POLITECNICO DI MILANO
School of Industrial and Information Engineering
Master of Science in Mechanical Engineering

Performance Improvement of the Operating Theater by Resequencing Surgeries

Supervisor: Prof. Andrea Matta

Claudio SERRAVALLE,
874422

Academic Year 2017/2018

Abstract

Operating Rooms account for roughly 40% of Hospitals' expenses and revenues [63]. The performance of the Operating Theater is thus vital for the overall economic efficiency of the Hospital. This project has been carried out in collaboration with Hospital Bichat (Paris, France) and involves discrete event simulation with stochastic surgery and cleaning durations, including personnel constraints and PACU beds. Input data of surgery durations, PACU Length of Stay (LOS) and first case delay have been analyzed from historical data recorded by the Hospital. Simulation has been used to (1) quantitatively evaluate the impact of Turnover, PACU saturation and First Case Delay over the overall time losses of the Operating Theater, (2) propose a scheduling heuristic which considers the performance of the Operating Theater and personnel's satisfaction. ANOVA has been used to validate the positive effect of the heuristic over the Operating Theater's makespan. Informal interviews with caregivers and a structured literature review have been conducted to set personnel's satisfaction constraints. To incentivize the application of this project, the simulation model has been integrated with Excel to produce a user friendly interface.

Keywords Discrete event simulation; optimization operating rooms; scheduling heuristic; data analysis; operating theater performance

Contents

Chapter 1

Introduction

This project is focused on the research of prospective performance improvements in the Operating Theater Scheduling and Staffing of Hôpital Bichat-Claude Bernard in Paris, while including some constraints to match care givers' expectations and satisfaction. Both issues relevantly impact the overall economic performance of the Institution: process optimization impacts the productivity of the system, while personnel's satisfaction is expected to negatively impact the turnover rate. The project is narrowed on elective patients, since this is the core business of Hospital Bichat (18 out of 21 rooms dedicated to elective patients).

Considerations about personnel's satisfaction will be developed in Chapter 3, while some economic considerations about Operating Theaters follow below in this chapter.

The specific focus on Operating Rooms' optimization is economically justified by its relevance on total costs. Roughly 40% of costs in Hospital Departments can be attributed to Operating Rooms Macario et al. [63].

Expenses attributed to Operating Rooms' activity are prominent. Raft et al. [79] present the cost structure of Cancer Institute of Nancy, France, (a system with 4 ORs) and find that the cost of one active OR and PACU account for €10.80/minute. Authors argue that $\approx 65\%$ of the direct costs should be attributed to wages, while $\approx 35\%$ to medications and equipment. There is thus a predominance of fixed costs over variable costs. In the UK, the median cost of Operating Theater time is £16/min, with a range between £12 and £20 per minute [105]. In the United States, Operating Rooms cost range between $22 and $133 per minute, with an average cost of $63/minute [84]. Macario [62], presumably refering to the United States, argues that the cost of Operating Rooms for basic surgical procedures ranges between $15 and $20 per minute, excluding physician costs. Costs significantly drop in less developed countries. Šárka and Michaela [89] analyze costs in a Hospital in Czech Republic and find that Operating Room costs range between €90 and €175 per operating hour. Hariharan and Chen [40] analyze the expenditures of a Hospital in Trinidad and find $92/hour in 2009.

Due to the significance of fixed costs, AP-HP (Assistance Public Hôpitaux de Paris) and ARS

(Agence Régionale De Santé) publish annual reports including performance targets and benchmarkings of French Hospitals [30]. Macario [61] proposes a list of 8 performance indicators to assess OR efficiency: excess staffing costs, start-time tardiness, case cancellation rate, PACU admission delays, contribution margin per OR hour, turnover times, prediction bias, prolonged turnovers. Out of the eight indicators, start-time tardiness, turnover times and prolongerd turnovers can be directly attributed to the need of increasing OR utilization, in order to maximize the exploitation of fixed costs.

Inefficiencies in the Operating Theater lead to major economic losses. Ang et al. [3] argue that economic losses due to process inefficiencies at Imperial College NHS Trust account for $\approx$ £$350,000$/OR/year.

In this project, stochastic discrete event simulation has been used to replicate Hospital's behavior, two similar heuristics have been proposed for resequencing surgeries within the workday, and some managerial insights have been extracted from the simulation model. A tool has been developed to facilitate the usage of simulation by Hospital's managers.

1.1 Problem Statement

Hospital Bichat presents an average utilization rate of elective Operating Rooms of $\approx 76\%$. The main reported factors affecting this value are turnover time, first case delay and PACU saturation.

Hospital managers are not able to clearly quantify the impact of the three factors over the overall time loss during the working day. A first output of the project is the quantitative assessment obtained through discrete event simulation.

In terms of performance optimization, issues related to PACU saturation and turnover time could be addressed through proper rescheduling and resource allocation. In particular, one main issue related to delays in turnaround is the limited capacity of cleaning teams. Over 14 out of 18 Operating Rooms, one cleaning team is allocated on two specific Operating Rooms. This implies that two contemporary endings make one of the two operating rooms wait for the cleaning.

Conceptually, the problem is the application of one server two to operations, so that the two operations cannot be performed simultaneously.

Figure 1.1 represents the cleaning problem as a Petri Net. t_1 and t_2 represent the end of a surgery, when the Operating Room is available for the cleaning. t_3 and t_4 represent the beginning of the cleaning. In order to fire, t_3 and t_4 require both an empty room (surgery ended) and an available cleaning team (i.e. cannot do two cleanings at the same time). t_5 and t_6 represent the end of the cleaning, and when they fire, a new token is added to P_3.

Regarding PACU, regular saturations produce blockings of the Operating Rooms, thus reducing the productivity of the Operating Theater. The Hospital seeks improvements in this field. In this case, the scheme is analogous to Figure 1.1, with 15 ORs coupled by only one server (with 14 tokens in this case).

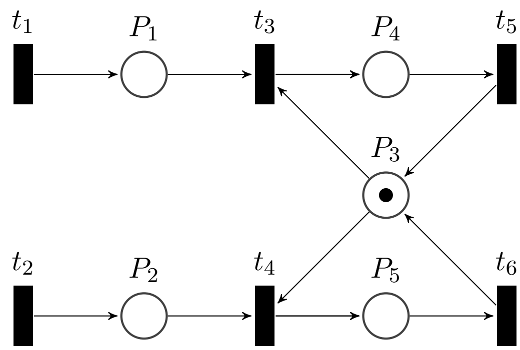


Figure 1.1: Petri Net which conceptualizes the cleaning problem

1.2 Goals of the project

The main goal of the following project is providing Hospital decision makers with managerial insights aimed at reducing the makespan of the Operating Rooms with a fixed list of surgeries to be performed. The proposed solutions should be both feasible, economically convenient, and acceptable for care givers'. For example, scheduling surgeries by increasing duration, even if it were positively affecting the simulated performance of the Operating Rooms, would not comply with general recommendations for quality of care, safety and would increase the probability of overtime, thus it would not be accepted by most professionals and would not lead to actual adoption. As the first simulation project carried out in Hospital Bichat, a second and broader scope is to create and leave to following researchers a useful starting point for future studies (see Chapter 9.4).

1.3 Use Cases

The outcome of the following project should be used by Hospital Managers both at strategic and operative level:

- Strategic level: “What-If” scenarios regarding resource allocation;
- Operative level: Scheduling “What-If” scenarios can be used to generate optimal schedules for the Operating Theater. The overall schedule of the Operating Theater is generated once per week and submitted to general consensus among Hospital professionals.

1.4 Methodology

At the beginning of the project, a Synopsis has been created in collaboration with Prof. Jouini (Full Professor of Simulation at École CentraleSupélec), Prof. Longrois (Full Professor, Practicing Anesthesiologist and Chairperson of the National Anaesthesiologists Societies Committee) and

Dr. Commagnac (IBM Global Healthcare Center of Excellence Leader). In the Synopsis, Goals, Methodology, Timeline and Participants have been defined.

In this Chapter, the Metodology of each step of the project is defined.

Literature review Literature references have been both scoped from the web and received from past collaborators of French Institutions (for Reports and Guidelines) received by French national and local Healthcare Institutions. Web researches have been carried out scoping from Scopus, INFORMS journals and papers collected by Prof. Franklin Dexter, Professor at University of Iowa, Department of Anesthesia (available at `https://www.franklindexter.net/`). In case of limited findings, researches have been extended to Google and Google Scholar.

Wellbeing and Satisfaction no partipants to the project had a background in psychology nor were qualified to carry out a rigorous scientific analysis to define factors affecting the Wellbeing in Hospital Bichat. Therefore, a literature review to verify that management and organizational issues affected the Wellbeing of the personnel has been conducted. Some informal discussions have been carried out with caregivers of Hospital Bichat and some actions have been taken in order to match their expectations. Despite the awareness that this approach does not produce scientific results (therefore the "Wellbeing" is not an outcome of the project), trying to satisfy some discussed issues can be useful for Hospital Managers.

Conceptual modeling Conceptual modeling has been performed by visits to the Hospital coupled to expert descriptions. A first validation has been carried out during the the creation, by probing respondents and receiving same information by different workers.

Validation of the conceptual model The conceptual model has been submitted to Prof. Longrois, the Hospital manager, who validated the correctness of the model.

Data analysis Literature reviews, graphical inspections and numerical analysis have been performed on received data to fit distributions. For missing data, expert opinions have been used to estimate input parameters.

Simulation modeling Simulation has been implemented on Arena V. 14.70, and integrated with Excel through VBA codes.

Validation of the simulation model Validation has been performed by comparing simulation results with historical realizations.

Chapter 2

State of the Art

The academic literature is rich of applications of simulation models, in particular discrete event simulation, to test improvements for healthcare systems.

According to Gunal and Pidd [38], the topic has experienced a consistent increase of interest during mid-2000s, when the literature throughput has almost doubled with respect to the early-2000s.

Zhang [110] collected 211 papers tackling the topic of discrete event simulation in health care. In terms of performance, the most recurring KPIs are Utilization Rate (UR), patient waiting time (mostly tackled in emergency and outpatient systems), overtime, makespan and patient throughput. AP-HP (Assistance Publique Hopitaux de Paris) in the annual report 2012 [30] reported eight indicators to be measured in the operating theaters: rate of non-exploitable interventions, rate of interventions out of catalogue, overture rate, utilization rate, overtime, rate of non-planned interventions, percentage of non-utilized time and punctuality at the opening time. According to the association, the desired performance of the operating theatres consists in an overture rate >90% and utilization rate >80%.

Agence Régionale de Santé Bretagne in a report in 2011 [17] benchmarked the performance of the Hospitals in Bretagne, considering two graphs : Utilization Rate vs. Overture Rate and Rate of Overtime vs. Utilization Rate. The desired performance is the combination of utilization rate >80%, overture rate >90% and overtime rate < 5%.

Cardoen et al. [13] collected 120 publications from 1950 to present days, dealing with planning and scheduling of operating rooms. One of the output of the review is the prominent use of discrete event simulation, especially in recent years.

Jacobson et al. [44] carried out a literature review of applications of discrete-event simulation in health care clinics. They performed a structured taxonomy and divided studies into three main blocks: patient flows and scheduling problems, resource allocation, lack of implementation. Taking inspiration from this taxonomy, the State of the Art has been divided into four main blocks:

1. Sequencing

2. Scheduling
3. Staffing
4. Simulation models to test the adoption of different technologies/configurations

According to Liu et al. [58], decision making in Hospital Management can be divided into three levels: strategic, tactical and operational level. The Operational level consists in Patient Scheduling, Tactical level in the construction of a Master Surgical Schedule, at the Strategic level the management deals with a problem of resource allocation.

2.1 Sequencing

Bai et al. [6] propose a gradient-based algorithm to sequence multiple Operating Rooms constrained by a single PACU. The objectives include waiting time reduction, idle time of the Operating Room, blocking time of the OR (due to PACU constraint), OR overtime and PACU overtime.

Zhang and Xie [111] develop a Simulation-Based optimization model to dynamically sequence surgeries in multiple operating rooms minimizing OR overtime, OR idling and surgeon waiting time, which occurs when the surgeon arrives but the OR is not available.

Pham and Klinkert [77] use a generalized job shop approach to minimize the makespan in multiple Operating Rooms sharing PACU with deterministic surgery duration and the assumption that recovery does not start until the patient enters PACU.

Mancilla and Storer [65] develop a heuristic solution based on Benders' decomposition to minimize waiting time, idle time and overtime considering stochastic surgery duration. No resource constraints are included in the model.

Robinson and Chen [83] generate a heuristic based on the structure of the optimal solution to manage the tradeoff between doctors' idle time and patient waiting time. The problem considers stochastic durations and an appointment approach for the scheduling.

Denton and Gupta [19] develop a two-stage stochastic linear program for appointment scheduling. Authors consider a single server and aim at minimizing tardiness, customer waiting time and facility idle time.

Bosch and Dietz [9] create a heuristic to minimize waiting time and overtime in a medical oppointment system, considering stochastic service duration.

