes adding walls, masking the staff that is not involved in the schedule execution, changing the appearance of the patients depending on how long they have waited or on their urgency level, etc.

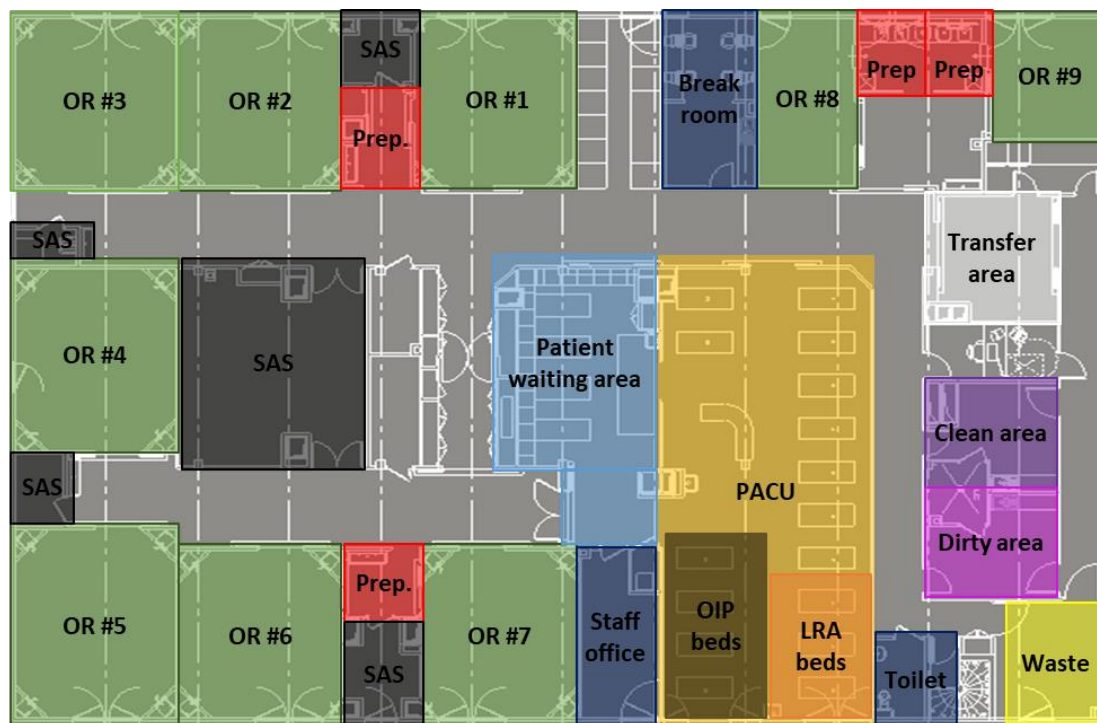


Figure 76 – Surgical suite layout we used to create our digital twin. This figure was presented in Chapter I of our manuscript.

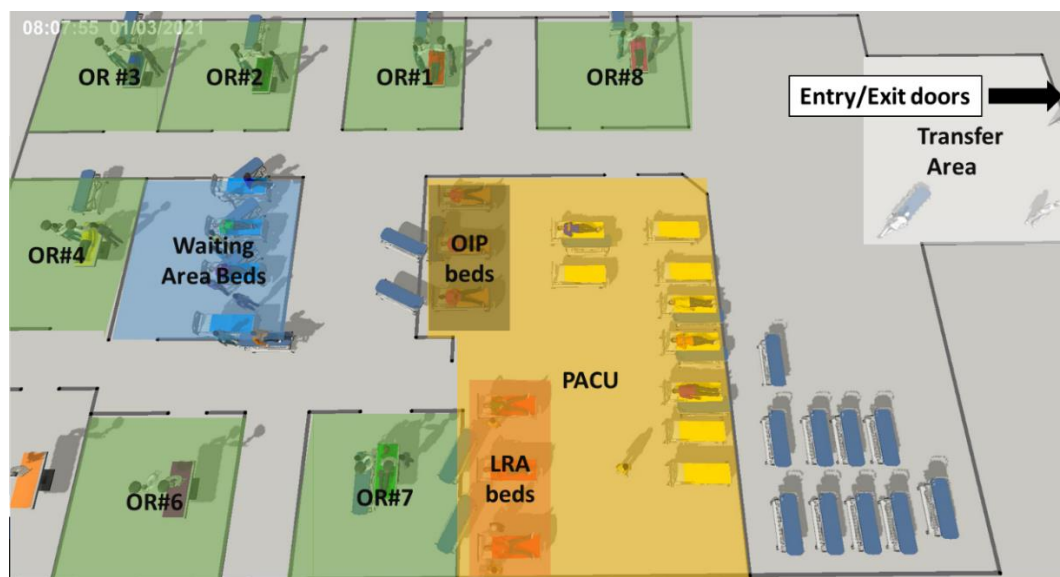


Figure 77 – 3D view of our surgical suite digital twin.

2.2.2. First video: illustration of the patient pathway during schedule execution.

In this video, we display the 3D view of our surgical suite digital twin during the execution of an operating schedule. We display an overview of the suite (00:00 and 00:46), the suite entrance/exit (00:12), the patient waiting area (00:22), the operating rooms (00:30), and the PACU (00:38).

In the videos, the processes are slightly different than the ones presented in the manuscript as we also consider the anesthesiologist nurse, the stretcher-bearers, and the stretchers. However the three phases remain the same: preoperative, perioperative, and post-operative. We discuss the construction of the surgical suite processes we have modeled in our SS-DT in Chapter IV.

2.2.3. Second video: KPI computation during schedule execution.

In this video, we display parts of the dashboard side to side with the 3D view to highlight how the indicators and the schedules are updated as the schedule execution goes. Figure 78 is a screenshot taken from that video. The top table (#1) computes the KPI related to OR usage and the Gantt diagram below describe the performed schedule of each OR (#2), and the provisional master surgery schedule (#3).

We discuss the KPIs from table #1 in Chapter I. Other examples of the surgical schedule (#2) and of the master surgery schedule (#3) are displayed in Chapters VII and VIII.



Figure 78 – Screenshot from the second video.

2.3. Another dashboard example

In Figure 79, we display an example of dashboard that can be built in our surgical suite digital twin. We do not focus on the values displayed; this is to illustrate what kind of information a user can have access while running a schedule execution in our SS-DT.

We differentiate between three types of elements: parameters (green), tables (blue), and graphs (orange). We briefly describe each of them below.

2.3.1. Parameters (green)

We use parameters to configure the environment in which the schedule is executed. All these parameters are available in the experimenter; we use them to create the different experimentations needed to apply our prospective and retrospective analysis.

Parameters in table #1 configure the number of beds available for the waiting area, the PACU, the loco-regional anesthesia, and the ophthalmologic sedation. In our study case, we set their value so that they would not create unreasonable patient waiting times.

Parameters in table #2 are used in Chapter VIII to configure the DT environment to perform the experimentations required to apply our prospective and retrospective analysis – which are describe in Chapter III. They can also be used to configure the DT environment in case of OR manager training.

We used the following color code:

- **Black:** Training environment modalities (methodology in Chapter III and theoretical application in Chapter VI).
- **Blue:** Uncertainties on duration variability (Chapter V).
- **Orange:** Choice of either provisional or performed schedule.
- **Green:** Resource constraints and process modeling (Chapter IV).
- **Yellow:** Non-elective cases arrival and scheduling strategies (Chapter VI).

2.3.2. Tables (blue)

Table #1 gives some overall information about the current schedule being executed.

Table #2 describes KPI related to OR usage. Each row corresponds to a KPI (either a rate or a value in minute), and each column corresponds to a OR, the entire surgical suite, or the waiting line. We did not discuss the use of the waiting line in the manuscript: it can be used to visualize the KPIs related to the cases that have arrived during schedule execution and which were not scheduled in any OR.

Table #3 displays KPI related to the patient pathway and the patient waiting time (PWT). Each row corresponds to a KPI (total PWT, PWT for all or specific human resources, PWT for all or specific material resources, duration of each patient step). The KPI are all displayed in minutes. The columns indicate the minimum, maximum, and average values of these KPI across all the patient pathway executed, as well as the sum of the values for all the patients of the day.

We discuss the choice and definition of most KPIs from table #2 and table #3 in Chapter I, and we use them for analyzing our study cases in Chapters VII and VIII.

