Proceedings of the 2022 Winter Simulation Conference
B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C.G. Corlu, L.H. Lee, E.P. Chew, T. Roeder, and P. Lendermann, eds.

A SIMULATION-BASED APPROACH FOR ASSESSING THE IMPACT OF UNCERTAINTY ON PATIENT WAITING TIME IN THE OPERATING ROOM

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ABSTRACT

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.*

1 INTRODUCTION

With healthcare demand rising worldwide, hospital services are increasingly needed. This particularly impacts operating rooms (ORs) where patients account for 60% of hospital admissions (Fügener et al. 2017). As a consequence, OR planning and scheduling activities are of increasing interest. They comprise decisions from four hierarchical levels: strategic, tactical, offline operational and online operational.

Firstly, at the strategic level (long-term), hospital management aligns the forecasted care demand with the available OR resources. Secondly, at the tactical level (medium-term), hospital management schedules on a weekly basis the available OR time slots for each practicing surgical specialty. Thirdly, at the offline operational level (short-term), the OR staff schedules the following week’s cases: they allocate an OR time slot and a start time to each surgical operation. Finally, at the online operational level (real-time), the OR

978-1-6654-7661-4/22/$31.00 ©2022 IEEE

manager makes decisions on the day of the surgery to smooth OR schedule execution (Hans and Vanberkel 2012). In this article, we will focus on the operational levels.

The scientific community has shown an increasing interest for planning and scheduling under uncertainty in the operating room. However, based on our on-site observations and staff interviews, we noticed that most surgical suites still only use deterministic approaches. Discrete-event simulation (DES) can simulate the execution of a deterministic schedule in a stochastic environment. This lead us to the following research question: **"How can discrete-event simulation help assess the impact of uncertainty on patient waiting time in the OR?"** In this article, we propose a simulation-based approach for assessing the impact of uncertainty on patient waiting time in the OR. We propose a 3-step methodology: (1) modeling the OR schedule execution in a deterministic environment, (2) implementing configurable uncertainties to obtain a stochastic environment, and (3) experimenting with different uncertainty-related scenarios and analyzing the results. We applied our methodology to a simulated OR inspired from the *Hôpital Privé de La Baie, from the Vivalto Santé French health group.*

The remainder of this article is organized as follows: Section 2 defines common terms we will use in the paper, Section 3 is our literature review, and Section 4 our methodology. Section 5 describes the results and discusses them. Finally, in Section 6, we present our limitations, our conclusions, and perspectives for further work.

2 TERMINOLOGY

We define terms that we will use frequently in the article below in Table 1.

Table 1: Terminology.

Term	**Definition**
Operating Room (OR)	The OR is the room where surgical cases are performed.
Surgical Suite	The surgical suite is the service area that comprises patient waiting rooms, the post-anesthesia care unit (PACU), storage rooms, staff changing rooms, offices and operating rooms (Alameda and Macario 2017). It is common to use the term "OR" to describe the surgical suite. The contrary is not true.
Case	A case is comprised of the time during which the patient is in the OR (surgery) and the time during which the staff cleans the room after the surgery (clean-up).
Elective case	Elective patients can wait before their surgery. Their case are planned ahead of time (Zhu et al. 2019).
Non-elective case	Non-elective patients arrive unexpectedly and need to be treated right away. They are divided into urgent and emergent patients. Urgent patients need to be admitted immediately but their surgery can be postponed. Emergent patients need to their surgery to be performed at once (Zhu et al. 2019).
Provisional Schedule	The provisional schedule is the schedule available at the start of the day. It describes the sequence of cases with their allocated resources. It comprises elective cases and urgent cases.
Performed Schedule	The performed schedule is the actual schedule that was followed during the day. It is different from the provisional schedule, as unexpected events and uncertainty are inherent in medical practice. It comprises elective cases, urgent cases and emergent cases.