Marcon et al. [66] use dicrete event simulation to study the impact of different sequencing rules on PACU and show that the best rules are those which smooth most the flow, thus Half Increase and Half Decrease, and MIX OR Time. They show that Longest Case First is detrimental for the performance of PACU.

Denton et al. [21] develop a stochastic linear programming model for the minimization of patient waiting time, facility idle time and tardiness for the sequencing of surgeries. Authors also propose the following heuristics: sequencing by increasing mean, increasing variance and increasing covariance.

Choi and Wilhelm [15] study the effect of sequencing surgeries following normal, lognormal and gamma distributions. The goal of the study is to find the optimal sequencing to minimize patient waiting time, surgeon idle time, OR idle time and staff overtime.

2.2 Scheduling

Denton et al. [22] consider a surgery-to-OR scheduling problem, assuming the complete set of surgeries to be known in advance. The goal of the scheduling heuristics is to optimize the tradeoff between fixed costs of opening individual operating rooms and total cost of overtime. Authors do not consider minimization of idle time as well as constraints to match care givers' expectations. They formulate both deterministic and stochastic models. The authors propose solutions using DORA, MRORA and SORA algorithms.

Begen and Queyranne [8] study the scheduling problem on a single processor (such as Operating Rooms) to minimize the expected underutilization and overutilization costs, in a scenario in which each job has a stochastic duration given by a discrete joint probability distribution. The system consists on a single OR with all patients arriving on schedule. Therefore, surgeries lasting less than expected produce underutilization costs, while longer surgeries produce waiting time for the patient. The authors optimize the tradeoff among underitilization, overtime and patient waiting time.

Rath et al. [82] develop a two-stage mixed-integer stochastic dynamic programming model with recourse aimed at minimizing daily expected resource usage and overtime costs. The model includes parallel resources: Anesthesiologists, Operating Rooms, Nursing Teams and equipment. The model has been fed with stochastic surgery durations.

Denton et al. [20] analyze an outpatient system in Rochester, MN, USA. The measured performance indexes are patient waiting time and overtime. Patient waiting time has been split into two indicators: waiting for intake (does not apply to inpatient systems) and waiting for surgery. The objective function has been set to a weighted average of these three indexes. Monte-Carlo simulation has been used to test two different OR allocation scenarios and a simulated annealing (SA) approach to find a schedule which minimizes the objective function.

Ozen et al. [73] apply MILP to optimize the schedule for a tradeoff among utilization levels, financial performance, overtime allowance, and case mix. Researchers neglect the effect of PACU. Authors develop a three-stage approach: 1) case mix optimization to balance Net Operating Income and Utilization, 2) maximimazion of Staged Surgeries (surgeries on the same patient conducted over multiple days) 3) determination of Surgeon Schedules.

Henderson et al. [42] carried out another project in the same outpatient system in Minnesota. The authors used Arena and stochastic surgery durations. Four heuristics have been tested: increasing mean, decreasing mean, increasing variance and increasing coefficient of variation, with the objective of minimizing patient waiting time and overtime. Both Operating Rooms and PACU beds have been considered as capacity constraints, but no human resources have been modeled.

Lamiri et al. [51] develop a column generation approach for the planning of elective surgeries over a fixed time horizon. The goal is to minimize costs associated to serving patients and operating room's utilization costs.

Díaz-López et al. [28] studied the correlation between waiting time, waiting rate and occupation rate through a simulation-optimization model for a Hospital in Bogotà, Colombia.

Dexter and Traub [26] test two different scheduling approaches: Earliest Start Time (schedule in the OR with the earliest possible time) and Latest Start Time (schedule in the OR with the latest possible start time which would allow the completion of the intervention). The researches argue that applying more sophisticated optimization algorithms would achieve little improvements despite non-intuitive solutions and the computational burden.

Wright et al. [109] show that allowing surgeons to adjust the expected duration of a surgery reduces the deviation with respect to the pure application of the software prediction.

Dexter et al. [25] studied multiple scheduling approaches to smooth PACU inflow and adjust nurse staffing. Two alternative strategies have been pointed (but not explored in the paper): time reduction of patients' stay in PACU and matching the number of PACU nurse to cope with the oscillations in the demand. Discrete event simulation with stochastic durations has been used to test the dispatching rules. Lognormal distributions have been assumed for surgery durations and PACU recovery.

Latorre-Nùnez et al. [54] developed a metaheuristic genetic algorithm for a scheduling problem, taking into account human resources, the availability of ORs, as well as PACU availability and emergency surgeries. The objective function is the makespan minimization. No constraints for quality of care and personnel satisfaction are taken into account, and the model uses deterministic durations.

Rajaram and Rath [80] applied a simulation model to UCLA Ronald Reagan Medical Center and showed that an increase in the performance of an operating theater can be better achieved by focusing on reduction in time variability than by focusing on buying medical equipment. A proposed approach to reduce time variability is detailed data collection to have better predictions.

Freeman et al. [31] combined mathematical programming and simulation to address case mix planning under uncertainty. Due to the amount of conflicting goals, the simulation did not produce a single result but a pool of solutions from which the decision maker can choose, according to the goals of the Institution of interest.

Ozkarahan [74] Ozkarahan (2000) developed a goal programming model to address idle time, overtime and satisfaction of surgeons, patients and staff. Surgeons' satisfaction has been defined as a weighted average of workload and meeting the OR preferences.

Azari-Rad et al. [5] developed a discrete event simulation model (using Simul8) on a Canadian hospital, for scheduling surgeries to test three “What-If” scenarios: scheduling earlier surgeries with low LOS, scheduling according to increasing and decreasing surgical variation and the addition of 2 beds in surgical wards. The target of the optimization was reducing cancellations. The researchers found that sequencing according to average LOS is the most effective dispatching rule for that facility.

Saadouli et al. [87] developed a MILP algorithm for scheduling, to address the issue of recovery in OR due to a fully occupied PACU, and they tested the schedule with a simulation model (implemented on Arena). Operating rooms and PACU beds are the only resources considered in the model.

Roshanaei et al. [85] extend the scheduling problem from a single Hospital to a set of collaborative Hospitals, pooling surgeons, patients and ORs. They study a patient-to-surgeon allocation problem and use a MILP algorithm to find the optimal solution. The authors conclude that Hospital can extract individual benefit from the sharing of resources.

Schmid and Doerner [91] combine a scheduling and a routing study, to achieve an optimal schedule taking into account the routing of Hospital personnel. A cooperative hybrid metaheuristic has been used for the optimization of both issues.

Liu et al. [59] propose an heuristic for Operating Rooms scheduling under an open scheduling approach. Deterministic surgery durations have been used in the formulation of the problem. The objective of the study is cost minimization, taking into account opportunity cost of underutilization and overtime cost of overutilization. Dynamic programming has been used to solve the problem.

Ta-Chung and Cheng-Che [101] develop a mixed-integer programming model for staff scheduling, taking into account Fatigue Minimization, expressed as a combination of working hours and workload, and Day Off preferences. The article is not focused on Healthcare systems, but rather general for workers on schedule (the paper tests the model on air traffic controllers).

Lin et al. [57] develop a mixed-integer programming model to study a nurse scheduling problem taking into account Hospital requirements and nurse fatigue. Fatigue is calculated based on the Dawson and Fletcher fatigue model.

Molina-Pariente et al. [70] develop a MILP model to optimize Operating Room Planning and Scheduling in a open scheduling scenario, taking into account team composition for the duration of the schedule, in terms of experience of the surgeon and of his assistant. The objective is the minimization of tardiness (difference between scheduled and actual date of surgery) and maximization of scheduled patients.

2.3 Staffing

Ghanes et al. [33] use DES to address the issue of staffing in an emergency department. Sensitivity analysis has been used to provide a picture of costs-gain of increasing human resources. Lenght of stay, costs and door-to-doctor time for urgent patients are the three considered output variables.

Komashie and Mousavi [48] applied modelled an Emergency Department with Arena, testing five different "What-If" resource scenarios, considering addition of nurses, doctors and beds. The objective was the reduction of patients' queues.

Simwita and Helgheim [95] developed a simulation model to analyze the impact of five different resource allocation scenarios. No discussion about possible improvements due to rescheduling the new scenarios has been carried out.

Lowery and Davis [60] developed a simulation model to measure the required to meet the workload. The Hospital was evaluating the opportunity of renovating a surgical suite, reducing by two the number of ORs.

Ghanes et al. [33] applied a simulation and optimization model aimed at optimizing the staffing of an emergency department close to Paris, minimizing average length of stay (LOS) and average doctor-to-doctor time (DTDT) for urgent patients.

Paoletti and Marty [75] developed a Monte Carlo stochastic simulation model to study the consequences of staffing each anesthesiologist on more than one operating room. Authors also tested the opportunity of adding a floating anesthesiologist to cover prospective emergencies. The goal of the optimization was to minimize the risk of staffing failure, namely the probability that during a surgery the presence of an anesthesiologist were required with no one immediately available.

Busby and Carter [11] study a discrete-event simulation for Emergency Departments, taking surge into account. Tested "What-If" scenarios include both resource allocation and scheduling. The goal is to support decision-makers with a decision aid tool, to properly choose policies in order to match desired requirements, among which OR utilization, overtime, undertime, number of used beds, patient throughput and patient waiting time.

2.4 Adoption of new equipment and configurations

Asamoah et al. [4] made use of discrete event simulation on an outpatient scenario to test a prospective application of RFID tracking devices on patients to gather real-time information of their position and estimate queues on each department.

Koppk et al. [49] propose an integer linear programming optimization algorithm to address the problem of allocating operating hours to operating rooms, considering the uncertainty of surgery durations. The objective is to find an allocation configuration which maximizes the probability of a perfect day, i.e. the probability to end all planned surgeries without cancellations and without overtime.

Ruiz-Patiño et al. [86] perform an analysis to evaluate the congestion due to PACU and perform a sensitivity analysis to assess the congestion varying the number of available beds. They also perform a rough cost estimation and argue that the investment in 2 additional PACU beds would be justified.

Chan et al. [14] use discrete-event simulation to test different layout scenarios of the Operating Room, in order to minimize the duration of the surgery. The goal and the methodology differ from this project, it is a different application of DES, aimed at optimizing the time performance of the Operating Theater.

2.5 Contribution

2.5.1 Research

The research contribution of this project is twofold. First, some constraints related to caregivers' satisfaction have been incorporated in the model. Insights coming from informal interviews with patients in the Hospital have been compared and validated with the literature in Chapter 3.

Second, the issue of limited resources to begin surgeries has been considered. Specifically, limited turnover teams and limited anesthesiologists (required to be in the Operating Room during anesthesia induction) have been included. To the best of literature research, no research paper has tackled the issue of contemporary beginning of anesthesia induction in different Operating Rooms. With regards to turnover teams, Dexter et al. [24] performs a sensitivity analysis of turnover time with respect to the number of staffed turnover teams. Interventions performed in four months of Hospital activity have been extracted from the dataset. Surgery durations have been considered determistic (equal to the realized value). Gul [37] develops a stochastic program and a heuristic to improve appointment scheduling with limited turnover teams. The author considers, as in this project, that operations cannot be moved from one OR to another and that the list of surgeries is a constraint of the model. The author does not include a simulation model to test the goodness of the results with respect to other resources (such as PACU availability), and considers that the sequence of surgeries is constrained. He studies only how to set the optimal appoimtment time to minimize surgeon's idle time and patient's waiting time. For the case in Bichat, patients are hospitalized one day before surgery takes place, thus there is no need to deal with appointments. Conversely, since patients, at the beginning of the day, are all waiting in Hospital Wards, it is possible and meaningful, to optimize the sequence of surgeries.

2.5.2 Hospital management

The value proposition for the Hospital lies in the improved transparency and quantitative assessment of Hospital's wasted time (where it comes from and how much for each category), as well as in managerial insights to improve the scheduling and rearranging turnover teams to improve performance and meet caregivers' satisfaction.

Chapter 3

Wellbeing

3.1 Introduction

Prof. Longrois, the head of Anesthesia in Hospital Bichat, pointed that lack of Wellbeing and burnout negatively impact the performance of the Operating Theater. Lack of Wellbeing directly impacts productivity, and it also leads to high turnover rates, with newcomers typically less productive than established personnel. Low performance of the Operating Theater attracts less investments from national funds, which are distributed proportionally to the efficiency of the hospitals. With low funds, the hospital struggles to improve its structures, which are one of the drivers of absence of Wellbeing, thus feeding the vicious circle of malaise and suboptimal performance.

Furthermore, Prof. Longrois pointed that the current French system exhibits a lack of Anesthesiologists. To his saying, when Hospital Bichat opens job positions for Anesthesiologists, no candidates apply and the recruitment is burdenous. This statement is supported by the WFSA (World Federation of Societies of Anesthesiologists) statistics: in France there are 15.06 Anesthesiologists per 100,000 citizens, against 25.92 in Italy, 30.92 in Germany and 17.85 in the United Kingdom [72]. Furthermore, as reported by the 2017 annual report of the Ordre National des Medecins, Île-de-France is a low density region in France in terms of Anesthesiologists [45]. As reported by Pontone et al. [78], in 2019 the demography of French Anesthesiologists is expected to be favorable, except for Île-de-France, where a further deficit of Anesthesiologists is expected.