2.3.3. Graphs (orange)

The graphs in #1 display (from left to right) information related to the OR throughput, the patient stay time in the OR, and the patient waiting time for each OR.

Graph #2 describes the patient pathway steps for each patient; each row corresponds to a patient.

Graph #3 does the same for the OR; each row corresponds to an OR.

Graph #4 is the master surgery schedule: it describes the planned shifts for each OR; each row corresponds to an OR.

We use graphs #3 and #4 in the Part III of our manuscript (Chapters VII and VIII) for the study case analysis.

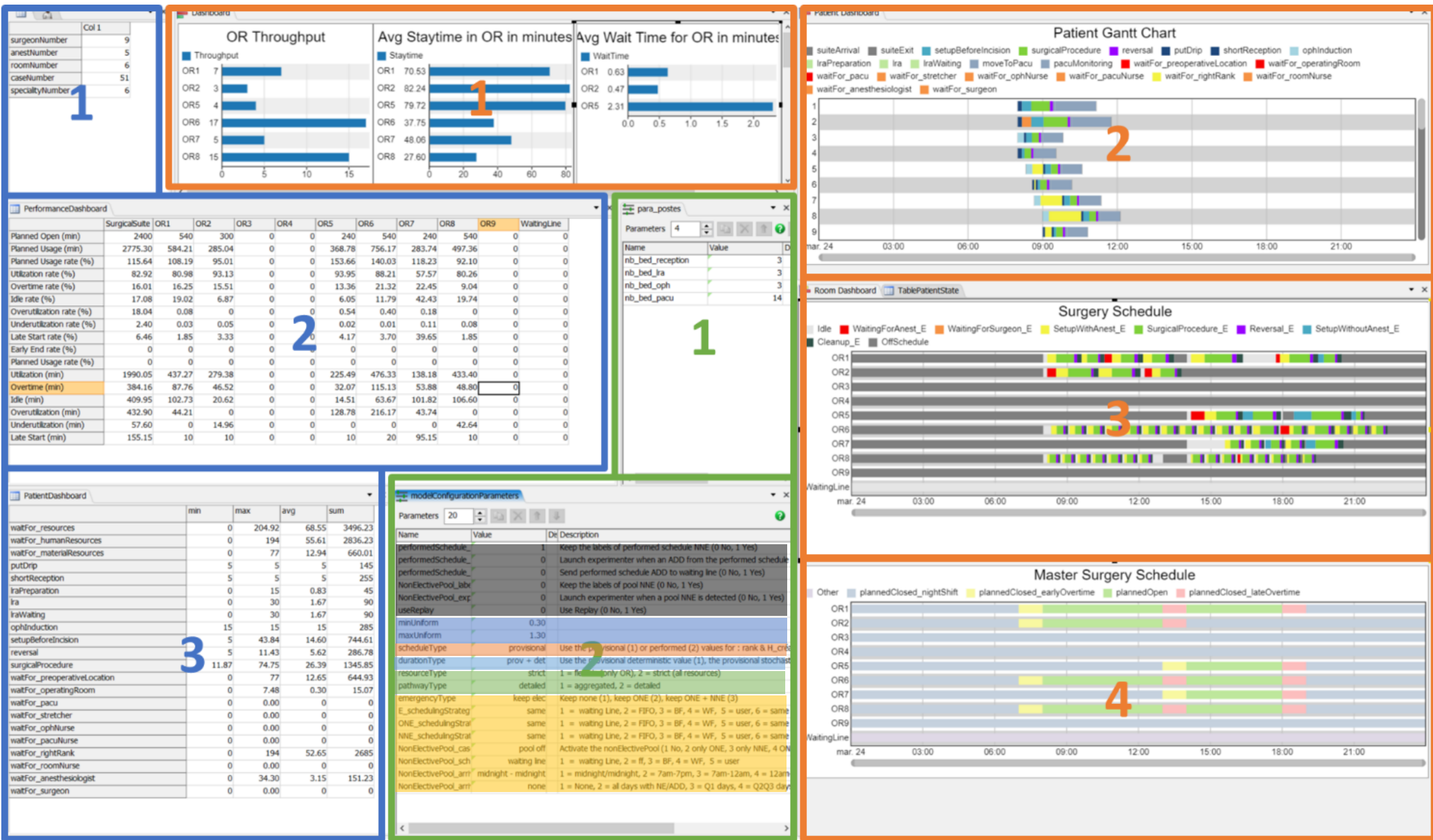


Figure 79 - Dashboard example that can be made in our surgical suite digital twin.

3. Appendix #3 – description of publications

In this document, we a list of our publications and their respective abstract.

3.1. List of publications

3.1.1. Journal

Rifi, Leah, Franck Fontanili, Maria Di Mascolo, and Cléa Martinez. 2022. “Framework for a Retrospective Analysis of Operating Room Schedule Execution.” *International Journal of Healthcare Technology and Management* 19 (1): 37. <https://doi.org/10.1504/IJHTM.2022.123579>.

3.1.2. Conferences with proceedings

Rifi, Leah, Franck Fontanili, Cléa Martinez, Maria Di Mascolo, and Virginie Fortineau. 2023. “A Simulation-Based Approach for Assessing the Impact of Uncertainty on Patient Waiting Time in the Operating Room.” In *Proceedings of the Winter Simulation Conference*, 1057–68. WSC '22. Singapore, Singapore: IEEE Press.

Rifi, Leah, Clea Martinez, Maria Di Mascolo, and Franck Fontanili. 2022. “Proposition d’un outil d’aide à la décision pour la régulation des blocs opératoires.” In *GISEH 2022 - 11e Conférence Francophone en Gestion et Ingénierie des Systèmes Hospitaliers, Saint-Etienne, France*. <https://imt-mines-albi.hal.science/hal-03763576>.

Rifi, Leah, Franck Fontanili, and Michel Jeanney. 2020. “Proposition d’une Démarche Outillée d’analyse Rétrospective Du Déroulement Du Programme Au Bloc Opératoire : Application à La Régulation.” In *GISEH 2020 - 10ème Conférence Francophone En Gestion et Ingénierie Des Systèmes Hospitaliers*. Valenciennes, France. <https://hal.science/hal-03229530>.

3.1.3. Book Chapter

Abdoune, Farah, Leah Rifi, Franck Fontanili, and Olivier Cardin. 2023. “Handling Uncertainties with and Within Digital Twins.” In *Service Oriented, Holonic and Multi-Agent Manufacturing Systems for Industry of the Future*, edited by Theodor Borangiu, Damien Trentesaux, and Paulo Leitão, 118–29. Studies in Computational Intelligence. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-24291-5_10. This was first presented in the 2022 SOHOMA workshop.

Rifi, Leah, Franck Fontanili, and Michel Jeanney. 2022. “A Tool-Based Approach to Analyze Operating Room Schedule Execution: Application to Online Management.” In *Healthcare Systems*, 179–93. John Wiley & Sons, Ltd. <https://doi.org/10.1002/9781119902614.ch12>.

Rifi, Leah, Franck Fontanili, and Michel Jeanney. 2022. “Démarche outillée d'analyse du déroulement du programme au bloc opératoire : application à la régulation.” In *Systèmes de Soins et de Santé : défis d'aujourd'hui et opportunités de demain*, pp191-204. ISTE Group, ISBN 9781784068677. <https://www.istegroup.com/fr/produit/systemes-de-soins-et-de-sante/>

3.2. Summary

3.2.1. Journal

2022 - Framework for a Retrospective Analysis of Operating Room Schedule Execution.

The execution of an operating room schedule is constantly disrupted, which can decrease the initially targeted performance. Online operational management (OnOM), which oversees daily activity, can reduce the deviations caused by disruptions between the initial schedule and the performed schedule. To support this process and encourage continuous improvement, we suggest a framework for analysing schedule execution in retrospect. The objectives are twofold: 1) to identify deviations and determine their root causes; and 2) to assess the relevance of the decisions made to reduce these deviations. This approach relies on a logbook to gather qualitative data on disruptions, and a dashboard to objectify the situation with computed indicators. We present an example of a schedule execution analysis in an anonymised French General Hospital.

3.2.2. Conferences with proceedings

2022 - A simulation-based approach for assessing the impact of uncertainty on patient waiting time in the operating room.