3 LITERATURE REVIEW

3.1 Operating Room Performance

The scientific literature abounds with measures for assessing the performance of operating schedules. Cardoen et al. (2010) and Samudra et al. (2016) identify 9 main performance measures: waiting time, throughput, utilization, leveling, makespan, patient postponement, financial measures, preferences and idle time.

First, as stated by the review's authors, articles do not always use the same definition for the same indicator. Thus, it is necessary to redefine measures in each article. Second, performance measures are not independent. For instance, patient waiting time is closely related to patient throughput and all utilization-related measures are related to each other. Third, compromises need to be made between the measures in order to satisfy the stakeholders. For instance, management is interested in having a high OR utilization rate, patients want to minimize their waiting time and nurses prefer to work overtime as little as possible. Thus in the literature, authors usually use a group of KPIs or create an objective function. Aringhieri et al. (2022) develop matheuristic algorithms to consider both the patient priority maximization and the workload balance during the OR planning and scheduling process. Cappanera et al. (2018) use a goal programming approach to determine the number and nature of cases to be scheduled while considering OR utilization, bed utilization, number of scheduled cases, and due date fulfillment rate. In this article, we focus on patient waiting time. **Patient waiting time** is the time during which the patient is ready for the next step but has not yet started it because of a lack of resources (staff, material, architectural). This choice is coherent with both the scientific literature and the needs identified during our on-site observations. Note that we assume that the constraints on material resources have been considered before the day of the surgery. Thus, they have not been considered in our study. We assess the robustness and stability of the organization by studying whether or not the average patient waiting time varies with the occurrence of random disruptions.

3.2 Using discrete-event simulation for OR scheduling

The methods developed to deal with the OR planning and scheduling problem can be divided into two fields: mathematical programming and simulation (Zhu et al. 2019). In this paper, we focus on discrete-event simulation (DES), an approach which has been used in the healthcare environment for more than 20 years (Evans et al. 1996). Other simulation approaches exist, such as the Monte Carlo simulation (Denton et al. 2006) and the Markov Decision processes. DES allows systems with strong complexity and diversity to be modeled. It is more flexible than mathematical programming and can especially be useful when dealing with a stochastic environment. Examples of DES applications are: assessing the performance of OR management strategies, OR scheduling or OR schedule evaluation.

Schoenfelder et al. (2021) use simulation to assess the impact of different management policies related to the patient pathway, emergency handling and staffing level. Persson et al. (2017) study the relevance of DES use when evaluating OR scheduling strategies such as reducing turnover time and adding an extra OR. Allen et al. (2014) propose a DES approach to study when and how frequently OR schedule display should be updated to obtain both schedule accuracy and staff satisfaction. M'Hallah and Al-Roomi (2014) use DES to optimize OR utilization while dealing with offline and online surgery scheduling. Schultz and Claudio (2014) propose a surgery scheduling method where case rank is determined by case duration and the case duration level of variability. Wang et al. (2016) propose a deterministic method to build a common schedule for three collaborating hospitals where both patients and resources are shared. Roshanaei et al. (2017) assess the performance of this same deterministic schedule in an uncertain environment using DES. Similarly, we use DES to study a deterministically built OR schedule in a stochastic environment. Like Roshanaei et al. (2017), we model constraints on downstream resources, but then we add constraints on OR upstream resources, as well as providing highly detailed patient pathways and related processes. Finally, we shift our focus from OR performance to patient waiting time. Ewen et Mönch (2014) use a multi objective evolutionary algorithm to solve a real-world surgery scheduling problem. They assess the performance of the found solutions with discrete event simulation, which allows them to consider staff availability, stochastic surgery durations and stochastic patient arrivals. In this article we consider these three items as well as patient care requirement uncertainty.