3.2 Key Players

The objective of the project is to take into consideration the wellbeing of all caregivers involved in the operating theater, which are the following ones:

- Surgeons
- Anesthesiologists

- Nurses: Anesthesia nurses, OR nurses, PACU nurses
- “Brancardiers” (transportation staff)
- Cleaning teams

PACU nurses work on a fixed schedule, with predetermined tasks and always in the same room. Their Wellbeing has thus been neglected by the model, not for poor consideration of this professional category, but for the awareness that a DES model would be completely inappropriate to capture its Wellbeing.

Transportation staff carries out his tasks in the whole hospital, hence it would not be meaningful to model its Wellbeing, since the DES model includes only the Operating Theater.

3.3 Drivers of wellbeing and burnout found in the literature

No specific literature has been found about the wellbeing of Hospital Cleaners.

Therefore, in terms of wellbeing, Hospital personnel has been divided in three key categories:

- Surgeons
- Anesthesiologists
- Nurses

Anesthesia nurses and OR nurses have been tackled as a single category since their national contracts do not differ significantly and, from a DES perspective, they perform similar tasks (though they have distinct roles in the real system).

Examining the literature, both general and professional specific drivers have been found.

3.3.1 Surgeons

About surgeons, several stressors are described in the literature. Due to the extremely vast amount of stressors, only the main categories have been reported.

Stressors:

1. Work-life interaction [34, 12, 88]
2. Night calls [34, 93]
3. Workload [34, 93, 12, 88, 81]
4. Financial conditions of the Hospital [88]

5. Relationship with colleagues [36]
6. Communication with patients [36]

Table 3.1: Scientific papers which tackle the six stressors of surgeons

Source	1	2	3	4	5	6
Gifford et al. (2014) [34]	T	T	T			
Cambpell et al. (2001) [12]	T		T			
Saleh et al. (2007) [88]	T		T	T		
Rama-Maceriras et al. (2012) [81]			T			
Shanafelt et al. (2009) [93]		T	T			
Guest et al. (2011) [36]					T	T

3.3.2 Anesthesiologists

Stressors:

1. Workload [46, 32, 56, 52, 106]
2. Night calls [64]
3. Sense of responsibility [53, 108]
4. Surgeons do not respect anesthesiologists [53, 46]
5. Ethical issues [53]
6. Politics and administration [108, 46]
7. Remuneration [46, 106]
8. Clinical problems [81, 56]
9. Variability of workload [56]
10. Overtime and interference with family life [106]

Wellbeing:

1. Control over the job [71]
2. Physician-patient relationship [108, 46]
3. Clinical outcomes [108, 46]
4. Predictability of the workday [27]

Table 3.2: Scientific papers which tackle the nine stressors of anesthesiologists

Source	1	2	3	4	5	6	7	8	9	10
Larrsson et al. (2005)[53]			T	T	T					
Rama-Maceiras et al. (2012) [81]								T		
Lederer et al. (2005) [56]	T							T	T	
Larrsson et al. (2010) [52]	T									
Malberg et al. (2007) [64]		T								
A. Wong (2011) [108]			T			T				
Jenkins et al. (2001) [46]	T			T		T	T			
Gaba et al. (1994) [32]	T									
Wang et al. (2015) [106]	T						T			T

Table 3.3: Scientific papers which tackle the six stressors of surgeons

Source	1	2	3	4
Nyssen et al. (2003) [71]	T			
A. Wong. (2011) [108]		T	T	
Jenkins et al. (2001) [46]		T	T	
Dunn et al. (2007) [27]				T

3.3.3 Nurses

Stressors:

1. Workload [102, 47, 16]
2. Time Pressure [18]
3. Conflicts with physicians and other nurses [102]
4. Fear of mistakes sense of responsibility [102]
5. Lack of respect and recognition [47]
6. Lack of support from the management [102, 47]

Table 3.4: Scientific papers which tackle the six stressors of surgeons

Source	1	2	3	4	5	6
Tyler et al. (1992) [102]	T		T	T		T
Khowaja et al. (2005) [47]	T				T	T
Chou et al. (2012) [16]	T					
Durawad et al. (2015) [18]		T				

Wellbeing:

1. Quality of care [103]
2. Supportive management [103]

3.4 Outcome of informal discussions

The topic of stressors and drivers of satisfaction has been informally discussed with 5 different caregivers, three Anesthesiologists, one Anesthesia Nurse and one OR nurse. As mentioned in the Methodology, there is no scientific outcome but some useful actions can be taken to meet the expectations.

The following issues have been tackled:

- **Overtime:** conflicting opinions have been received about this issue. Overtime has been pointed to be a minor issue for caregivers who live alone, while it is perceived more negatively when it conflicts with family life. This aspect has been pointed in the literature too (see above). In order to reduce the probability of Overtime and increase the probability of cancellation, surgeries are typically scheduled by decreasing expected duration (but rarely executed in this order).
- **Specialy allocation:** some specialties require more workload than others. No conflicting opinions have been gathered. Unfortunately, specialty allocation is out of the scope of this project, so no actions can be taken to face this problem.
- **Schedule disruptions:** schedule disruptions have been reported to occur both at the very beginning of the day and during the workday. Since schedules are regularly discussed and approved by consensus, disruptions are negatively perceived.
- **Waiting time:** blocking conditions have been reported to negatively impact the satisfaction, because they lead to overtime and because care givers are disappointed when some resources are missing and operations cannot start (e.g. waiting for the cleaning, waiting for a free bed in PACU, waiting for the patient)

Chapter 4

Conceptual Model

4.1 Quick Overview

The conceptual model of the system can be quickly visualized as a four block discrete system:

- Preoperative block: all activities preceding the surgery: patient moved from hospital wards to the operating room and preparation of the patient for the surgery.
- Perioperative block: Anesthesia Induction e Surgical Act. The value adding activities of the system.
- Postoperative block: patients can be either discharged to PACU (standard case) or brought to the Reanimation Room (standard process for Chirurgie Cardiologique, it follows complications for other surgeries).
- Cleaning/Turnover: mandatory activities to be carried out between to consecutive surgeries.

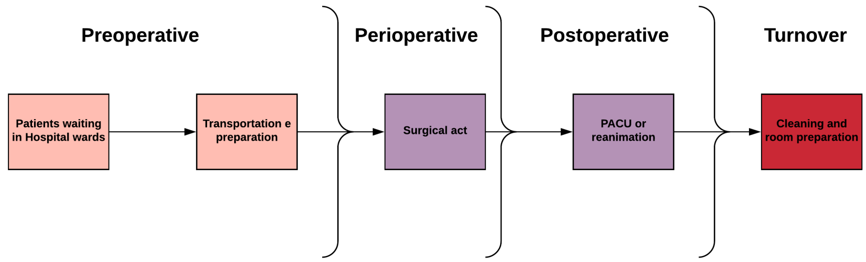


Figure 4.1: Quick graphical overview of the system

4.2 Detailed description

The operating theater of interest treats elective inpatients, i.e. patients with scheduled surgeries and mandatory hospitalization. Hospitalization occurs one day before the surgery, thus at opening time patients are waiting in Hospital Wards.

For each OR, the first patient of the day has a scheduled arrival (he is supposed to be there at the opening of the OR), while following patients come on call. This is due to the variability of surgeries' duration: the end of a surgeries is unknown in advance, hence patients are called when the OR is about to be available. The call is performed by a nurse who should anticipate the end of the operations of the OR in order to make sure the following patient arrives before the OR is available and avoid delays due to the late arrival of the patient. At the same time, as it has been reported by an Anesthesiologist of the Hospital, the call cannot be performed too much in advance. A long wait in front of the Operating Room might results in anxiety of the patient, which may complicate the beginning of the Anesthesia Induction. As reported by a respondent in the Hospital, there are frequent deviation from this ideal scenario: nurses may not be available to call the Hospital Wards before the end of the surgery in case of intense workload or may forget to call in advance.

"Brancardage" (transportation personnel) is entitled to move patients around the Operating Theater (OT). In particular, "Brancardiers"" are required to move patients from Hospital Wards to the the Operating Theater. Brancardiers are currently not specifically allocated to the OT, but they perform activities across the whole Hospital.

Anesthesia Induction is performed after the preparation of the patient and involves one Anesthesiologist and one Anesthesia Nurse. One Anesthesiologist can work on two Operating Rooms at the same time (except for Anesthesia Induction activities, when the presence of an Anesthesiologist is required by law), while one Anesthesia Nurse is always required for each OR. If the Anesthesia Nurse is absent, the intervention cannot start. Prof. Longrois suggested that an average of 1.2 anesthesia nurses should be available on each room, so that pauses and absence can be covered by the redundant nurses.

During the extent of the surgery, complications may arise, which lead to the involvement of the Intensive Care Unit (ICU). ICU involvement is a standard protocol for some types of surgeries (mainly for Cardiologic interventions). "Brancardiers"" are in charge to move the patient from the Operating Room to ICU. Patients moved to ICU are excluded from the flow of PACU, they will recover in ICU and will be differently reintroduced in the system according to the specific case. During surgeries, cleaning teams may be used for missions out of the OR (e.g. bringing blood samples to the laboratory).

After each surgery, if ICU is not required, patients are moved to PACU by "Brancardiers" (if "Brancardiers" are not available, other professionals takeover this task), for their post-anesthesia recovery. In PACU, there are 14 beds available, but some of them can be used for ICU, when it is not able to fulfill its demand. Specialized nurses work in PACU, they are not modeled because they do not participate in the processes of the Operating Theatre. PACU nurses cannot be a blocking resource because they are able to manage PACU at full capacity. Moreover, they always work in PACU, which is always utilized (with different rates), hence there is no sharp distinction busy/idle. From a discrete event perspective, there is no way to model this type of resource. If PACU is full, post-anesthesia recovery takes place in the OR, with the assistance of one Anesthesia Team. During periods of PACU full saturation, the recovery is sped up. By expert judgment, 25-30% has been pointed out as a reasonable decrease of PACU hospitalization.

By national regulation, an Anesthesiologist has to sign a document to allow the dismissal of a patient. After the signature of the Anesthesiologist, PACU nurses call the “Brancardage”. The patient waits for the “Brancardiers” in PACU and the dismissal from the Operating Theater is carried out right upon arrival.

After the end of the surgery, cleaning procedures take place. Cleaning teams are in charge of cleaning operations. There is typically one cleaning team assigned to two different ORs. Currently, cleaning teams are not flexible, they are working on the ORs they have been assigned to.

After the cleaning, OR nurses procure instrumentations for the following surgery, and the OR is available again. Since only elective patients are treated by this project (no urgencies, no emergencies), recorded rates of mortality are very low, to the point that they have been neglected because they would not significantly impact the performance of the operating theatre and the wellbeing of the personnel.

The full picture of the conceptual model (for one operating room) has been attached to Appendix A.

4.3 Scheduling Approach

Two main scheduling approaches are generally adopted in Hospitals [22]:

- *block-booking*: the Hospital provides the surgeon with time slots for surgeries who plans surgeries by filling the available slots. Surgeons directly provide patients with a date of surgery. This approach is more straightforward and convenient for the patient, who immediately receives a slot for the surgery, but it is suboptimal in terms of performance because it does not allow for a case-mix optimization of the schedule. The list of surgery is a fixed input data to the system.

- *open-booking*: surgeons submit cases which are pooled by the system. Surgeries are then allocated to ORs to create a schedule. This approach is more effective to improve the performance, because surgeries can be allocated to ORs with large degrees of freedom.

Hospital Bichat works with a block-booking policy. The reason of this policy has been pointed by Prof. Longrois: in France, and in particular in Île-de-France, there is more capacity then demand, thus there are no significant waiting lists for elective surgeries.

Waiting lists in France is a controversial and discussed topic. The OECD/EU report of 2016 [1], points that waiting time is not considered an important policy issue for France, Germany, Belgium and Germany. There are no records about waiting times for these countries.

Siciliani and Hurst [94] show that countries which do not record waiting times exhibit higher capacity than the other countries, in terms of public expenditures on Healthcare, acute care beds over 1000 inhabitants and number of physician over 1000 inhabitants. The combination of free access to private beds under public health insurance and incentives for specialists are pointed as additional reasons for minimal waiting lists in France. To quote the article: *The health system in France is regarded as delivering high quality services, with freedom of choice and generally no waiting lists for treatments*.