Demand for surgical care is rising worldwide, making the organization of the operating room (OR) a topic of strong interest. During the last two decades, the number of papers on methods for OR planning and scheduling under uncertainty has increased significantly. However, most hospitals neglect this aspect, and use deterministic approaches to schedule their surgical interventions. This leads us to the following research question: "How can discrete-event simulation help assess the impact of uncertainty on patient waiting time in the OR?" To answer this question, we suggest a 3-step methodology: (1) building the deterministic model of the studied OR, (2) implementing uncertainties on activity durations, patient arrival times and patient care requirements, and (3) experimenting with different uncertainty-related scenarios and analyzing the results. We have applied this methodology to a use-case inspired from our partner's OR: Hôpital Privé de La Baie, from the Vivalto Santé French health group.

2022 - Proposition d'un outil d'aide à la décision pour la régulation des blocs opératoires.

La performance d'un hôpital est fortement liée à la performance de son bloc opératoire. La communauté scientifique s'intéresse particulièrement à la construction du programme opératoire (PO). L'étape d'exécution du programme est cependant moins étudiée. Durant cette étape, la qualité du PO peut être dégradée par des perturbations aléatoires (ex : arrivée d'urgences). Notre question de recherche est la suivante : « Comment gérer les perturbations aléatoires durant le déroulement du programme opératoire afin de maintenir le niveau de performance visé ? ». Pour y répondre, nous proposons de construire un jumeau numérique asynchrone du bloc opératoire et de l'utiliser comme outil d'aide à la décision pour la régulation. Cet outil permettra d'étudier a posteriori les dysfonctionnements d'une journée opératoire, de tester l'impact de modifications du

PO en cours d'exécution sur la performance du BO, et d'étudier la robustesse d'un PO prévisionnel. Nous proposons une démarche générique pour construire un modèle de simulation permettant de simuler l'exécution d'un programme opératoire prévisionnel ou réalisé dans un environnement déterministe ou stochastique. Nous avons appliqué cette démarche dans le bloc opératoire de l'Hôpital Privé de La Baie (Avranches, Normandie) du groupe Vivalto Santé.

2020 - Proposition d'une démarche outillée d'analyse rétrospective du déroulement du programme au bloc opératoire : application à la régulation.

Au bloc opératoire, la réalisation du programme prévisionnel est ponctuée de perturbations aléatoires qui peuvent dégrader notablement la performance initialement visée. La régulation a pour mission de piloter l'activité du bloc au quotidien et de réduire les écarts de performance entre le prévisionnel et le réalisé. Pour y parvenir, nous proposons une démarche outillée d'amélioration continue basée sur une analyse rétrospective du déroulement du programme opératoire. Cette démarche a pour but (1) de mettre en évidence les écarts entre le prévisionnel et le réalisé et de déterminer leur(s) cause(s) racine(s) et (2) d'évaluer la pertinence des décisions prises par la régulation pour corriger les écarts. Elle se base sur deux outils : un journal de bord qui permet le recueil de données qualitatives sur la gestion des anomalies et un tableau de bord dont les indicateurs permettent d'objectiver la situation. La méthodologie de conception de cette démarche s'appuie d'abord sur une observation approfondie du terrain. Ensuite, un cycle itératif en trois phases : concevoir, construire et tester permet de construire progressivement la démarche et ses deux outils. Un exemple de l'analyse du déroulement du programme opératoire dans une salle interventionnelle du CH de Narbonne illustrera l'applicabilité de cette démarche outillée.

3.2.3. Book Chapter

2022 - Handling uncertainties with and within digital twins.

The Digital Twin (DT) is often used in environments characterized by uncertainty and complexity, where operating conditions are prone to variability based on external and internal factors. Thus, the literature about DT emphasizes the importance, limitations, and absence of uncertainty quantification. However, there is no explicit review discussing uncertainty in complex systems and within the digital twin model. Such an explicit review could improve the conception, construction, and utilization of DT in environments that are both dynamic and stochastic. Thus, this article aims to (1) describe how a DT can help manage uncertainties in a dynamic system, and (2) explain how DT should deal with uncertainties inside the model.

2022 - Démarche outillée d'analyse du déroulement du programme au bloc opératoire : application à la régulation.

Dans ce chapitre, les auteurs se concentrent sur la régulation, une fonction généralement assumée par un.e infirmier.ère confirmé.e ou un médecin expérimenté. Les auteurs présentent l'analyse du croisement des informations entre les déviations attribuables, ou potentiellement attribuables, à la

gestion en ligne et les informations sur les perturbations décrites dans le journal de bord. Ils détaillent la méthodologie qui leur permet, par itérations successives, de générer leur démarche outillée. Les auteurs détaillent également les outils sur lesquels cette démarche s'appuie. Enfin, ils illustrent son applicabilité à travers un exemple concret de gestion en ligne au Centre Hospitalier de Narbonne.

2022 - A Tool-based Approach to Analyze Operating Room Schedule Execution: Application to Online Management.

In this chapter, the authors define operating room (OR) as the surgical room where staff perform surgery on patients, and operating suite as the surgical department that houses all the ORs. They focus on online management, a function generally performed by an experienced paramedic or medical officer. The authors present the analysis of the intersection of information between deviations attributable, or potentially attributable, to online management and information on disruptions described in the Logbook. They detail the methodology which allows them, through successive iterations, to generate their tool-based approach. The authors also detail the tools upon which it is based. Finally, they illustrate its applicability through a concrete example of online management at the Centre Hospitalier de Narbonne.

4. Appendix #4 – description of the dt-dss

4.1. Introduction

In this appendix, we provide a comprehensive overview of the DT-DSS, including its input, output, parameters, and tools. Subsection 1 is dedicated to the description of the parameters, while subsection 2 is for the surgical suite processes.

Figure 80 offers a bird's-eye view of the DT-DSS. The **input** data is a relational database made of three tables; it describes the master surgery schedule as well as each case attributes and durations. The **output** is a dashboard that consists in performance KPIs (i.e. OR overtime and OR utilization), patient waiting time indicators (i.e. for resources for or material) and of a Gantt Chart Diagram of the state of each OR (idle time, waiting for resources, setup, procedure, etc.). The **parameters** are the following: the initial schedule type, the process type, the constraints on resources, the duration type, whether to keep or not the NE cases of the initial schedule, whether to add or not NE arrivals to the Initial schedule, and the number of replications. The DT-DSS is built using a **modeling and simulation tool**: Flexsim Healthcare ®. It allows to model material resources, human resources, and surgical suite processes, and to simulate schedule execution.