3.3 Describing Uncertainties in the Surgical Environment

To this day, the scientific community has provided several reviews on the OR planning and scheduling issue (Cardoen et al. 2010; May et al. 2011; Van Riet and Demeulemeester 2015; Samudra et al. 2016; Zhu et al. 2019). As disruptions are inherent in the OR schedule execution, as noted in (Dexter et al. 2004), these reviews show an increasing interest in stochastic approaches to scheduling. In the following paragraphs, we propose a list of uncertainties issued from our on-site observations and our literature review (Cardoen et al. 2010; May et al. 2011; Zhu et al. 2019). We have included the first four in our model.

Activity duration uncertainty refers to the gap between estimated and performed activity durations. This can be caused by patient conditions, surgical complications, staff skills, staff composition, procedure specialties or a lack of resources. We observed 2 estimation methods: estimation by the surgeon alone or with the OR manager, and an n-month rolling horizon average or median. Methods found in the scientific literature include probability distribution-fitting (the most commonly used are lognormal, gamma and normal), Monte Carlo simulations, or machine-learning algorithms.

Patient arrival time uncertainty depicts the fact that we cannot know exactly when patients will arrive in the OR. For outpatients, lateness can be caused by weather, traffic, or individuals' personal situations. For inpatients, it can be due to stretcher bearers being overwhelmed. When a patient does not come to the OR, it is called a **patient no-show**.

Patient care requirement uncertainty refers to the fact that professionals cannot always know in advance what care patients will need during their stay at the hospital. Indeed, patient situations evolve and are not always predictable. Patients can thus be **cancelled** or **postponed** before entering the OR or while being in the OR for medical or material reasons. This uncertainty can lead to insufficient human, material, or architectural resources. This also encompasses the **patient pathway step uncertainty**: one patient can follow several patient pathways.

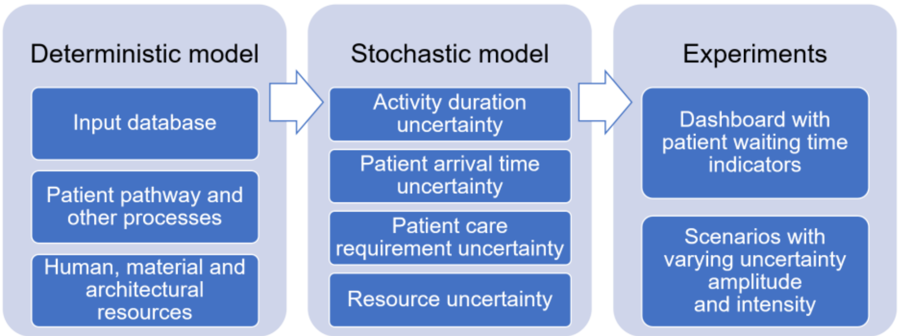
Hospitals deal with **resource uncertainty** as they have to timely provide human, material and architectural resources to meet patient care demand. However, arrival uncertainties, restrictions imposed to reduce OR costs, delays in support services, or breakdown of medical equipment can lead to resources being unavailable or unusable. Resource uncertainty also encompasses OR upstream and downstream services that have a direct impact on OR schedule execution. Inpatient surgical services or the outpatient department lacking human resources can lead to patient tardiness.

Patient arrival uncertainty is the unpredictable arrival of non-elective patients. This is inherent in surgical services accepting non-elective patients. Emergency arrivals can be modeled through (i) the number of arrivals and the interarrival time, and (ii) a Poisson distribution.

4 METHODOLOGY

In this section, we illustrate our methodology with a use case inspired by HPB (Figure 1).

Figure1: Methodology steps.



First, we built a deterministic model to simulate schedule execution. Second, we modeled uncertainties on activity duration, patient arrival time and patient care requirement. Resource uncertainty was inherent in the model design, as the simulation software automatically prevents resources from being used by several patients at the same time. We then implemented these uncertainties in the model so that we could simulate the schedule execution in a stochastic environment. Third, we created 4 scenarios with different disruption intensity levels. We studied the impact of the uncertainties on patient waiting time by comparing its value in the different scenarios. We built the deterministic and stochastic models as well as designed the experiments over the course of several months. In this article, we ran our simulation over 23 operating days. This allowed us to get insights into the monthly impact of uncertainties. However, we could have chosen other simulation lengths. For instance, running the experiment over 1 week (the usual horizon used for planning and scheduling cases), could help assess the robustness of the operating schedule.