4.4 Assumptions document

The goal of simulation (opposed to analytical procedures) is to reduce the number of assumptions and to capture as much as possible the proper functioning of the real system. Due to some non-transparencies in the real system and to its inherent complexity, some simplifying assumptions have been placed on top of the simulation model. The use of a written and well defined assumptions document has been recommended by Law [55].Below the list of assumptions:

1. Anesthesiologists, anesthesia nurses and OR nurses are 100% flexible. Anyone can work in any room with any team mates. According to Prof. Longrois, the real system is slightly more rigid, flexibility is judged to be around 80%. Nevertheless, flexibility within the Operating Theatre is a prominent trend. According to Peltokorpi [76], personnel flexibility can be hypothesized to be a source of increased productivity;

2. Surgeons are perfectly rigid and they do not introduce any constraint to the system;

3. Except for a delay at the beginning of the day, all scheduled human resources are always available;

4. Surgeries follow the scheduled sequence. This is the most restrictive assumption, since it is clear that the real system is currently unable to stick to a predefined plan. This is due to the rare disruptions caused by urgent patients coming to the Hospital, complication with patients and resource availability. With the current data measured by the Hospital it is not possible to predict how and when disruptions occur, thus this assumptions is constrained by the transparency of the current system. An intuitive method to overcome this limitation is to introduce dynamic tracking systems to dynamically reschedule after the occurrence of unexpected disruptions;

5. No emergency case disrupts the schedule. This assumption is now valid because in July 2018 the Hospital has opened one OR fully dedicated to emergency cases. Thanks to this room, the disruption of the schedule due to emergencies should be, according to the opinion of Prof. Longrois, absolutely negligible.

6. No cancellation policies have been included in the model. This implies that the system measures the makespan of all active Operating Rooms with no cancellations.

7. Couples of parallel Operating Rooms do not change over time (THO1 and THO2 together, URO1 and URO2 together, etc.)

8. Surgery durations are sequence and time independent. It is likely to find correlations between surgery durations and the schedule (e.g. a long surgery in the morning is unlikely to require the same time in the afternoon). This assumption has been introduced due to the partially transparent data set received from the Hospital and to lack of time for performing additional analysis.

Chapter 5

Arena Model

The simulation model has been implemented on Arena, commercial software developed and licensed by Rockwell Automation. The presented model has been implemented on version 14.70.

For the sake of clarity, the description of the model has been divided in subsections:

1. Structure of the model: description of the blocks and interactions among them;

2. Resources and Variables: resources involved and how variables affect the simulation.

5.1 Structure of the model

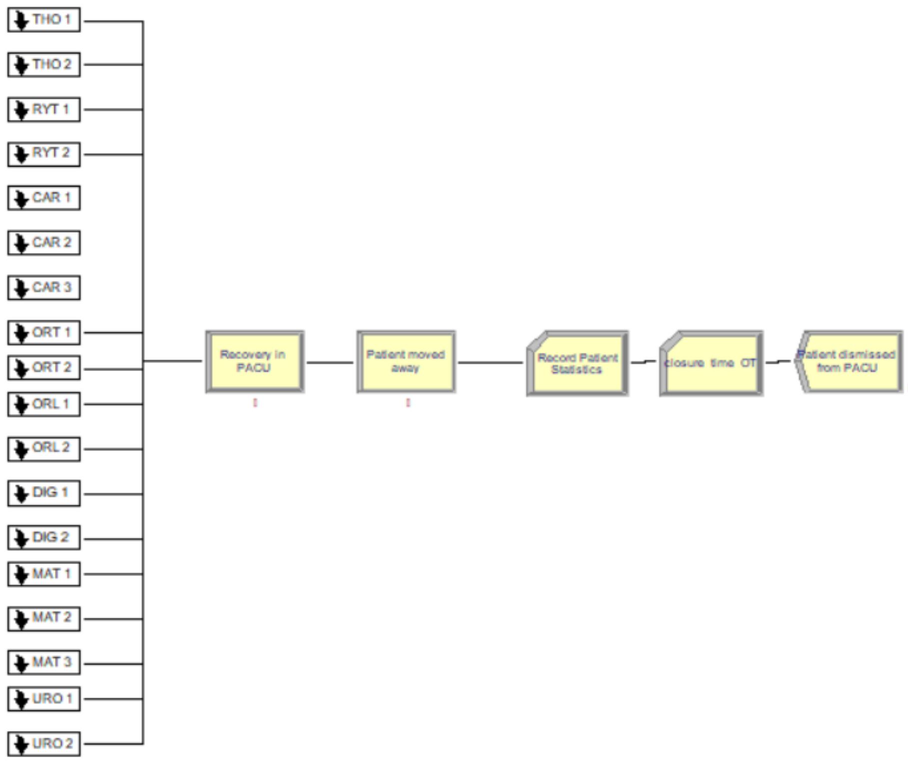


Figure 5.1: Overall overview of the Arena Model

As shown in Figure 5.1, the model can be conceptually divided into two main parts:

1. Preoperative and perioperative activities, which involve one specific OR for each patient
2. Post Anesthesia Recovery, which accounts for a single branch for all patients. When a patient gets to PACU (Post Anesthesia Care Unit), the following steps are independent on the type of his surgery

The procedures of each OR are standardized, thus each main Submodel follows the same structure, with some different names of the blocks and slightly different resources involved (See Section 6).

Hence, the structure of only one OR will be discussed in the following paragraphs. The room on top of the model has been chosen: THO 1, which stands for "Chirurgie Thoracique (Thoracic Surgery) Room 1". The reader can easily deduce the scheme of the other rooms.

Expanding the submodel, the picture is an almost straight flow chart, inclusive of other submodels. See Figure 5.2. The chart can be conceptually divided into six regions:

1. Creation of the patient
2. Transportation to the operating room
3. Anesthesia and surgery
4. ICU (Intensive Care Unit)
5. Turnover activities
6. Postanesthesia procedures

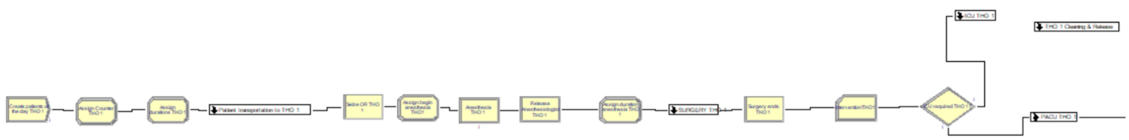


Figure 5.2: The overall flow of a operating room

5.1.1 Creation of the patient

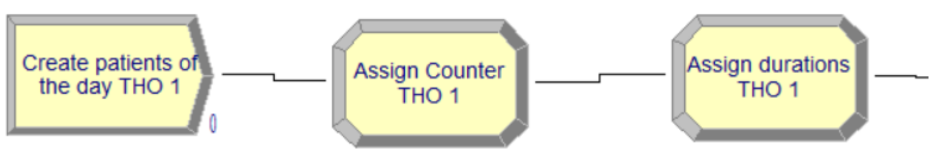


Figure 5.3: Blocks which model patient creations

In the first block, all patients are created at the same time at the beginning of the day. Since the OT treats elective patients, all patients are scheduled and the list of patients is thus known before the beginning of the activities (how Arena loads the daily schedule is presented Section 5.3, where the integration with Excel has been explained in details).

In the second block, a counter (global variable) is updated. The goal of this variable is to provide a real time information about the number of patients present in the system. It is used to identify the serial number of the patient in the following block as well as to allow for a check that the simulation model loads the correct number of patients.

The third block assigns to each patient its attributes. Precisely, it assigns:

- The Anesthesia Module of the surgery, which can be short, medium or long. This attribute affects the duration of the Anesthesia Process.

- Cleaning module: since in general different surgeries require different cleaning time, each patient carries out an attribute with the duration of the cleaning
- Patient ID. In the previous block a global variable has been used as a counter, here an ID is assigned to each patient so that he can be tracked and recognized if necessary
- Class of surgery: frequent, infrequent, rare. This attributes determines the distribution for surgery duration (see Data Analysis Chapter)
- Surgery duration: for frequent surgeries,mean and sigma to feed the lognormal distribution. For infrequent and rare interventions, minimum, average and maximum of the triangular distribution
- PACU length of stay: mean and sigma to feed the lognormal distribution
- ICU Scheduled. This attribute states if a patient has been scheduled to recover in the ICU after the surgery or he will follow the standard procedure

5.1.2 Patient transportation

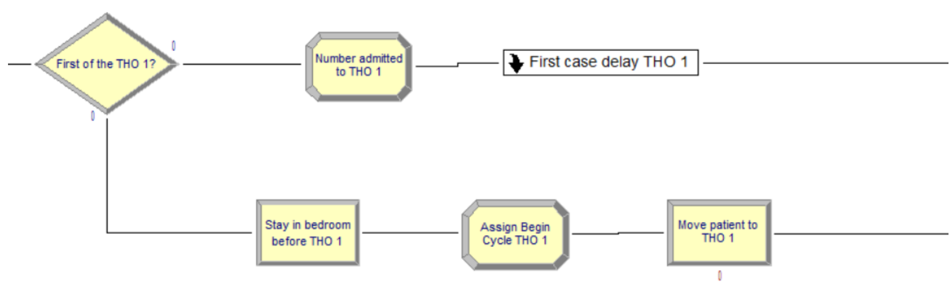


Figure 5.4: Transportation from hospital wards to the operating room

The first decide block is used to differentiate the first patient of the day from the others (the first one is scheduled to arrive in the OR at the beginning of the day, the following ones are called when the surgery is about to end). After the first patient, a global variable is updated in the following Assign Block and all patients will follow the lower branch.

For the first patient, a delay block is added to take into account that activities do not always begin on time at the beginning of the day.

In the lower branch, the first block is a Hold. It is used to model the following patients of the day who are waiting in Hospital Wards. The signal to release one patient is given later in the chart when the previous patient leaves the OR.

In the following block an attribute is assigned to print on each patient the time his surgery cycle begins.

The last block of the lower branch is used to model the actual transportation of the patient from Hospital wards to the Operating Theater. This activity is performed by “Brancardiers”, specialized professionals who are in charge of moving patients within different sections of the Hospital.

5.1.3 Anesthesia and Surgery

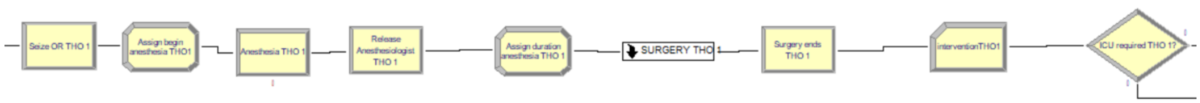


Figure 5.5: Transportation from hospital wards to the operating room

Seize OR THO 1 The seized resources are the following ones:

- OR: anesthesia occurs in the OR, so the availability of the operating room is strictly required
- Anesthesia nurse: one anesthesia nurse is required to assist the patient from the beginning of anesthesia to the end of the surgery. Without an anesthesia nurse available in the OR, no surgery can begin
- Anesthesiologist: the presence of an anesthesiologist is required for the beginning of anesthesia. Even if an anesthesiologist can monitor two ORs at the same time, he must be fully allocated to one patient to put him to sleep (mandatory by law).

Assign Anesthesia Begin THO 1 At the beginning of the surgical act, a time attribute is assigned to the patient to record the beginning of the anesthesia.

Anesthesia THO 1 This block has been placed to decouple Surgery and Anesthesia Induction. It is a delay process and the duration of the delay follows a triangular distribution whose parameters have been assigned at the very beginning.

Release Anesthesiologist THO 1 The anesthesiologist is released. In reality, Anesthesiologists are not idle after the end of anesthesia induction, but the induction is the only moment when full allocation of one Anesthesiologist to an Operating Room is required (crisis excluded, not modelled in this project). After the induction, Anesthesiologists can work on two Operating Rooms at the same time.

Assign Duration Anesthesia THO 1 The following block measures the duration of Anesthesia Induction and attributes it to the patient.

Surgery The splitting of surgery classes is shown in Figure 5.6. Frequent surgeries follow the upper branch, while unfrequent and rare types of surgeries are directed to the second branch. In both cases, a surgeon is seized to perform the intervention. Since the analyzed data refer to $Patient_{OUT} - Patient_{IN}$, the duration of Anesthesia induction has been subtracted to the delay of these blocks.

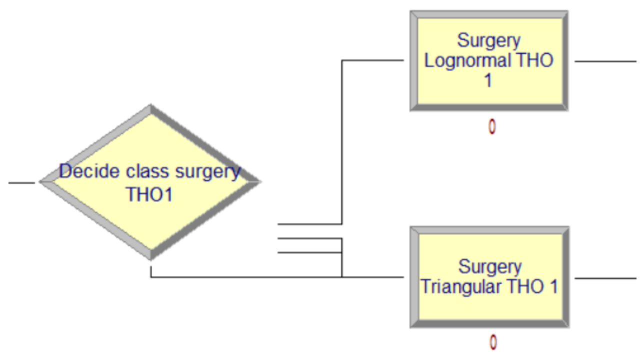


Figure 5.6: Distinction between frequent, unfrequent and rare surgeries

Surgery ends THO 1 Release module. The surgeon is released after the end of the surgery

Record intervention duration THO 1 This module is used to record the time between the first assign of this section (begin of anesthesia induction) and the end of the surgery.

ICU required THO 1 Decide block to differentiate patients with a scheduled ICU recovery.

5.1.4 ICU

This section of the model is reserved to patients who need recovery in the ICU. The chart is shown in Figure 5.7.