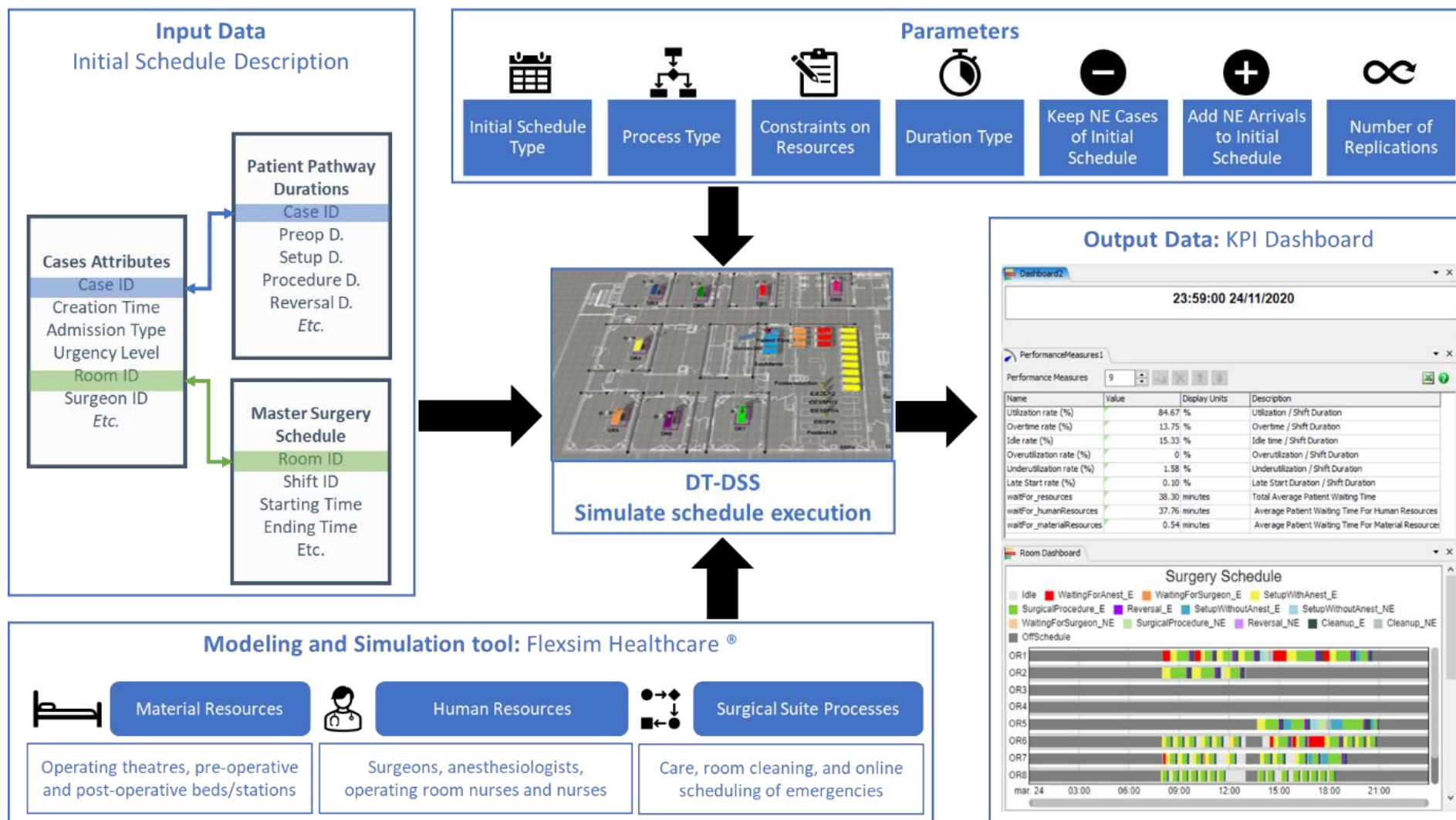


Figure 80 – Bird-Eye View of the DT-DSS with input, output, parameters and tool description.

4.2. Parameters

In Chapter VIII, we describe the 7 different parameters we use to configurate the DT-DSS: the initial schedule type, the process type, the constraints on resources, the duration type, whether to keep or not the NE cases of the initial schedule, whether to add or not NE arrivals to the Initial schedule, and the number of replications. Below, we propose a justification as to why the replication number can be set to either 1 or 30.

Due to the stochastic nature of the simulated environment, it is of great importance to run a certain number of replications in order to acquire a confidence interval with respect to the obtained results. The number of replications was estimated using the graphical method of Figure 81, in which a value of ~ 30 replications would result in a confidence interval deviation of the cumulative mean average of $\%_{overtime}$ of less than 7.5%. The focus on the $\%_{overtime}$ was due to the fact of it being the most sensitive KPI to parameter uncertainty (see Chapter 2 on uncertainty duration modelling).

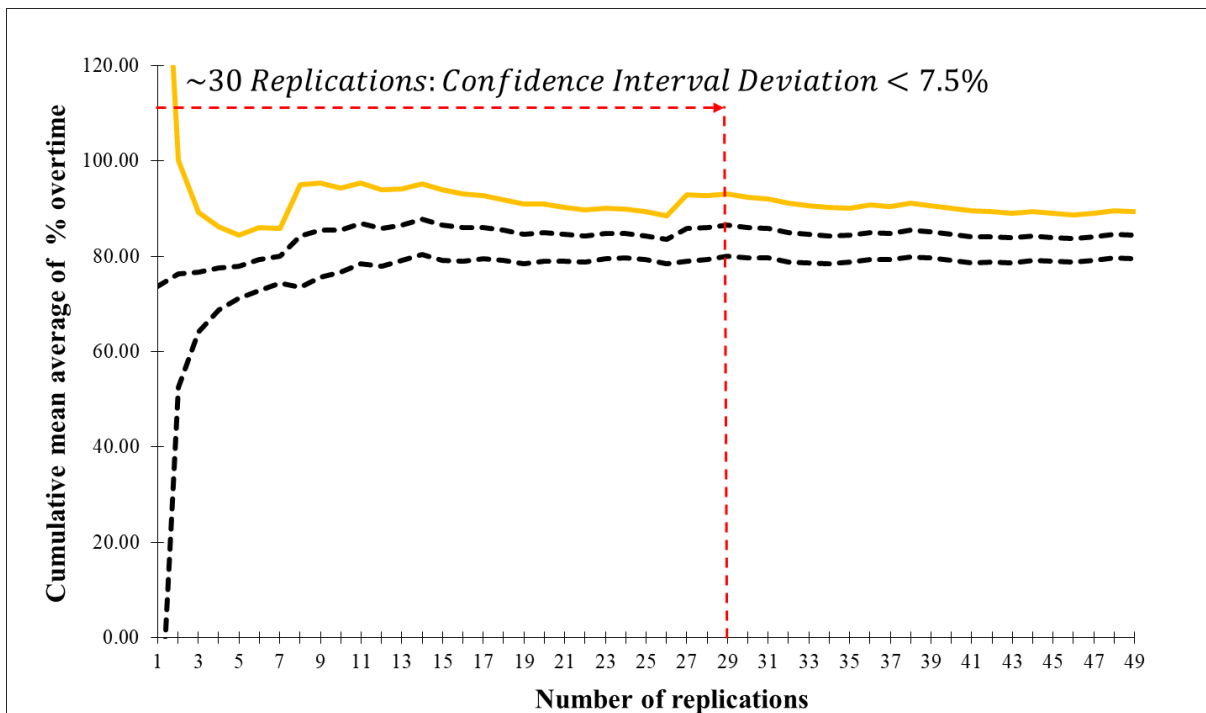


Figure 81 - Estimation of the number of replications using a graphical method.

Table 65 - Description and Possible Values of the DT-DSS Parameters

#	Name	Description	Possible Values
1	Initial Schedule Type	The initial schedule type can be either a provisional schedule or a performed schedule. The provisional schedule is a staff-validated schedule built along the strategic, tactical, and offline operational scheduling and planning decisions, while the performed schedule is the description of how the schedule was really executed during the online operational step (real-life surgery day).	Provisional Performed
2	Process Type	The process can be modeled as either an aggregated or a detailed process (see Chapter IV). The aggregated process is based on the available timestamped data in the OR software, while the detailed process is a model based on the available timestamped data in the OR software <i>and</i> our on-site observations.	Aggregated Detailed
3	Constraints on Resources	The constraints on resources can either be flexible or strict (see Chapter IV). Strict resource constraints are the (possibly incomplete) constraints described by the OR database timestamps, while the flexible resource constraints are the constraints on the operating room only.	Flexible Strict
4	Duration Type	The simulated durations can either be determinist or stochastic (see Chapter V). In our mode, a determinist duration is a fixed value known in advance while a stochastic duration is a value extracted from a statistical or an empirical law based on historical values.	Determinist Stochastic
5	Keep NE Cases of Initial Schedule	The simulated schedule can either contain the NE cases present in the initial schedule or not.	Yes No
6	Add NE Arrivals to Initial Schedule	The simulated schedule can either contain additional NE cases that were not present in the initial schedule or not.	Yes No
7	# Replications	The number of replications is set to 1 when the scenario is determinist and to 30 when the scenario is stochastic.	1 or 30

4.3. Description of the patient pathway

Once a patient is admitted in the surgical suite, it follows the flowchart proposed in the Figure 82. Each **box** within the flowchart represents a **process**, while **diamonds** denote **intersections**.

To enhance readability, the color inside the box indicates the **type of constraints on resources** (blue for **flexible**, yellow for **strict**), while the color of the box's contour indicates the **pathway type** (blue for **detailed**, yellow for **aggregated**, green for both). It's noteworthy that certain processes remain identical whether they are aggregated (based on the database timestamps) or detailed (based on the database timestamps plus observations).

The outcome of the intersections "Pathway Type?" and "Resource Type?" is determined by the model parameters (respectively "process type" and "Constraints on Resources").

Processes #1 to #6 represent the patient pathway used for the prospective analysis (detailed processes with strict constraints on resources) and processes #7 to #11 represent the patient pathway mostly used for the retrospective analysis (aggregated processes with flexible constraints on resources). The rest of the processes are either not used or are used during the training processes.