4.1 Deterministic Model

4.1.1 Preparing the Model Input

Our partner provided us with data describing the schedule performed in March 2021 for all of their 8 ORs. The real life database (DB) accounts for 1884 cases and considers both elective and non-elective patients. For each case, the record shows: the patient ID, the OR number, the surgery date, the surgeon ID, the anesthesiologist ID, the anesthesia type, the surgery type, the provisional case rank, the performed case rank, as well as the nine following timestamps: patient in service, patient in room, induction start, induction end, incision, suture, patient out of room, patient in PACU, patient out of PACU. Provisional case durations, clean-up durations, canceled patients, and whether the patient is elective or non-elective do not appear on that database. For simplicity, we dropped the cases where the patient did not receive surgical care and stayed in the PACU. The real-life DB performed schedule presents 4 types of errors : (a) missing timestamps, (b) impossible timestamp order in the same patient pathway (example : the patient starts the procedure before entering the OR), (c) impossible timestamp order between 2 patients' pathways (example : patient B enters the OR while patient A is still inside), and (d) the same resource can be required by two patients at the same time. Error (a) stems from the fact that the data is manually inputted into the OR software and that human mistakes can be made. Error (d) comes from the fact that the OR software does not check if resources are used by only one patient at the same time. Errors (b) and (c) are due to both reasons. We make a few comments about error (a). First, the percentage of cases with a recorded "induction end" timestamp amounted to only 7%. This led us to drop the "induction end" timestamp column from the database. Second, the percentage of cases with at least one missing timestamp amounted to 13%. We could either keep only the cases without errors or correct them. However, since our objective was to simulate the execution of the complete schedule, we wanted to keep all the cases. Thus, we established some rules to build coherent timestamps to correct the real-life DB errors. Then, we structured our input DB as a two-table database: Patient Arrivals and Performed Schedule Durations (see Figure 2). The tables are linked by a Case ID which is unique. **Patient arrivals** describes the time the patient arrives in the OR as well as the labels linked to the patient pathway. **Performed schedule durations** lists the duration values for each of the patient pathway steps.

4.1.2 Modeling Fixed Resources and Patient Pathways

We used Flexsim Healthcare®, simulation and data analysis software, to model our use case.

In this subsection, we describe our different patient pathways and their related process. Figure 3 shows a part of our use-case OR layout. We represented the transfer area through which patients enter and exit the surgical suite (white), the OR #1, #7 and #8 (green), the patient waiting area (blue), and the PACU (yellow). The PACU has specific beds for preoperative care: beds for locoregional anesthesia (LRA, orange) and beds for ophthalmic induction preparation (OIP, brown).

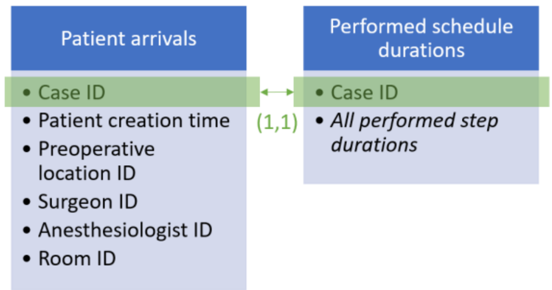


Figure 2: Database relational model.