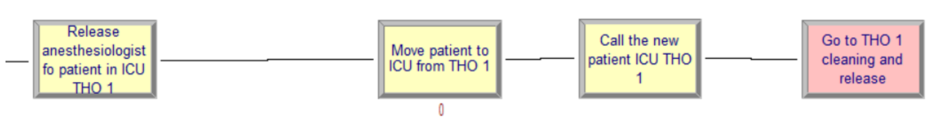


Figure 5.7: Flow in the ICU

Release anesthesiologist for patient in the ICU THO 1 After the patient leaves the OR to go to ICU, the anesthesia team is released. The anesthesia nurse who has been seized at the beginning of anesthesia induction and not yet released is now available for a new surgery. The anesthesiologist has been already released after the first part of anesthesia.

Move patient to ICU from THO 1 The transportation to ICU requires some time, which has to take into account some preparatory and mandatory procedures before the patient can leave the OR.

Call the new patient ICU THO 1 Signal block. When the patient leaves the OR the new one is called. A signal is given to the Hold block described in section 5.1.2 and the transportation of the new patient begins.

Go to THO 1 cleaning and release Route block. The entity goes to the first station of the cleaning and cleaning activities begin.

5.1.5 Cleaning of the operating room

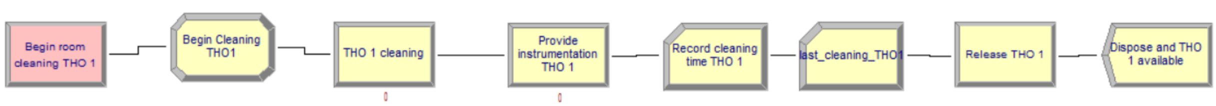


Figure 5.8: Turnover activities

Begin room cleaning THO 1 Station block. It collects dummy entities coming from other parts of the graph which state the beginning of the cleaning activities.

Begin cleaning THO 1 Assign Module to attribute the beginning of the cleaning.

THO 1 cleaning It is a Seize-Delay-Release block. The seized and released resource is a cleaning team. The duration of the delay follows a triangular distribution. Expert judgment used to define the parameters.

Provide instrumentation THO 1 It is another Seize-Delay-Release block. This time the seized and released resource is an OR nurse who has to procure the sterile instrumentation for the new surgery. This activity can clearly be performed only after the end of the cleaning and sterilization of the OR.

Record cleaning time THO 1 Record block used to measure the time required to clean the operating room (queues due to unavailability of resources are included in this measure).

Release THO 1 Once the room is clean and the sterile instrumentation has been procured, the Operating Room is available for a new surgery and it is thus released in this block.

Dispose and THO 1 available Dispose block for the dummy entity flowing in this submodel.

5.1.6 PACU

All patients who do not need a ICU hospitalization must go to PACU (Post Anesthesia Care Unit) to recover from Anesthesia. The chart is displayed in Figure 5.9

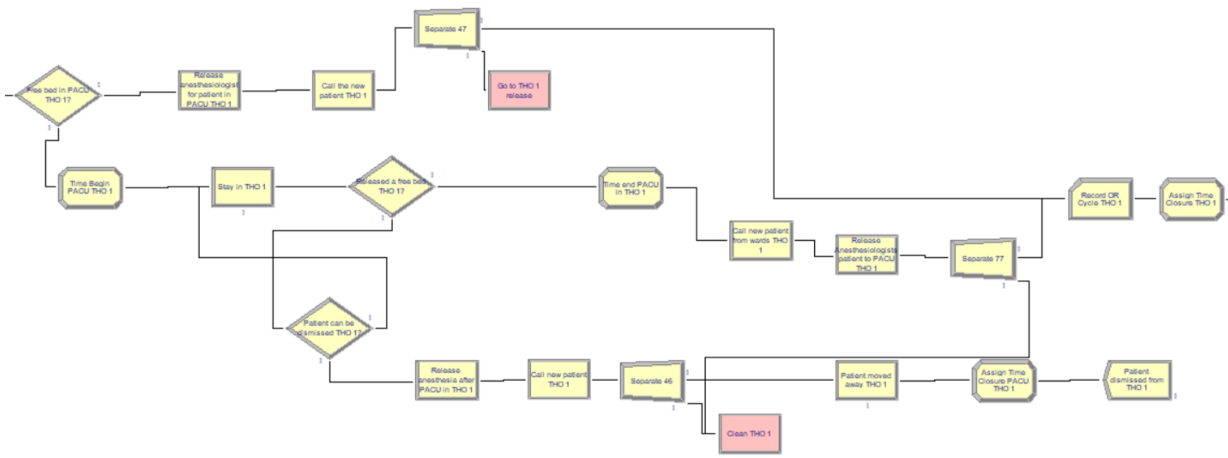


Figure 5.9: Submodel describing flows related to PACU

Free bed PACU THO 1 Decide block used to check and differentiate the route based on the availability of beds in PACU. If at the end of a surgery no bed is free, the patient cannot go to PACU and he has to stay in the OR, otherwise he can be moved to PACU.

Release anesthesiologist for patient in PACU THO 1 Release block. If PACU is free, one Anesthesia Nurse is released as the patient leaves the Operating Room.

Call the new patient THO 1 Once the OR is free, a signal is given to release one patient held in the hospital wards.

Separate It is a Separate block used to generate a dummy entity which flows in the cleaning submodel (Section 5.1.5). The other one (actual patient) proceeds in its journey.

Go to THO 1 Release Route block to move the dummy entity to the cleaning submodel. Since the OR is now empty, cleaning activities can begin.

Time Begin PACU THO 1 In case there is no free bed in PACU, a first Assign follows the Decide block to attribute to the patient the beginning time of Post Anesthesia recovery in the OR.

Stay in THO 1 Delay block to model the frequency of check of beds availability in PACU. Communications occur via telephone, but there is no continuous update of the availability, hence this discrete step has been introduced.

Assign time closure PACU THO1 This assign block overwrites a global variable to measure the makespan of the considered Operating Room.

Patient can be dismissed THO 1 A decide module to check whether the patient has been recovering enough to be dismissed or needs more time of Post Anesthesia recovery.

Release anesthesia after PACU in THO 1 If the patient can be dismissed an Anesthesia team is released in this block. The patient can leave the OT and the Anesthesia nurse is available for the a new surgery.

Call new patient THO 1 A Signal is given to release a new patient from the Hold block described in Section 5.1.2. After the patient is moved from the OR, a new one can be called.

Separate This Separate block is used to create a dummy entity which will flow in the cleaning submodel.

Clean THO 1 Route block to move the dummy entity to the cleaning submodel.

Patient moved away THO 1 It is a Seize-Delay-Release block. One “Brancardage”” team is seized and released and the delay is given by a normal distribution whose parameters have been derived by expert interviews

Released a free bed THO 1 After the decide block Patient can be dismissed, if the patient cannot be dismissed yet, a check whether there is a free bed in PACU is performed via phone (the frequency of call has been modeled in the Delay block Stay in THO 1). If there is no free bed, the patient goes back to Stay in THO 1 where he will wait for a new check of possibility of dismissal and availability of a PACU bed. If a bed got available, the patient leaves the room and proceeds the rest of his Post Anesthesia recovery in PACU.

Time end PACU in THO 1 This module assigns to the patient the time spent in the room which he should have spent in PACU.

Release Anesthesiologists patient to PACU THO 1 Since the patient can leave the OR, one Anesthesia Nurse is released.

Record OR Cycle THO 1 This block records the total time a patient has spent to complete the full surgery cycle (from the call in the Hospital wards to the beginning of his recovery in PACU). Note that those who completed the full recovery in the OR (highly unlikely case) are excluded from this calculation as well as those patients who move to ICU. In case a partial Post Anesthesia recovery occurs in the OR, it is included in this record.

Assign time closure THO1 Similarly to the previous assign block, this block overwrites a global variable to measure the makespan. It is place on the second possible branch that the patient can follow.

5.1.7 PACU recovery and dismissal

Going back to the Main Model, there are the last five blocks which describe the recovery in PACU and the dismissal

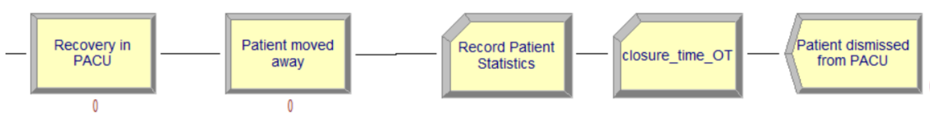


Figure 5.10: Part of the model in which all patients converge to PACU, complete their recovery and get disposed

Recovery in PACU This Seize-Delay-Release block collects all patients coming from all the ORs in the OT. The seized resource is a PACU bed and the delay follows a lognormal distribution whose parameters have been analyzed in Section 6.

Patient moved away At the end of the PACU recovery a “Brancardage”” team is called by a PACU nurse. This block is thus a Seize-Delay-Relase whose seized and release resource is a “Brancardage”” team. The delay has been derived from expert judgment.

Closure time OT A global variable is updated each time a patient leaves the system from this branch. When the last one leaves the system, the replication terminates and the last value assigned by this block represents the OT makespan.

Patient dismissal from PACU The patient is finally dismissed from the OT, thus the entity is eventually disposed.

5.2 Resources

The modeled resources are the following ones:

Human resources:

1. Surgeons
2. Anesthesiologists
3. Anesthesia nurses
4. OR nurses
5. Cleaning teams
6. "Brancardiers"

Medical equipment:

1. Operating Rooms
2. PACU beds

5.2.1 Surgeons

Surgeons are specialized professionals and have been modeled to work only in one Operating Room (this implies that each OR seizes a different resource). Since each surgeon appears only in one OR and in a single branch, there is no way this resource can block the system. The resource has been introduced only to measure the utilization rate, which impacts the wellbeing of the professional. Each type of surgeons is a different resource with a fixed capacity equal to 1.

5.2.2 Anesthesiologists

Considering the real system, Anesthesiologists work on two different ORs at the same time except for complications with the patient and for the beginning of the Anesthesia, when an Anesthesiologist is required to be present. Anesthesiologists can be thus a blocking state only if two surgeries are beginning at the same time (it occurs every day at opening time).

Generally, the number of Anesthesiologists varies between morning and afternoon. For the sake of completeness and to provide more flexibility for future scopes, the schedule has been created from 8:00 to 20:00 with a step of 30 minutes (it is possible to define a different number of Anesthesiologists on each block of 30 minutes).

5.2.3 Anesthesia nurses

One anesthesia nurse has to be present during the whole surgery. No surgery starts without an Anesthesia Nurse. In case an Anesthesia Nurse has to be absent for a period during a surgery, another nurse has to replace him, or an Anesthesiologist has to look for the patient. This is a sub-optimal situation for the safety of the patient because, since an Anesthesiologist has to monitor two rooms at the same time, if in the other room a complication occurs, some problems arise. A patient cannot be left (by law) without a nurse or an anesthesiologist so the anesthesiologist cannot leave the room to deal with the complication until a stopgap is provided.

Anesthesia nurses are granted a lunch break to be (generally) spent between 12:00 and 14:00. The duration of the lunch break is approximately 40 minutes.

Between 12:00 and 14:00 the number of anesthesia nurses dramatically decreases and it is unlikely that any surgery can begin.

The structure of the schedule is analogous to the one of anesthesiologists.

5.2.4 Cleaning teams

Cleaning teams have been allocated in the following way:

- Team 1: THO1 and THO2
- Team 2: RYT1 and RYT2
- Team 3: CAR1
- Team 4: CAR2
- Team 5: CAR3
- Team 6: ORT1 and ORT2
- Team 7: ORL1 and ORL2
- Team 8: DIG1 and DIG2
- Team 9: MAT1 and MAT2

- Team 10: MAT3
- Team 11: URO1 and URO2

5.2.5 Global Variables

Global variables are both referred to the whole OT (instead of being specific for one operating room or a surgery case) and without a schedule. Global variables include:

- Number of PACU beds
- Mean and sigma of PACU duration
- Durations and probability of first case delays
- Parameters for the cleaning
- Frequency of check of PACU availability (in case of congestion)
- Mean and sigma transportation to ICU
- Mean and sigma dismissal from PACU

5.3 Implementation issues

Before presenting the integration between Arena and Excel, some considerations should be discussed.

Prof. Longrois, at the very beginning of the project (before the writing of the synopsis), pointed that several research projects have been carried out with the Academia, resulting in a ”waste of time” for the Hospital, because of lack of implementation. This statement was not aimed at criticizing research itself, but he pointed that him, as a manager, was more interested in the managerial insights coming from the implementation than in scientific outcomes.

Prof. Matta, during a midterm review of the project, pointed that the implementation of an actually used tool is non-trivial, due to the natural approach of physicians, who tend to be rigid with regards to simulation and computed aided management [10].

Brailsford [10] presents some barriers to the implementation of operations research simulation models in Hospital Management as well as some hints to overcome them.