In the subsequent subsection, we propose a brief presentation of modeling processes #1 to #6 with Flexsim Healthcare ® software – in other words: patient flows. Note that the processes #7 to #11 are similar but simpler: they only require operating rooms as resources and have less detailed processes. Thus, we provide screenshots of the flowcharts we modeled in Flexsim healthcare. The color code is the following:

- **Light Orange:** resources that the patient can acquire (e.g. OR, surgeon, nurse...).
- **Green:** actions to change the state of the OR used by the patient. Examples of OR state are: "idle", "setup", "procedure". The evolution of the OR state is then displayed in the dashboard' Gantt Diagram.
- **Orange:** actions to change the state of the patient. Examples of patient' states are: "idle", "waiting for OR", "waiting for surgeon" or "procedure". This especially allows us to compute the KPI related to patient waiting time.
- **Deep blue:** physical action in the surgical suite. Examples of physical actions are: "setup before incision", "procedure" and "reversal".
- **Red:** actions that support the automatic scheduling of non-elective cases in the ongoing schedule. We will not develop how they work together in this manuscript.
- **Yellow:** actions to send notifications to the user in the Flexsim console. An example of notification can be "At t = 9:30, patient #3 entered the operating room."
- **Light Blue:** other actions that make up the patient pathway.

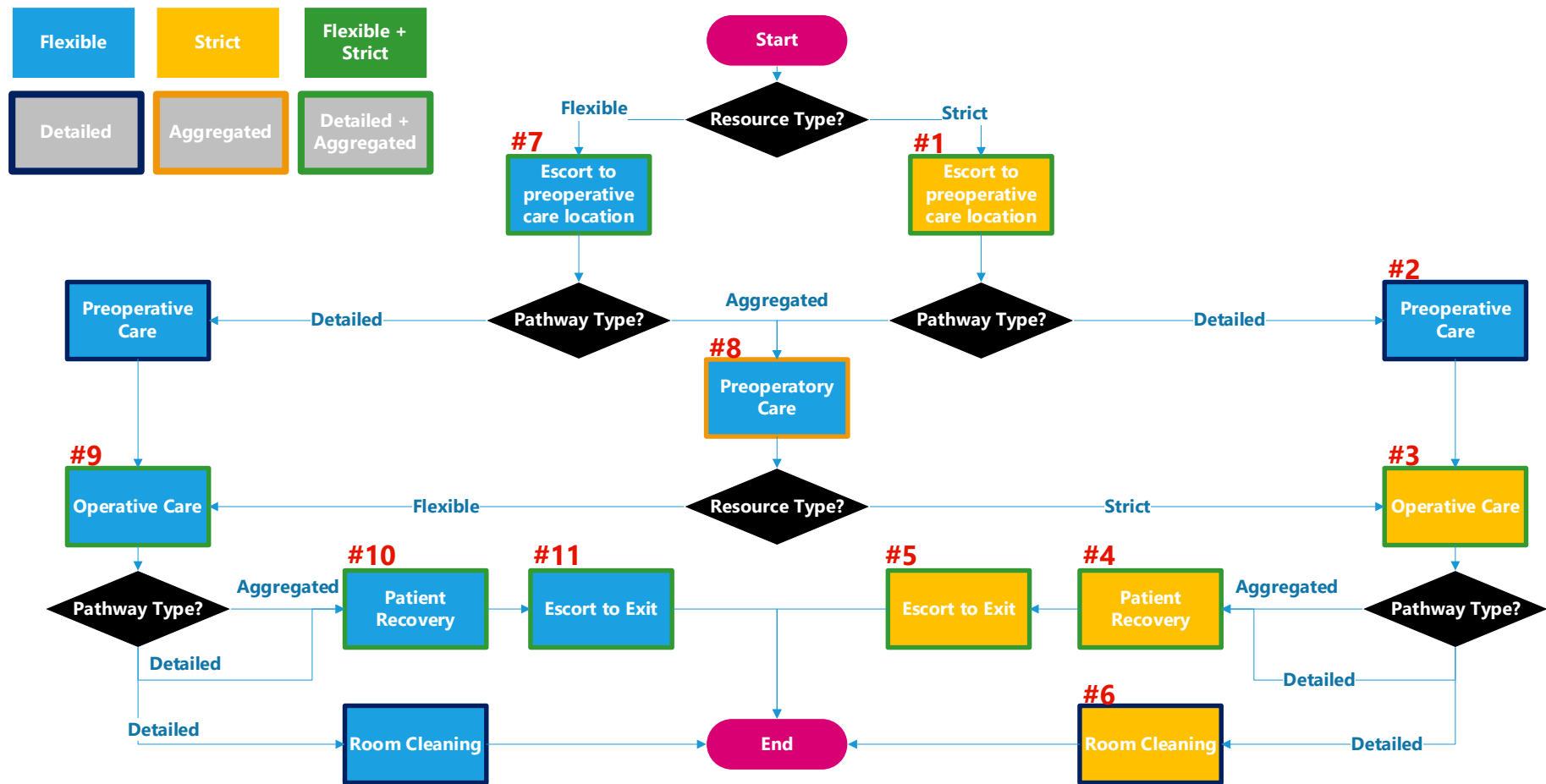


Figure 82 – Patient Pathway Flowchart as Found in the DT-DSS

FlexSim HC Patient Flow (process) #1: Escort Patient to its Preoperative Location (Figure 83). This first process starts with the arrival of the patient in the surgical suite and ends with the patient arriving at the preoperative location. The patient can be canceled on arrival based on its own attributes (e.g. the patient has a rash that has gone unnoticed), or based on a cancellation percentage that is defined by the user. In this study we have used neither.