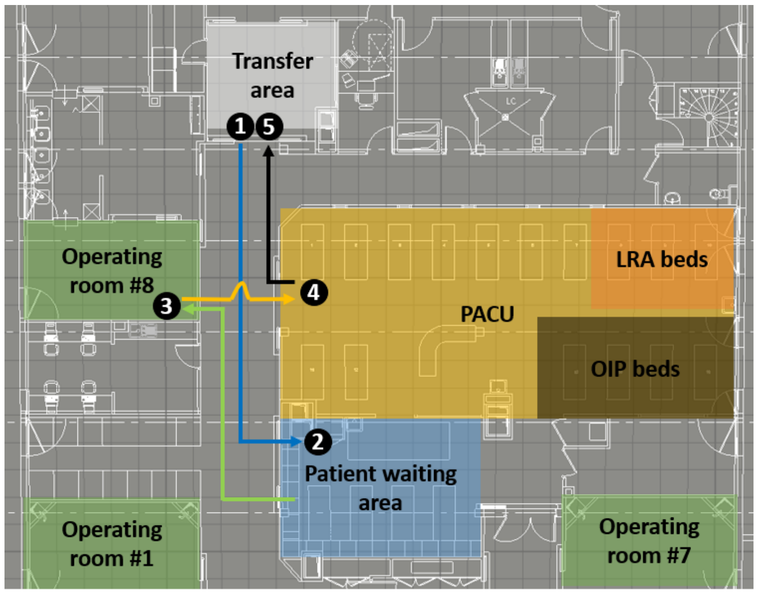


Figure 3: Commented part of the OR layout.

We modeled a total of 8 possible patient pathways in the surgical suite based on the available timestamps and our on-site observations (see Table 2). The changes among them depend on the preoperative care location, whether or not the patient is put on a drip before entering the OR, and whether or not the patient receives anesthesia in the OR (2 options).

Table 2: Description of the possible patient pathways.

Preoperative location	**Patient waiting area**				**LRA beds**		**OPI Beds**	
Put on a drip before entering the OR	Yes		No		Yes		Yes	
Induction in the OR	Yes	No	Yes	No	Yes	No	Yes	No
# pathways possible	4				2		2	

The arrows on Figure 3 represent the path of a patient receiving preoperative care in the patient waiting area and using OR #8. First, the patient enters the surgical suite through the transfer area (1). Then, a stretcher bearer carries the patient to the preoperative care location (2). Once the PACU nurses finish the preoperative care steps, the OR nurses welcome the patient and bring him/her in the room (3). In the OR, the patient undergoes the following steps : setup, induction (if required), procedure, and reversal. **Setup** is the step during which the staff finishes preparing the material and installs the patient for the induction and/or the procedure. **Induction** is the time required to give the anesthesia to the patient and to install him/her for the procedure. The **procedure** is the duration between the incision (procedure start) and the suture (procedure end). **Reversal** is the step between the end of the procedure and the patient going out of the room. When the surgery is over, 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 out of the OR (5).

To simplify the model, we considered that the anesthesiologist has to be present for the induction if induction is required, that the surgeon has to be present for the procedure only, and that the nurses have to be present throughout the procedure. The model allows the time spent waiting for the anesthesiologist (before the induction) and the surgeon (before the procedure) to be simulated.

We considered 1 stretcher bearer, 2 nurses per OR (not nominative, 16 total), nominative surgeons, nominative anesthesiologists, one PACU nurse for the OIP and unlimited PACU nurses for the other tasks. The model has 12 PACU beds of which 3 can be used for LRA, 3 OIP beds and 8 ORs. There is no constraint on material resources.

We will now describe the values we used for the deterministic model. **Activity durations** and **patient arrival times** are all fixed values computed during the model input preparation. **Cancellation percentage** is set to 0%: we consider that all the scheduled patients undergo their surgery as planned. **Drip percentage** is set to 0%: we consider that PACU nurses are never available to put the patient on a drip before entering the OR.

Figure 4 describes the OR performed schedule of March 1st, 2021. Each line represents the activity of an OR. Green indicates that the OR is empty during a shift (idle), blue that the patient is in the room (surgery), orange that the staff is cleaning the OR (clean-up) and grey that the OR is empty during breaks (OR closed). A red line indicates the shift start time; a yellow line, the shift end time. The idle sections between 2 surgery sections are the waiting time for the staff (anesthesiologist or surgeon). The idle time between a clean-up and the following surgery is the time during which the OR is ready to receive the patient but the patient is not ready to come in yet. The schedule is not optimal: 7 ORs have overtime after 6pm, and yet all of them have idle time throughout the day.