Wilson [107] analyzed 200 papers tackling the topic of simulation in healthcare. Only 16 of them lead to some implementation. Although this paper is clearly outdated (1981), thus results are not valid from a quantitative point of view, issues reported seem to be actual: failure in properly specifying data collection, extensive use of solicited data from expert opinions, difficulties and non-transparencies in model validation and exclusively technical (but politically unaccepted) proposals.

Harper and Pitt [41] propose some guidelines to facilitate the implementation of simulation models in Healthcare.

The abovementioned considerations lead to the following question: *What shall this project include to facilitate and incentivize the adoption of the developed simulation model?*

Apparently, the question above leads to the definition of two main requirements of the project. The first one is trivial: simulation must lead to useful managerial insights, otherwise there is no point in adopting it. The second requirement is less trivial, and has to do with the interface of the tool.

Regarding the tool, a first questions arises: *What is the ideal tool?*. In other words, what is the tool that perfectly matches the habits and expectations of Hospital Managers? The answers is again trivial: the ideal tool should allow managers to get results without any efforts. Managerial insights should not come with any time investment. Hospital managers are typically busy and hard-working professionals, skeptical about the adoption of software-based management, due to the inherent complexity and case specificity of the subject matter.

At the state of the project, because of the limited available time and absence of economic resources, the ideal tool has been considered out of target. The specification of a target tool, which is by definition worse of the ideal but at the same time meaningful and affordable, has been defined. Instead of focusing on what should the end user do, the focus is what he should not be required to do.

The end user must **not** be required to:

- Use Arena to simulate the system: Arena is an engineering-oriented tool, user-friendly for engineers but requires a minimum training for its usage, which must not be required to Hospital decision makers
- Perform data analysis: interpreting data and fitting distributions is both non-intuitive and time consuming. Decision makers must not be obliged to perform statistical considerations
- Input distribution parameters: even with premade data analysis, decision-makers must not be required to deal with parameters and distributions, both to reduce the likelihood of mistypings and to reduce the perceived complexity of the interface
- Code "What-If" scenarios: the end user must be allowed to use the software through a graphical interface, thus no coding must be required
- Scope the results from a large data set: Arena by default returns a large amount of data, either on a `.txt` file or on a dedicated extension. The end user must receive only useful results, properly rearranged if necessary.

5.4 Integration Arena-Excel

As introduced by this section's title, the proposed solution to achieve the target tool is the integration of Arena's simulation model with Excel.

The principle behind the integration is presented in Figure 5.11.

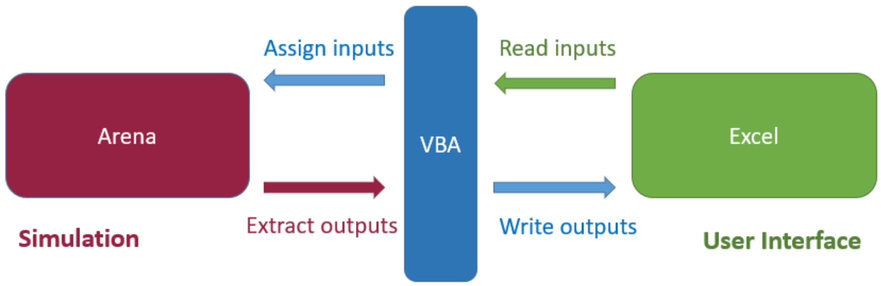


Figure 5.11: Scheme of the principle behind the integration Arena-Excel

The end user deals only with Excel, which works as the User Interface. VBA codes have been interposed between Arena and Excel. VBA reads inputs from Excel and assigns them to Arena's simulation parameters (variables, attributes, resources, schedules, etc.). Simulation is performed in Arena (run in background so that users do not perceive it) and at the end of the simulation, VBA extracts outputs and write them in Excel.

The advantages of the proposed solution are the following ones:

- Transparent inputs for the developer: the developer (in this case the author) can test the model with clear inputs displayed on Excel Sheets, thus largely reducing the probability of mistakes and enhancing the credibility of the simulation model
- Excel is an easy-to-use software for anyone, thus more easily accepted and adopted by Hospital Managers
- In the future, VBA user forms can be used to replace Excel, creating a more professional user interface
- Excel enables the fulfillment of the set requirements of the target tool

5.5 Overview of the tool

Since the code does not present any novelty nor significantly difficult instances, it has been omitted. It has been considered that the value adding part of this section consists in the conceptual design of the tool, rather than in its implementation.

Structure of the Excel file - Navigation Tab In order to ease the surfing and the usage of the Excel File, it has been divided into file Sheets, sequenced following the natural approach to the Simulation and marked by colors. First, three input Sheets, colored in Orange, then the Sheet to execute the simulation in green and finally a Sheet for the outputs in blue.

The navigation Tab is presented in Figure 5.12.

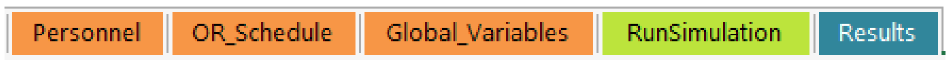
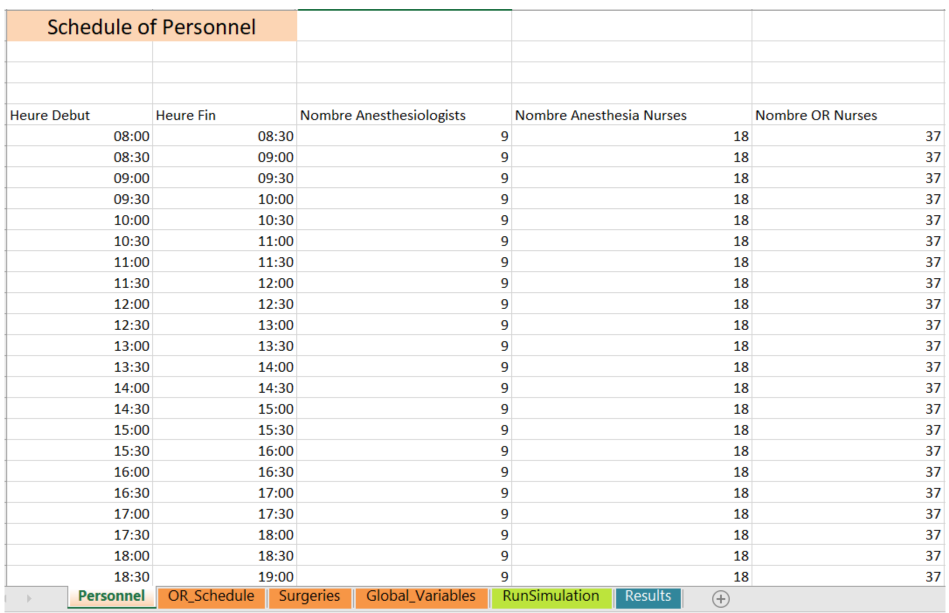


Figure 5.12: Navigation Tab of the Excel file

Human resources In the first Excel Sheet, named "Personnel", the end user can input the number of Anesthesiologists, OR Nurses and Anesthesia Nurses available on each slot of the schedule.

A screenshot of the Sheet is displayed in Figure 5.13.



Schedule of Personnel

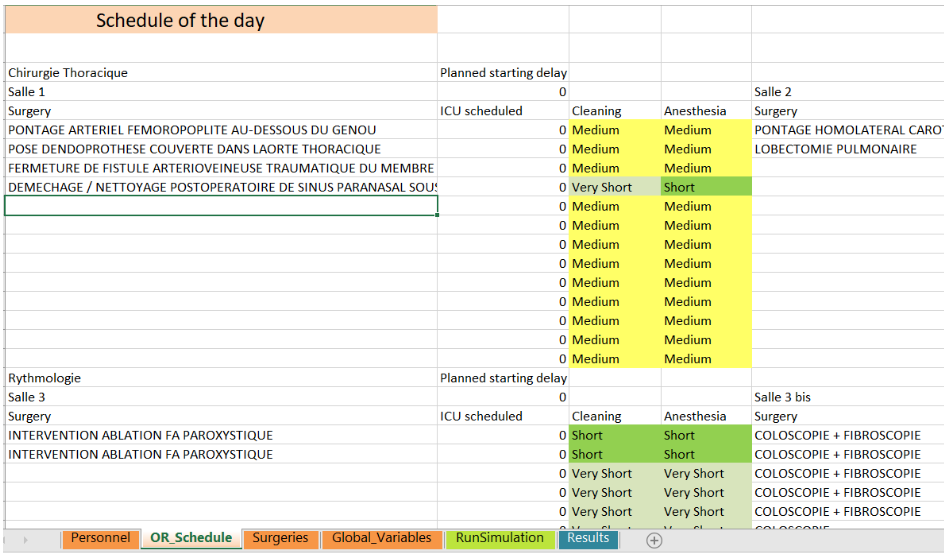
Heure Debut	Heure Fin	Nombre Anesthesiologists	Nombre Anesthesia Nurses	Nombre OR Nurses
08:00	08:30	9	18	37
08:30	09:00	9	18	37
09:00	09:30	9	18	37
09:30	10:00	9	18	37
10:00	10:30	9	18	37
10:30	11:00	9	18	37
11:00	11:30	9	18	37
11:30	12:00	9	18	37
12:00	12:30	9	18	37
12:30	13:00	9	18	37
13:00	13:30	9	18	37
13:30	14:00	9	18	37
14:00	14:30	9	18	37
14:30	15:00	9	18	37
15:00	15:30	9	18	37
15:30	16:00	9	18	37
16:00	16:30	9	18	37
16:30	17:00	9	18	37
17:00	17:30	9	18	37
17:30	18:00	9	18	37
18:00	18:30	9	18	37
18:30	19:00	9	18	37

Personnel OR_Schedule Surgeries Global_Variables RunSimulation Results

Figure 5.13: Screenshot of the Personnel Excel Sheet

OR Schedule In the second Excel Sheet, "OR_Schedule", the sequence of surgeries is defined for each OR. It is possible to state whether there is a scheduled ICU after the surgery and whether and to choose among three modules for cleaning and anesthesia procurement through a window menu. The number of surgeries scheduled on each operating room is directly loaded from the number of non-blank cells of each operating room. The sequence follows the order of appearance, from top to bottom.

Screenshot displayed in Figure 5.14. To be noted that end users do not type distribution parameters but the name of the surgery.



Schedule of the day				
Chirurgie Thoracique	Planned starting delay			
Salle 1	0			Salle 2
Surgery	ICU scheduled	Cleaning	Anesthesia	Surgery
PONTAGE ARTERIEL FEMOROPOPLITE AU-DESSOUS DU GENOU	0	Medium	Medium	PONTAGE HOMOLATERAL CARO
POSE DENDOPROTHESE COUVERTE DANS LAORTE THORACIQUE	0	Medium	Medium	LOBECTOMIE PULMONAIRE
FERMETURE DE FISTULE ARTERIOVEINEUSE TRAUMATIQUE DU MEMBRE	0	Medium	Medium	
DEMECHAGE / NETTOYAGE POSTOPERATOIRE DE SINUS PARANASAL SOU	0	Very Short	Short	
	0	Medium	Medium	
	0	Medium	Medium	
	0	Medium	Medium	
	0	Medium	Medium	
	0	Medium	Medium	
	0	Medium	Medium	
	0	Medium	Medium	
	0	Medium	Medium	
	0	Medium	Medium	
Rythmologie	Planned starting delay			
Salle 3	0			Salle 3 bis
Surgery	ICU scheduled	Cleaning	Anesthesia	Surgery
INTERVENTION ABLATION FA PAROXYSTIQUE	0	Short	Short	COLOSCOPIE + FIBROSCOPIE
INTERVENTION ABLATION FA PAROXYSTIQUE	0	Short	Short	COLOSCOPIE + FIBROSCOPIE
	0	Very Short	Very Short	COLOSCOPIE + FIBROSCOPIE
	0	Very Short	Very Short	COLOSCOPIE + FIBROSCOPIE
	0	Very Short	Very Short	COLOSCOPIE + FIBROSCOPIE

Personnel | OR_Schedule | Surgeries | Global_Variables | RunSimulation | Results

Figure 5.14: Screenshot of the Excel Sheet for OR Schedules

Global variables In the Sheet "Global_Variables", all inputs which are global (do not depend on the specific OR) and which do not require a schedule are defined. Since no interesting insights come from this Sheet, the screenshot has been omitted.

Run Simulation In the Sheet "RunSimulation", users can input the number of desired replications (according to the required accuracy of the result and to the willingness to wait for them) and run the simulation, clicking on "Run Simulation". The button executes Arena in background (it does not appear on the screen), the simulation starts with the previously defined inputs, at the end of the simulation results are written on Excel, Arena gets closed and Excel automatically activates the "Results" Sheet.

In this Sheet, the user can choose among possible Scheduling approaches and test them. When clicking on the rescheduling buttons, the order of interventions in Sheet "OR_Schedule" changes. To test the new schedule, users have to click on Run Simulation.

The screenshot of this Sheet is presented in Figure 5.15.