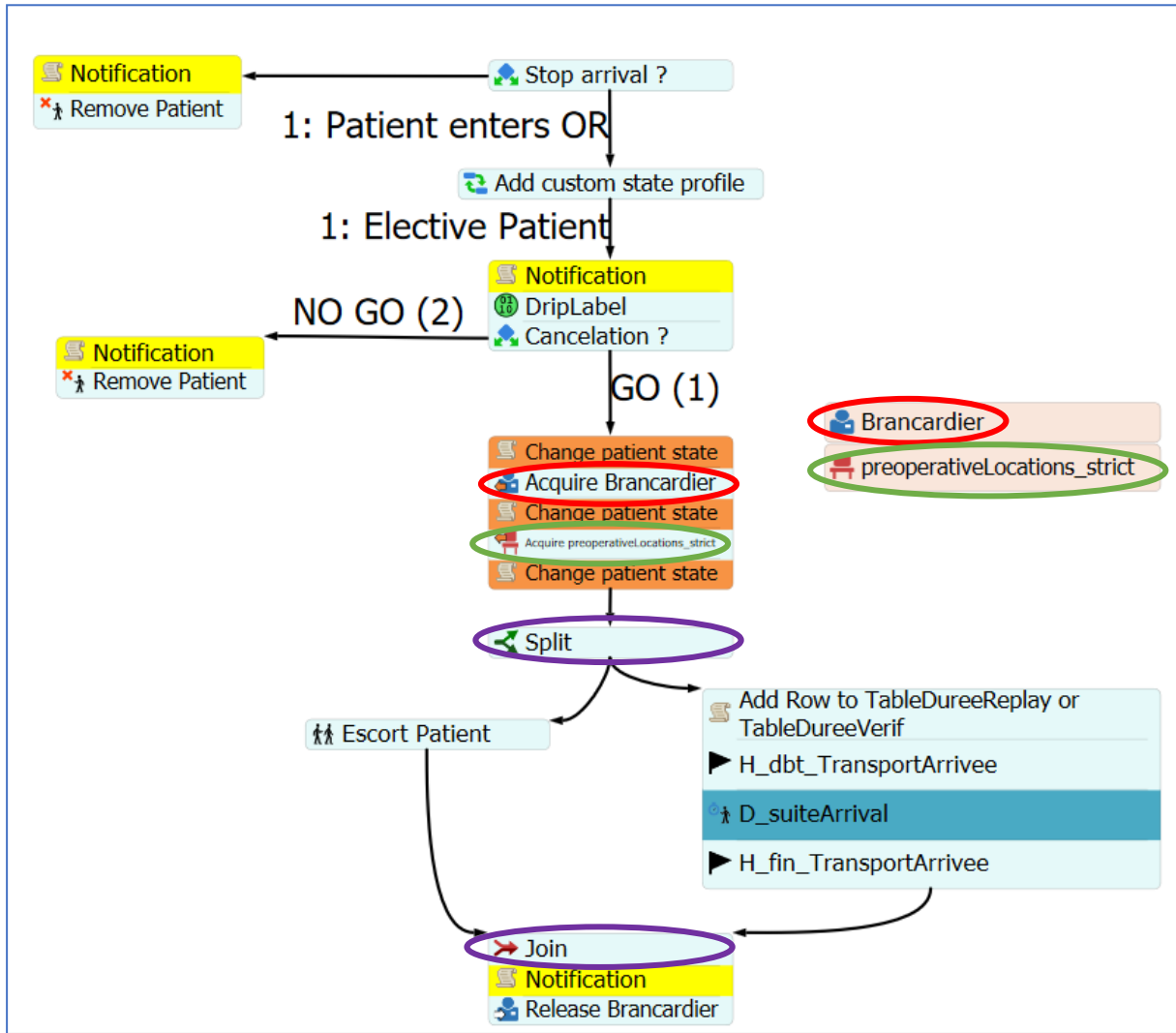


Figure 83 - Process #1: Escort Patient to its Preoperative Location

A note on this model: acquiring resources. We highlighted with a red circle the action of acquiring the stretcher-bearer (“brancardier” in French) and the stretcher resource itself. We did the same in green with the preoperative location. This is how Flexsim allows us to model assigning a resource to a patient. When the patient needs to acquire both a human resource and a material resource at the same time, we have decided to model it as the following: first we acquire the resources, then we acquire the location. This allows us to (1) model the patient waiting time for the human resource and for the material resource, (2) block a human resource rather than a material resource in case both are not available at the same time, which is what happens in real-life most often.

A note on this model: modeling walking time. We highlighted with a purple circle the actions “split” and “join”. After the “split” action, both downstream activities will

start at the same time. The activities after the “join” action will only start once both downstream activities after the “split” action are done.

FlexSim HC Patient Flow (process) #2: Preoperative Care (Figure 84). We display the flowchart of the preoperative care in Figure x and Figure x. The red rectangle corresponds to the part of the process that is common to both Figures.

The process starts with an action “stop preoperative” which allows to model the patient exiting the surgical suite just before starting the preoperative phase based on its attributes. Then, the process is divided into three strands based on the patient anesthesia type: (1) general, local or spinal anesthesia, (2) locoregional anesthesia, or (3) ophthalmologic induction.

A note on this model: patient queues rules. In our modeling, process #1 and process #2 are FIFO based: the first patient to arrive in the surgical suite is the first one to be escorted to their preoperative location, and the first one to receive preoperative care. However, (1) the sequencing of patients receiving perioperative care is based on the operating schedule, and (2) perioperative care resources can be required during the preoperative care. Thus, using the process highlighted by a green rectangle, we sort the patients so that only the one scheduled to be next can move on to the next phase of the patient pathway.

FlexSim HC Patient Flow (process) #3: Operative Care (Figure 85 and Figure 86). We display the flowchart of the operative care in Figure x and Figure x. The process models two situations:

- (1) Left-side process: the patient type anesthesia does not require the anesthesiologist to provide care in the OR, *or* there is not anesthesiologist assigned to the patient in the database.
- (2) Right-side process: the patient type anesthesia requires the anesthesiologist to provide care in the OR *and* there is an anesthesiologist assigned to the patient in the database

The rest of the operative steps are common to all patients.

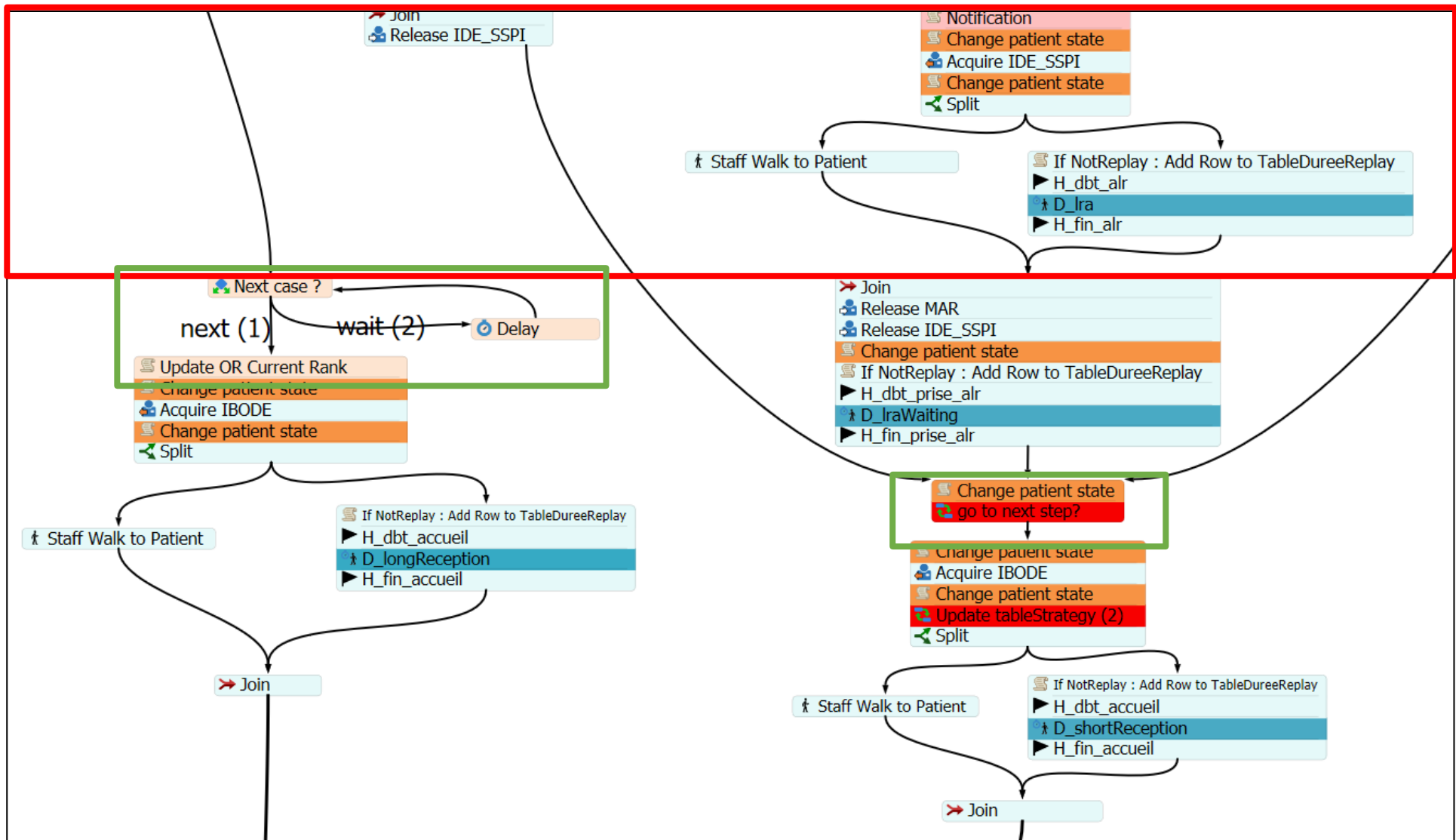


Figure 84 – Process #2: Preoperative Care (Part 2/2)