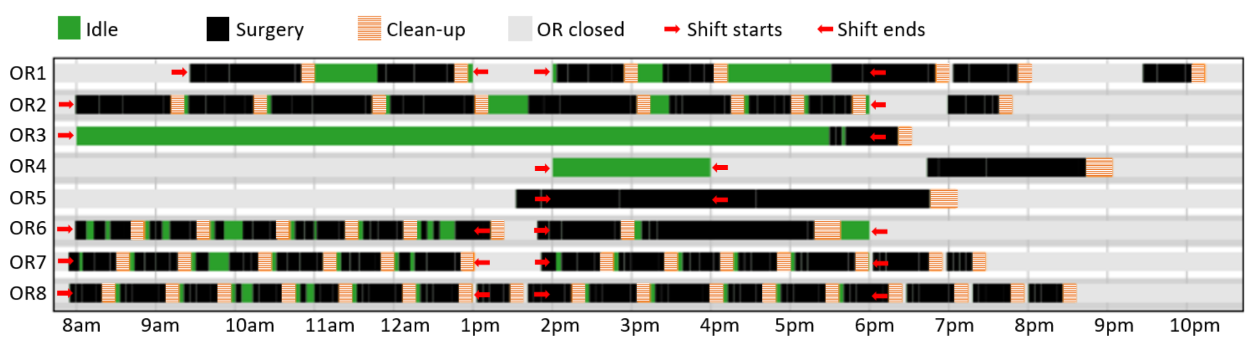


Figure 4: OR Gantt chart for one operating day.

We compared the values of the input and simulated patient pathway timestamps. Since the gap was not significant, we validated the deterministic model.

4.2 Stochastic Model

Here, we modeled uncertainties on activity duration, patient time arrival, and patient care requirement. Patient care requirement uncertainty included patient cancellation and whether or not a patient was put on a drip in the waiting room area. These uncertainties were configurable and could thus be modified from one scenario to another.

We modeled these uncertainties with on-site observations and exchanges with the OR staff. We started by modeling the stochastic **activity durations**. First, we did not have access to the provisional schedule so we used the performed schedule as a reference point. Second, the surgery type label was not standardized so we could not group the activity durations by surgery type in order to fit them into a specific distribution. Let the $value_{det}$ be the fixed activity duration used in the deterministic model and $value_{stoch}$ be the stochastic activity duration. The $value_{stoch}$ follows a uniform distribution multiplied by $value_{det}$ (1). The lower and upper bounds of the uniform law follow a uniform law themselves: (2) and (3). This enables us to have a different potential variability for each duration. Thus, a_{min}, a_{max}, b_{min} and b_{max} are configurable parameters. We present the uniform distributions used in Figure 5.

$$value_{stoch} = value_{det} * uniform(a, b) \tag{1}$$

$$a = uniform(a_{min}, a_{max}) \tag{2}$$

$$b = uniform(b_{min}, b_{max}) \tag{3}$$

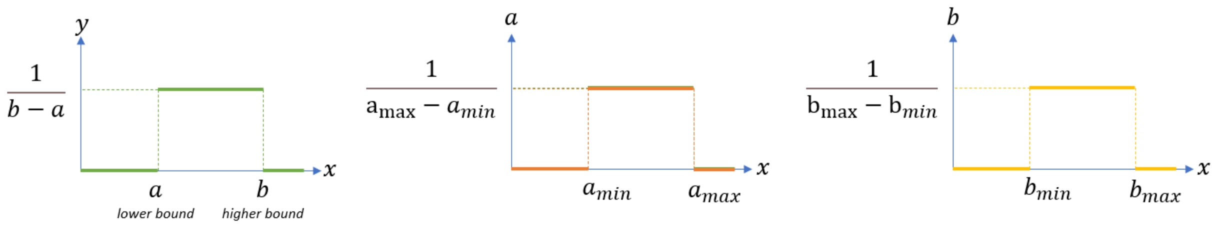


Figure 5: Uniform distributions used.