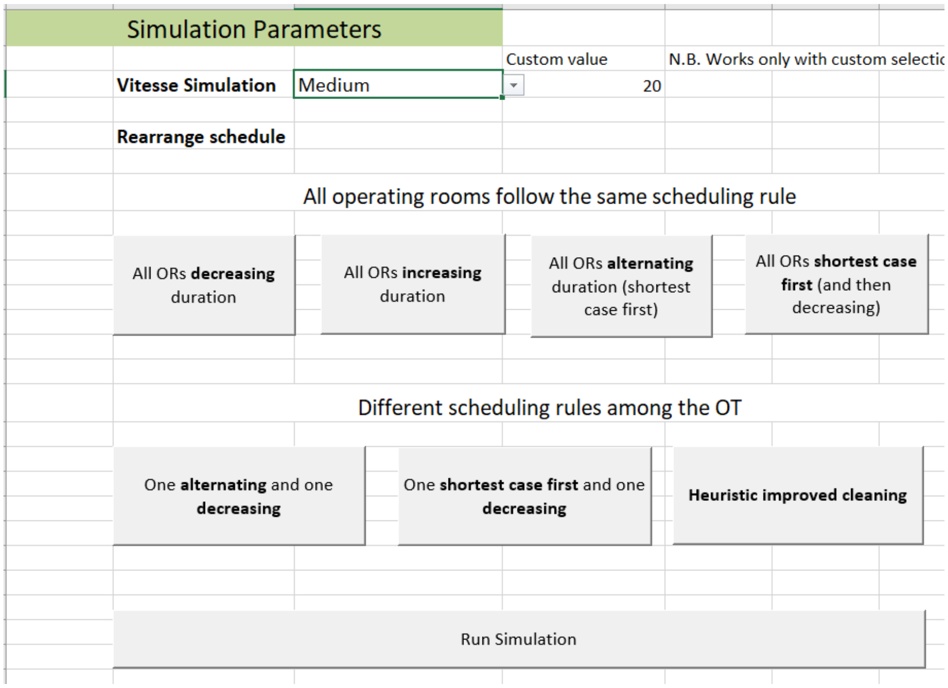


Figure 5.15: Screenshot of the Excel Sheet to reschedule and run the simulation

Results Finally, in the "Results" Sheet, the user can look at the simulation outputs. The plotted outputs are the following ones:

- OT Makespan
- ORs Makespan
- Human Resources Utilization
- ORs Utilization 1: $\dfrac{Surgery\ + Cleaning + Wait_{PACU}}{OT_{makespan}}$
- ORs Utilization 2: $\dfrac{Surgery\ + Cleaning + Wait_{PACU}}{OR_{makespan}}$
- ORs Utilization 3: $\dfrac{Surgery}{OR_{makespan}}$
- PACU Beds Utilization
- Wasted time in the ORs because PACU is blocking

Chapter 6

Data analysis

In this chapter, input data required by the model are analyzed. Two main categories of data can be pointed: durations and resources. Considering the simulation model as a Petri Net, the former represents transition delays and holding times, the latter the available tokens.

6.1 Durations

Hopital Bichat collects, for each patient, the following information on a single Excel Sheet:

- Operating block
- Operating room
- Type of operating room (elective surgeries or urgences)
- Specialty
- Type of intervention
- Visit date and time
- Scheduled date and time
- $Patient_{IN}$ date and time
- $Patient_{OUT}$ date and time
- Surgery room occupation time, calculated as $Patient_{OUT} - Patient_{IN}$
- Type of surgery (scheduled, scheduled today, urgent)
- Destination of the patient (Reanimation or PACU)

- Name of the surgeon
- Patient identifiers (identification number and age). To comply with the current privacy policies, the name of the patient has been erased from the submitted data set.

The Hospital also records the length of stay in PACU. Records are stored on paper, no digitalized system is present in the Hospital.

At the end of each year, the Hospital provides a report with the realized minimum, maximum, mean and median duration of each type of surgery. Realized data are then compared to their respective catalogue durations.

In terms of process durations, the following inputs are required by the model:

- Surgery duration
- Length of stay in PACU
- First case delay
- Transportation time from surgical wards to the operating theater
- Operating room cleaning time
- Duration of anesthesia induction

A rigorous data analysis has been conducted on the first three entry points, while for the last three items, because of lack of recorded data, no rigorous quantitative analysis has been carried out.

6.1.1 Surgery duration

Surgical time is affected by large variations. The recorded maximum duration of a type of operation can be greater by more than 5 times of the minimum duration (data sheet provided by Hospital Bichat, containing records of classic and urgent surgeries in 2017).

There is abundant literature regarding factors which affect the duration of a surgery, which include gender of the surgeon, age of the surgeon, frequency of the intervention, team composition, daytime and type of anesthesia [43, 99, 97].

The lognormal distribution has been used to fit surgery durations. The choice of using this distribution can be justified by means of four arguments:

- Intuitive explanation
- Literature literature review
- Visual inspection
- Numerical analysis

Intuitive explanation

In order to guarantee the safety of the patient, activities carried out in the OR are highly standardized. AP-HP (Assistance Publique Hôpitaux Paris) reports a mandatory check-list of activities to be performed in the OR. For the high level of required and standardized procedures, surgeries cannot be much shorter than the expected time, even when the surgery proceeds smoothly. Conversely, when complications arise, surgeries take much longer than expected. A cut on the left side and a long tail on the right side suggest a lognormal distribution.

Literature review

The lognormal distribution has been pointed in the literature as the best fitting model of the duration of the surgery. [98, 112, 68, 39, 2].

May et al. [68] compare normal and lognormal fits for surgical durations, with numerical results, suggesting that the lognormal distribution is more appropriate to describe the real data. The limitation of the candidates to normal and lognormal has been justified by previous results in the literature (does not specify which papers). Shapiro-Wilk test has been used to test the goodness of fit.

Hancock et al. [39] suggest a lognormal distribution by simply considering that typical distributions display a truncation on the left side and a tail on the right side, thus indicating a lognormal distribution. Zhou and Dexter (1998) analyzed a large set of data (almost 50,000) from the University of Iowa Hospitals and Clinics. They found evidence that lognormal distributions are a proper method to represent the real data.

Strum et al. [99] compare a Lognormal and Normal distribution to fit the data, they find that the lognormal distribution is superior to the normal one. Also, they find that the lognormal distribution is a legitimate tool to describe surgical durations. The study has been conducted on 40,076 surgical cases collected from a large teaching hospital (Institution not specified).

Alvarez et al. [2] fitted a lognormal distribution for aortic valve replacement surgeries in a Canadian Hospital. Both surgical times and turnover times have been fitted with a lognormal distribution, and the Fenton-Wilkinson approximation has been used to sum them up. The good fitting of a log-normal distribution can be intuitively explained because outlier surgeries tend to be much longer than the average rather than much shorter [112].

Saadouli et al. [87] directly assume surgeries to follow a lognormal distribution and estimate the parameters from a dataset with one month of realized surgeries.

Master et al. [67] verify that the logarithmic transformation of the duration histogram of lombar punctures in a pediatric hospital in the US, produces a fairly symmetric histogram (resembles a normal distribution).

Kougias et al. [50] define the lognormal modeling of surgical durations as traditional and directly estimate mean and standard deviation from historic data.

Visual inspection

Since in 2017 more than 1,000 types of surgeries have been performed, the consistency of the realized durations with respect to the literature has not been checked on the full dataset, only 4 surgeries have been properly analyzed: Coloscopie, Coloscopie+Fibroscopie, Endoscopie, Laparatomie Exploratrice. These surgeries have been chosen from different specialties and from the most frequent surgeries, so that a sufficiently large sample size has been used to fit the distibutions.

For each of them, visual inspection has been carried out comparing the normalized hinstogram of the realized durations with the best fitting lognormal probability density function. Visual inspection is shown in Figures 6.1, 6.2, 6.3, 6.4. An undeniable accordance between data and the fitting normal can be easily spotted.

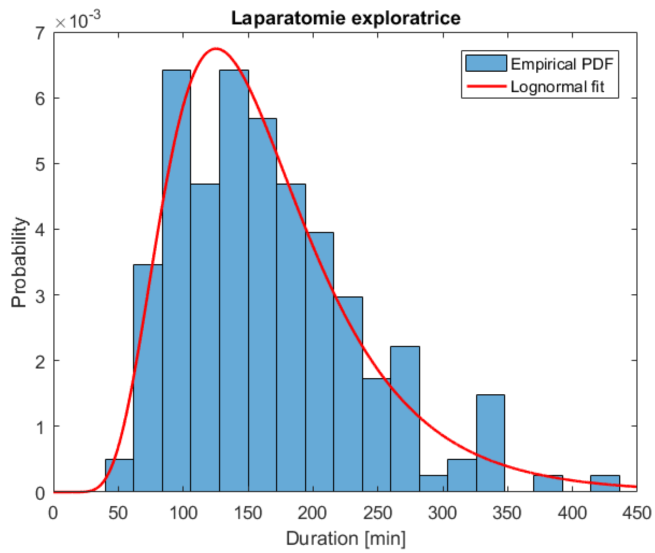


Figure 6.1: Empirical histogram and lognormal fitting for Laparatomie Exploratrice

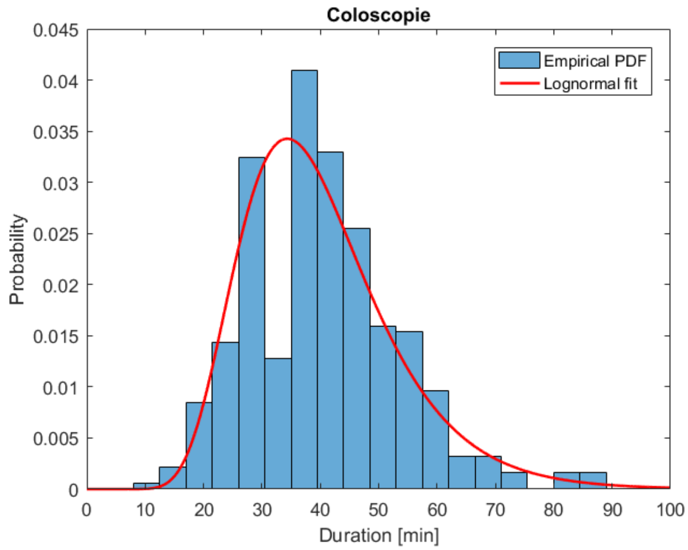


Figure 6.2: Empirical histogram and lognormal fitting for Coloscopie

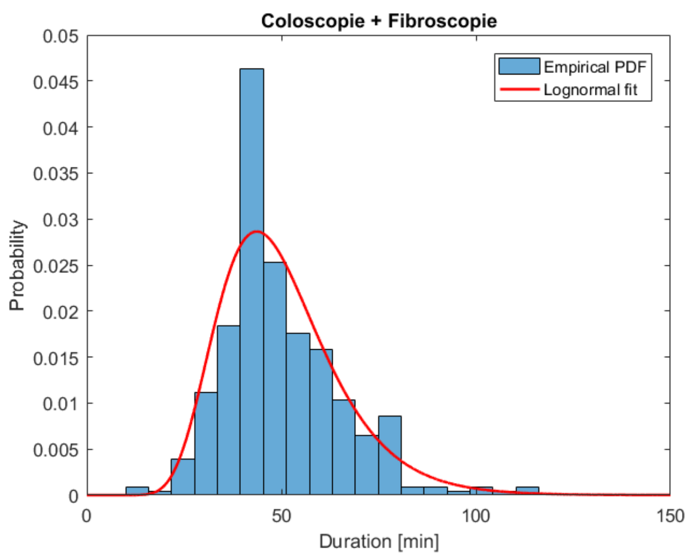


Figure 6.3: Empirical histogram and lognormal fitting for Coloscopie + Fibroscopie

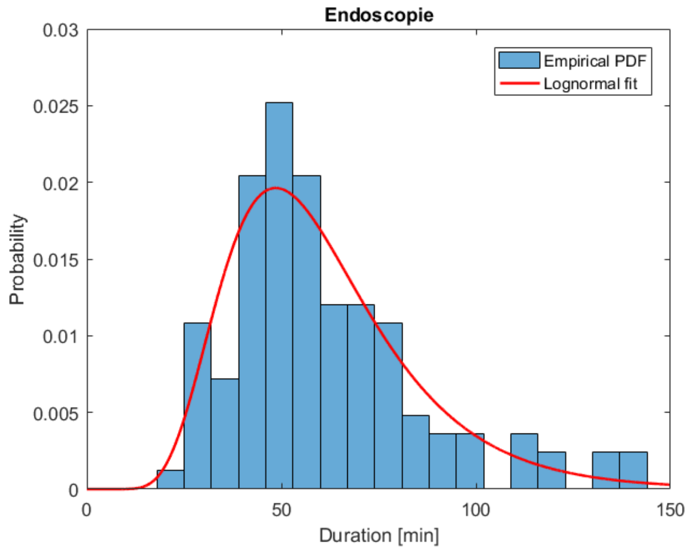


Figure 6.4: Empirical histogram and lognormal fitting for Endoscopie

Numerical analysis

A Shapiro-Wilks and Shapiro-Francia goodness-of-fit test has been carried out over the same four surgery types. In all cases, the test cannot reject the null hypothesis with a p-value equal to 0.05.