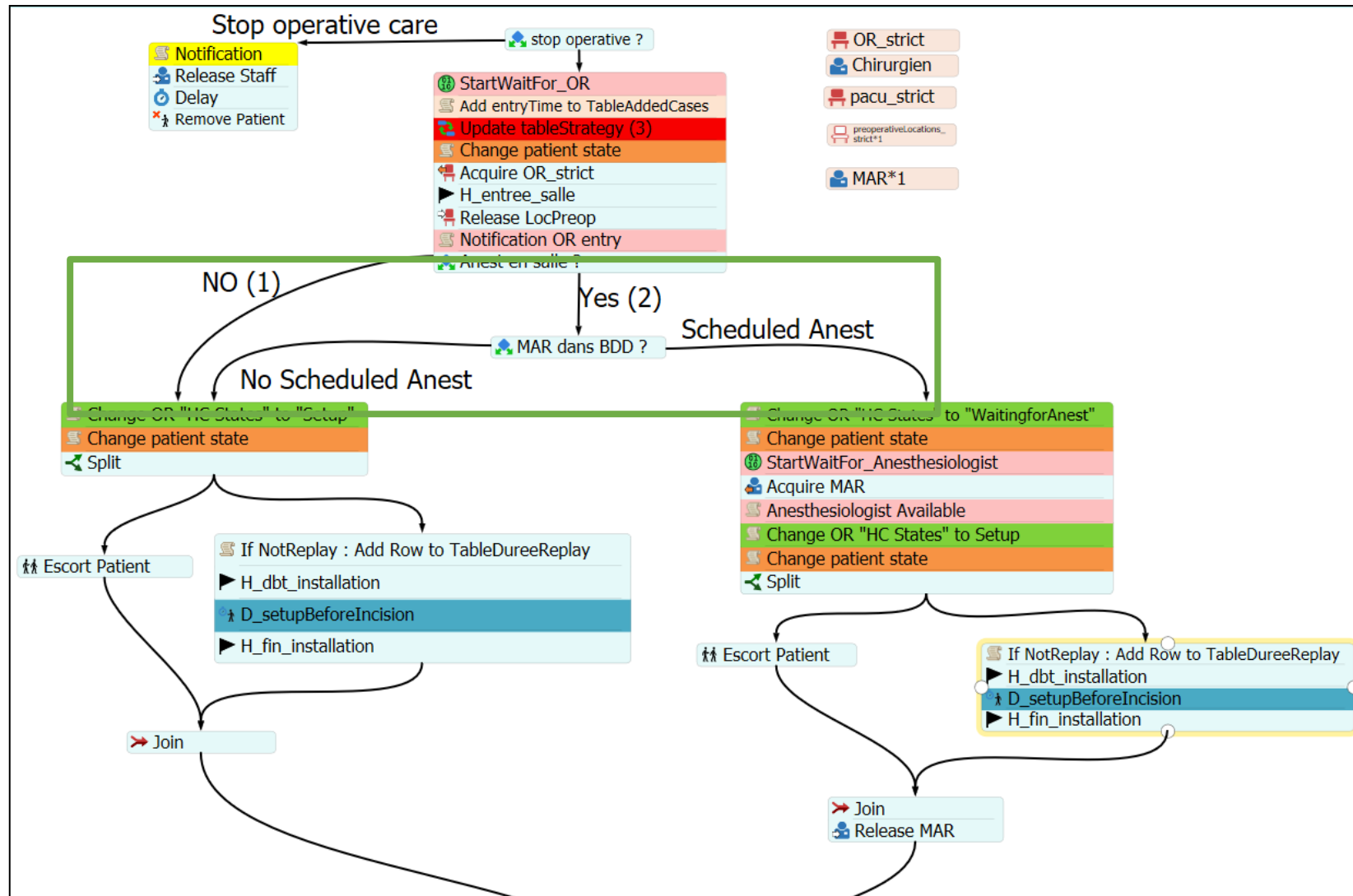


Figure 85 – Process #3: Operative Care (Part 1/2)

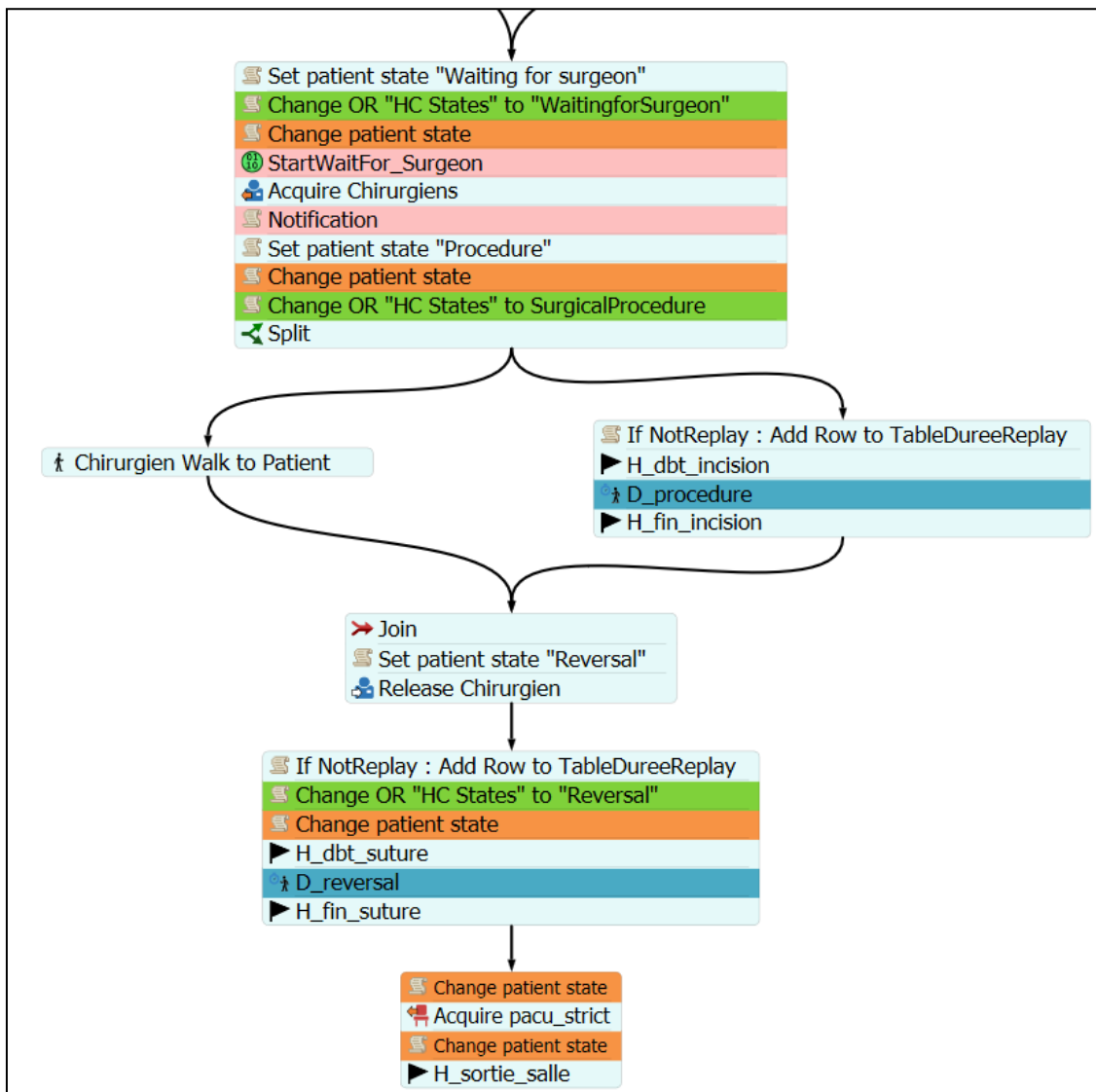


Figure 86 - Process #3: Operative Care (Part 2/2)

FlexSim HC Patient Flow (process) #4: Patient Recovery (Figure 87) & Process #5: Escort Patient to Exit (Figure 88). Once the patient’s surgery is over, they are moved to the recovery room, where they stay until their state is stabilized. After this, the stretcher bearer comes get the patient and escort them outside of the surgical suite.

FlexSim HC Patient Flow (process) #6: Room Cleaning (Figure 89). As soon as the patient exits the OR, an assistant nurse comes in and cleans it.