Then, we modeled the offset between real and the stochastic patient arrival time values with the triangular distribution (4), with i_{min}, i_{max} and i_{mode} being parameters.

$$time_{stochastic} = time_{real} + triangular(i_{min}, i_{max}, i_{mode}) \tag{4}$$

Finally, we decided to use percentages to describe the number of patients being cancelled, and the number of patients being put on a drip. We created two parameters (cancellation percentage and drip percentage) that can be set to a discrete value in [0; 1].

4.3 Experimentation Scenarios

We tested and compared 4 different scenarios in order to assess the impact of stochastic factors on the average patient waiting time in the OR.

For each scenario, we modified the parameters presented in Section 4.2. We use a_{min}, a_{max}, b_{min} and b_{max} for the activity duration uncertainty, i_{min}, i_{max} and i_{mode} for the patient arrival time, as well as the cancellation and drip percentages. Since we could neither differentiate the elective cases from the non-elective cases nor retrieve the cancelled cases of a day, we ran all of our scenarios on the list of performed cases.

In the first scenario, we simulated the schedule's execution in a deterministic environment. We used the fixed activity durations and the fixed arrival times from the database. We set the percentages of cancelled patients and the percentages of patients put on a drip in the waiting room area to none.

In the second, third and fourth scenarios, we simulated the schedule's execution in a stochastic environment. Activity durations followed equations (1), (2) and (3). Patient arrival times followed equation (4). Cancellation percentage and drip percentage were set to discrete values.

We ran preliminary tests to identify how each uncertainty impacted patient waiting time. We concluded that longer activity durations, late patient arrivals, and patients put on a drip before entering the OR increased patient waiting time, while patient cancellation decreased it. This is explained by the fact that when a patient n is cancelled, patient n+1 can be taken care of right away: they no longer need to wait for the resources that patient n would have used. Based on these results, we created four scenarios with an increasing impact on the patient waiting time. Table 3 displays the corresponding values of the parameters.

The probability of having longer activity duration increases from scenario 2 to 4. The lower bound of the uniform law stays between 90% and 100%, but the higher bound maximum goes from 110% to 150%. The probability of a late arrival increases from scenario 2 to 4. The i_{min} is set to -5 so that patients can arrive up to five minutes early. The i_{max} increases from 30 to 60 and i_{mode} from 0 to 10. Cancellation percentage decreases from S2 to S4.

Table 3: Scenario descriptions.

# Scenario	1	2	3	4
$\boldsymbol{a_{min}}$	1	0.9	0.9	0.9
$\boldsymbol{a_{max}}$	1	1	1	1
$\boldsymbol{b_{min}}$	1	1	1	1
$\boldsymbol{b_{max}}$	1	1.1	1.3	1.5
$\boldsymbol{i_{min}}$	0	-5	-5	-5
$\boldsymbol{i_{max}}$	0	30	45	60
$\boldsymbol{i_{mode}}$	0	0	5	10
Cancellation percentage	0	2.2	1.2	0
Drip percentage	0	100	50	0
Uncertainty impact	None	Weak	Moderate	Strong

For the cancellation percentage, we computed the ratio of cancelled patients in the real world and the number of cases in our database. We obtained 2.2%. For the drip percentage, we referred ourselves to the OR manager experience and set it to 50%.

The first scenario is deterministic (there are no random disruptions) so it did not need several replications. The other scenarios are stochastic. We want a 99% confidence interval. We tried running the experiments with 20, 15 and 10 replications and obtained the confidence interval for n replications.

5 RESULTS & DISCUSSION

In this section we present the scenario results. We ran the simulation for a total of 31 days (March 2021) with 23 working days. We used 50 replications to have a 99% interval confidence and a sample standard deviation of less than 5 minutes.

Figure 6 displays the average patient waiting time. It includes waiting time for staff (OR nurses, PACU nurses, the anesthesiologist, the surgeon and the stretcher bearer) and for location (patient waiting beds, LRA beds, OIP beds, ORs and PACU beds). In Table 4, we present the minimum, the maximum, the standard deviation and the confidence intervals relative to these indicators.

Table 4: Data summary with mean based on 99% confidence.

Scenario & Impact	**Mean (99% Confidence)**	**Sample standard deviation**	**Minimum**	**Maximum**
1 (None)	75.2	0.0	75.2	75.2
2 (Weak)	69.2<70.2<71.5	2.5	59.2	75.0
3 (Moderate)	87.8<88.6<89.4	2.2	84.8	93.5
4 (Strong)	110.1<111.8<113.5	4.4	106.9	137.3

We make a few comments about the **median value of the average patient waiting time** (MAPWT) for each scenario. In S1, each patient waits on average 75' which is 55% of the median deterministic makespan (136'). Between S1 and S2, the MAPWT decreases by 4' (from 75' to 71'). Between S1 and S3, the MAPWT increases by 14' (from 75' to 89'). Between S1 and S4, the MAPWT increases by 36' (from 75' to 112').

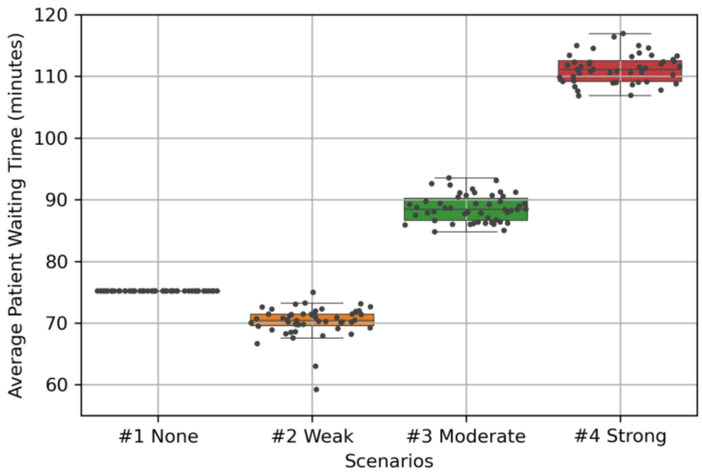


Figure 6: Replication box plot for each scenario.

We can conclude that even without random disruptions, the patient pathway is not smooth.

6 CONCLUSION AND PERSPECTIVES

Uncertainties are inherent in operating room schedule execution and can have an impact on patient waiting time. In this paper, we proposed a 3-step methodology for assessing this impact: (1) building the deterministic model of an OR, (2) implementing uncertainties, and (3) experimenting with different uncertainty-related scenarios. We worked on a use case inspired from our partner's OR: *Hôpital Privé de La Baie, from the Vivalto Santé French health group.* In this article we proposed a first version of our simulated OR model to illustrate the applicability of our method and the results it can provide.

In order to transform this model in a decision-support system, we plan on adding new features to it. Stochastic environment upgrades should include adding non-elective patient arrivals and using probability distribution fitting methods to model step duration uncertainty. Case management rules such as choosing a room for upcoming non-elective cases, postponing urgent cases that cannot be done within the allocated OR time, and rescheduling cancelled, and postponed cases should be also added. In addition, we would like to provide the user with a dashboard including patient waiting time, resource utilization, and resource overtime. Such an OR model could help to assess the impact of uncertainty on OR performance and could be used as a decision support system. First, with this model, we could assess how robust the OR is to each type of disruption and propose prioritized improvement projects. Second, we could simulate provisional OR schedules in order to assess their feasibility, performance and robustness ahead of time. This could allow staff to review their scheduling and better prepare for the operating day.

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