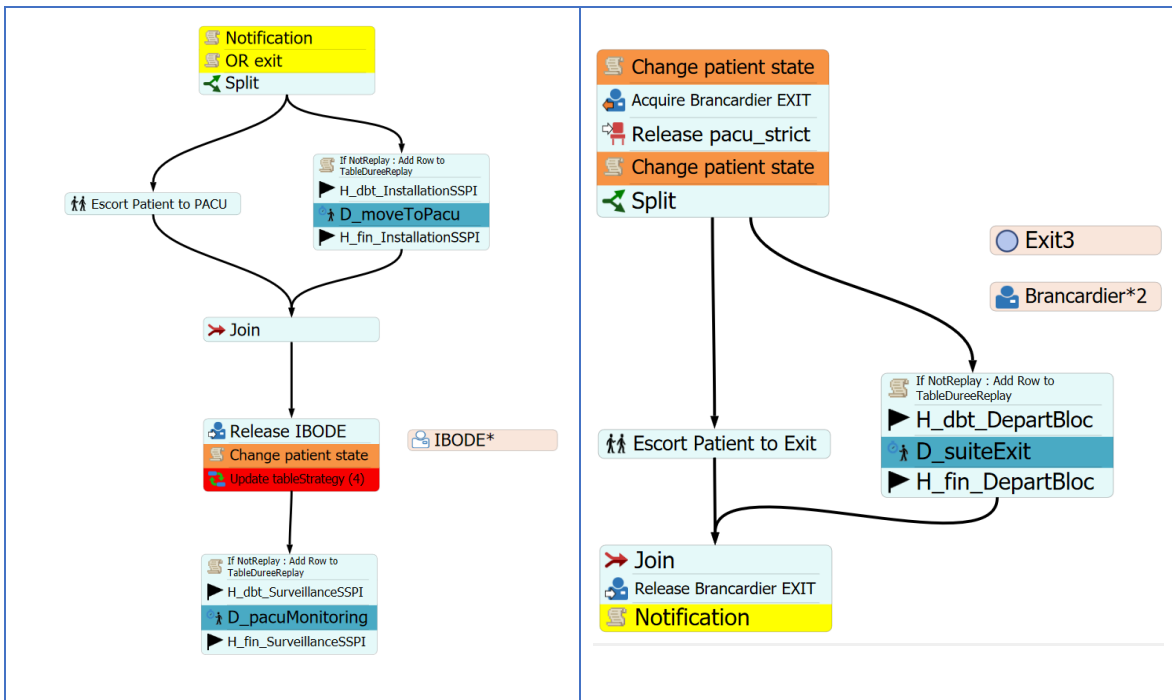


Figure 87 – Process #4. Patient Recovery

Figure 88 – Process #5: Escort Patient to Exit

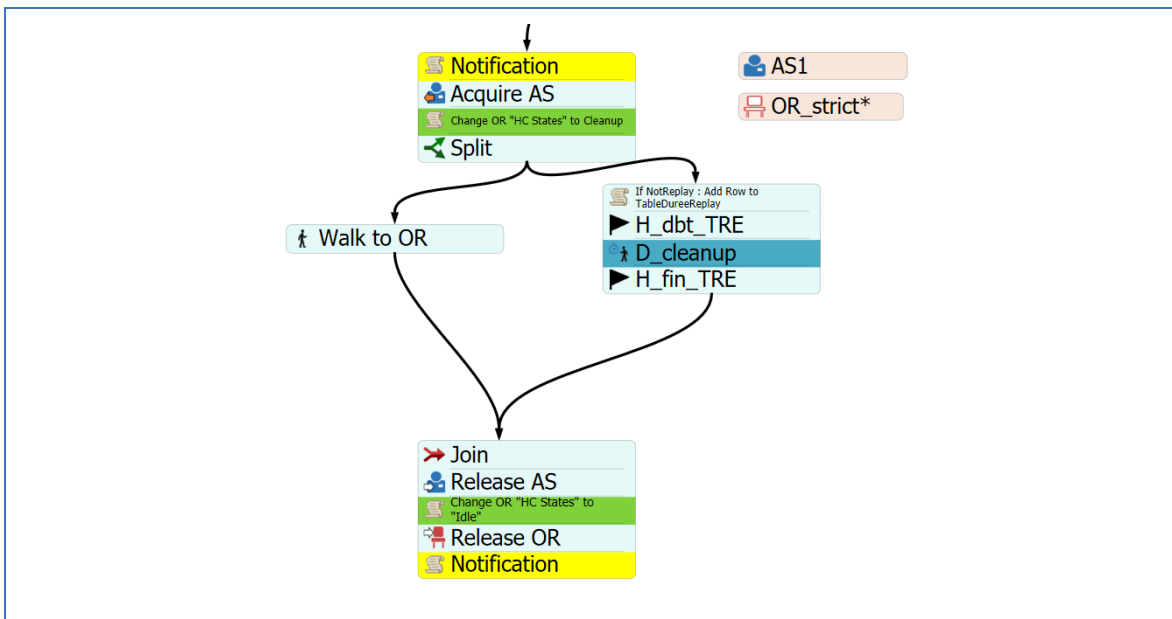


Figure 89 – Process #6: Room Cleaning

OUTIL D'AIDE A LA DECISION A BASE DE JUMENT NUMERIQUE POUR L'ANALYSE PROSPECTIVE ET RETROSPECTIVE D'UN PROGRAMME DE BLOC OPERATOIRE SOUMIS A DES INCERTITUDES

Résumé :

Avec l'augmentation de la demande de soins dans le monde, les services hospitaliers sont de plus en plus sollicités. Leur performance est étroitement liée à la performance de leur bloc opératoire. En effet, le bloc opératoire est un important centre de revenus et de dépenses puisqu'il représente 40% du budget de l'hôpital (Macario et al. 1997), et que 60% des patients viennent à l'hôpital pour une intervention chirurgicale (Fugener et al. 2017). Il est donc nécessaire que les blocs opératoires soient efficaces.

Cependant, cela est rendu difficile par la complexité de leur organisation due à la diversité des parcours patients, la multiplicité des métiers, les liens étroits avec les services amont et aval, la synchronisation de plusieurs ressources et flux logistiques (personnels, médicaments et dispositifs médicaux), etc. D'autre part, la variabilité des durées et les perturbations inhérentes à la pratique médicale, comme les cas d'urgence, sont les principaux facteurs et événements qui dégradent le programme opératoire et impliquent que le personnel prenne de fréquentes décisions pour maintenir l'activité du bloc opératoire de manière optimale. Par conséquent, les activités de planification et d'ordonnement du bloc opératoire intéressent de plus en plus la communauté scientifique.

Dans cette thèse de doctorat, nous nous concentrons sur les niveaux opérationnels hors ligne et en ligne (Hans et Vanberkel 2012). Ceci nous amène aux questions de recherche suivantes : (1) Comment évaluer la robustesse et la résilience du programme opératoire avant son exécution (dimension prospective) ? (2) Comment rejouer le programme opératoire pour avoir un retour d'expérience et évaluer les décisions prises lors de son exécution (dimension rétrospective) ?

La contribution de ce manuscrit est triple : (1) Nous proposons un système d'aide à la décision basé sur un jumeau numérique pour la simulation et l'analyse prospective et rétrospective de l'exécution du programme opératoire. (2) Nous décrivons une méthodologie standardisée pour concevoir, construire et mettre en œuvre cet outil dans n'importe quel bloc opératoire. (3) Cette méthodologie est appliquée à un bloc opératoire inspiré de l'Hôpital Privé de La Baie (groupe Vivalto Santé), afin de disposer d'une preuve de concept permettant de simuler un programme opératoire de façon prospective et rétrospective.

Mots clés : Bloc opératoire, Jumeau numérique, Régulation, Outil d'aide à la décision, Modélisation et simulation, Incertitudes

DIGITAL TWIN-BASED DECISION SUPPORT SYSTEM FOR THE PROSPECTIVE AND THE RETROSPECTIVE ANALYSIS OF AN OPERATING ROOM UNDER UNCERTAINTIES

Abstract:

With healthcare demand rising worldwide, hospital services are increasingly needed. Hospitals' performance is tightly linked to their surgical suite performance. Indeed, the surgical suite is an important revenue and expense center with over 40% of the hospital's budget dedicated to it (Macario et al. 1997) and 60% of the patient coming into the hospital for surgical intervention (Fugener et al. 2017). This makes it necessary for surgical suites to be efficient.

However, running a profitable surgical suite is quite hard and requires a methodological approach due to the complexity of its functioning: the diversity of patient pathways, the multiplicity of professions, the tight link with upstream and downstream wards, the synchronization of several resources and logistic flows (drug and medical devices), etc. On the other hand, durations variability and disruptions inherent in medical care like emergency cases are the main factors and events that degrade the scheduled execution and involve the staff making decisions frequently to preserve the surgical suite activity in an optimal way. Therefore, OR planning and scheduling activities are of increasing interest to the scientific community.

In this PhD thesis, we focus on offline operational and online operational levels (Hans and Vanberkel 2012). This leads us to the following research questions: (1) How can we assess the robustness and the resilience of the schedule before its execution (prospective way)? (2) How can we replay the schedule to have feedback and assess the decisions made during its execution (retrospective way)?

The contribution of this manuscript is threefold: (1) we propose a digital twin-based decision support system for the prospective and retrospective simulation and analysis of the operating room schedule execution, (2) we describe a standardized methodology to conceive, build and implement this tool in any surgical suite, (3) This methodology is applied to an operating room inspired by the Private Hospital of La Baie (Vivalto Santé group, France), in order to have a proof of concept allowing to simulate an operating program prospectively and retrospectively.

Keywords: Operating room, Digital twin, Operating room management, Decision support system, Modeling and simulation, Uncertainties.