The results of the tests for Coloscopie+Fibroscopie, Laparatomie Exploratrice, Endoscopie are presented in Figures 6.5, 6.6, 6.7.

```
. swilk log_endo

                   Shapiro-Wilk W test for normal data
```

Variable	Obs	W	V	z	Prob>z
log_endo	120	0.99002	0.960	-0.090	0.53597

(a) Shapiro-Wilks test Endoscopie

```
. sfrancia log_endo

                 Shapiro-Francia W' test for normal data
```

Variable	Obs	W'	V'	z	Prob>z
log_endo	120	0.99199	0.848	-0.330	0.62934

(b) Shapiro-Francia test Endoscopie

Figure 6.5: Goodness-of-fit test Endoscopie

```
. swilk log_lapa

                   Shapiro-Wilk W test for normal data
```

Variable	Obs	W	V	z	Prob>z
log_lapa	184	0.99233	1.065	0.144	0.44284

(a) Shapiro-Wilks test Laparatomie Exploratrice

```
. sfrancia log_lapa

                  Shapiro-Francia W' test for normal data
```

Variable	Obs	W'	V'	z	Prob>z
log_lapa	184	0.99416	0.886	-0.248	0.59807

(b) Shapiro-Francia test for Laparatomie Exploratrice

Figure 6.6: Goodness-of-fit test Endoscopie

```
. swilk log_colofibro

                   Shapiro-Wilk W test for normal data
```

Variable	Obs	W	V	z	Prob>z
log_colofi~o	394	0.99441	1.518	0.992	0.16058

(a) Shapiro-Wilks test Coloscopie+Fibroscopie

```
. sfrancia log_colofibro

                  Shapiro-Francia W' test for normal data
```

Variable	Obs	W'	V'	z	Prob>z
log_colofi~o	394	0.99336	1.945	1.437	0.07533

(b) Shapiro-Francia test for Coloscopie+Fibroscopie

Figure 6.7: Goodness-of-fit test Endoscopie

In case of Coloscopie, both Shapiro-Wilks and Shapiro-Francia reject the null hypothesis of a lognormal distribution. The same test has been then applied to the same data with an appropriate constant shift, such that the skewness of the underlying normal distribution is equal to zero.

As shown in Figure, Shapiro-Wilks and Shapiro-Francia do not reject the hypothesis of lognormality over the skewed distribution.

```
. swilk skew_coloscopie

                   Shapiro-Wilk W test for normal data

    Variable |        Obs       W           V         z       Prob>z
-------------+------------------------------------------------------
skew_colos~e |        418    0.99563      1.251     0.533    0.29695
```

(a) Shapiro-Wilks test Coloscopie skewed

```
. sfrancia skew_coloscopie

                  Shapiro-Francia W' test for normal data

    Variable |       Obs       W'          V'        z       Prob>z
-------------+-----------------------------------------------------
skew_colos~e |       418    0.99549      1.391     0.716    0.23696
```

(b) Shapiro-Francia test for Coloscopie skewed

Figure 6.8: Goodness-of-fit test Coloscopie skewed

Even from a visual inspection, it is possible to check that the lognormal distribution is fitting better the skewed data. Results in Figure 6.9.

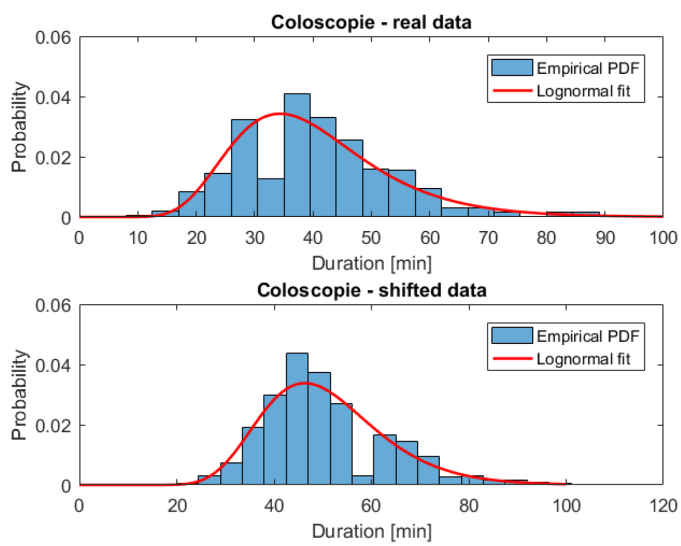


Figure 6.9: Empirical histogram and lognormal fitting for Coloscopie

At the same time, it is possible to see that the lognormal distribution better fits the shifted data. It is then possible to state that, even if from a rigorous perspective the lognormal distribution does not fit the data, it is not totally unable to catch the duration behavior.

In conclusion, considering the intuitive explanation, the large support of the literature, the visual inspection and the positive results of a goodness-of-fit in three out of four cases (and the positive results for the skewed distribution in the fourth case), the lognormal distribution has been chosen to feed the simulation model for surgery durations.

Unfrequent surgeries

In 2017, 16,058 total surgeries have been carried out, with 1,026 different types of surgeries. This data has been extracted from the annual report with aggregate data of each type of interventions (see Section 6).

This document is the result of a polishing work of the raw data collected for each intervention. The dataset received is thus “dirty”, with several records dissimilar by some details. Around 5,000 types of interventions were thus present in the data set. A polishing work has been carried out to reduce the number of interventions, without introducing unreasonable assumptions (e.g. an intervention on the left foot has been merged with the same one on the right foot). Sometimes, due to the lack of knowledge in medicines, further reductions have not been carried out. The number of types of interventions has been reduced to 2,139.

Considering the polished aggregate data set, the first point to be considered is the high number of very unfrequent interventions (see Figure 6.10).

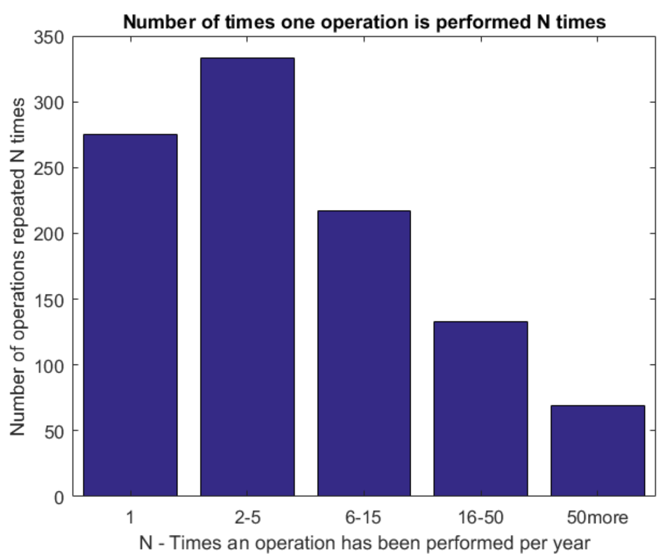


Figure 6.10: Distribution of the frequency of surgeries

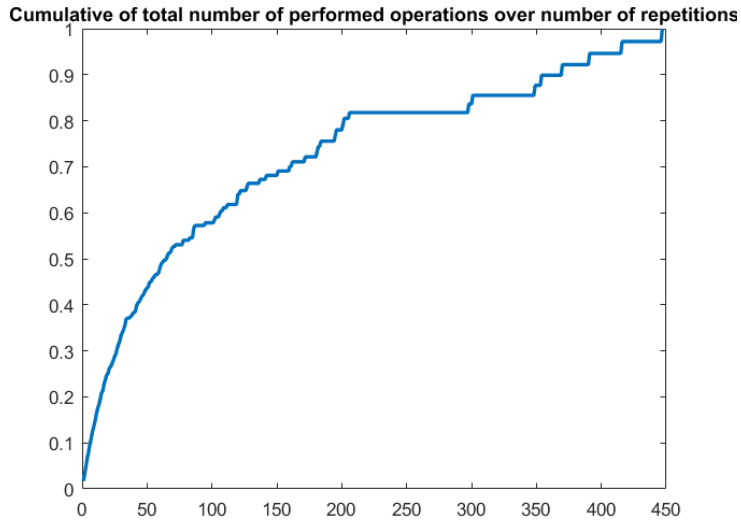


Figure 6.11: Distribution of the frequency of surgeries

Considering the cumulative distribution, Figure 6.11, surgeries repeated at least once per month (12 times in the data set) account for 84% of the total surgeries carried out in the hospital, surgeries repeated at least once every two months but less than once a month account for 8% of the total surgeries. The last 8% is allocated to surgeries repeated less than once every two months. Since the lognormal fitting would not produce credible results with too small sample sizes, the following rule has been applied:

- $size \geq 12$ (at least once per month): the pool of data has been considered sufficiently large to fit a lognormal distribution
- $6 \leq size < 12$ (at least once every two months): the pool has not been considered large enough to fit a lognormal distribution, but large enough to fit a triangular distribution, using maximum, minimum and average of the data set as input parameters
- $size < 6$ (surgery repeated less than once every two months): in this case the pool of data has not considered large enough to believe that the minimum realized duration represents the minimum possible realization (and same for the maximum). A triangular distribution with 0.65 average, average and 1.60 average has been used. The shape of this triangular is somehow consistent with the lognormal distribution.

6.1.2 PACU length of stay

In the Hospital there is no digitalized system to store the length of stay in PACU of each patient. Data are stored on paper. 100 samples have been extracted and analyzed.

A lognormal distribution has been adopted to fit the duration of PACU. Similarly to the case of surgeries, there is an intuitive explanation for the adoption of the lognormal distribution: anesthesiologists prefer to monitor a patient for at least some predefined time. Typically, it is very unlikely that a patient leaves the Post Anesthesia Care Unit in less than 40 minutes. Conversely, critical patients can stay for several hours.

F. and J.H. [29] tested a lognormal distribution for PACU duration,s using the Lilliefors test. Authors consequently use a lognormal distribution to feed a simulation model. Dexter et al. [25] directly feed a simulation model with a lognormal statistical distribution.

As for surgery durations, both visual inspection and goodness-of-fit tests have been carried out.

As it is visible in Figure 6.12, there is a clear accordance between the data and the best fitting lognormal distribution.

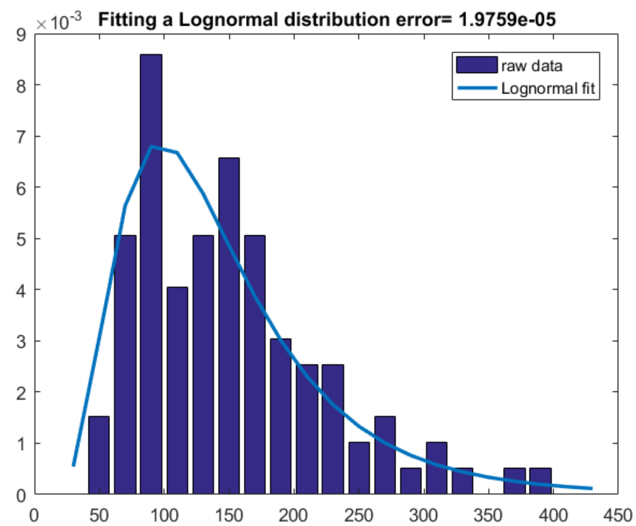


Figure 6.12: Empirical histogram and lognormal fitting for PACU length of stay

In terms of numerical analysis, Shapiro-Wilks and Shapiro-Francia have been executed over the logarithms of the recorded data. As shown in Figure 6.13, the results of the tests clearly indicate that it is not possible to reject the null hypothesis of lognormality.

```
. swilk logPACU

                   Shapiro-Wilk W test for normal data

    Variable │    Obs       W           V         z       Prob>z
─────────────┼──────────────────────────────────────────────────
     logPACU │    100    0.99338      0.546    -1.341    0.91000

. sfrancia logPACU

                  Shapiro-Francia W' test for normal data

    Variable │    Obs       W'          V'        z       Prob>z
─────────────┼──────────────────────────────────────────────────
     logPACU │    100    0.99335      0.605    -0.993    0.83957
```

Figure 6.13: Shapiro-Wilks and Shapiro-Francia tests to check the goodness-of-fit of the lognormal distribution

According to the opinion of interviewed Anesthesiologists and PACU nurses, the duration of PACU length of stay is not independent from type and specialty of surgery. However, since there was no digitalized database which would make extremely time consuming to analyze the distribution of PACU length of stay for each surgery, and since several surgeries are grouped together and consume the same resource, PACU length of stay has been assumed to be independent from the surgery.

6.1.3 First case delay

Scalea et al. [90] define a first case on time if the patient enters the operating room within six minutes after it has been planned.

From June 2018, 153 presumed first cases have been extracted. The Excel Sheet provided by the Hospital does not contain any information about a surgery being the first case, but knowing that all ORs open at 8:00 am (except for Chirurgie Cardiologique which opens at 7:30 am), it has been assumed that surgeries scheduled at 8:00 am are the first case of the day. Some schedule disruptions have been noted: it is extremely unlikely that a surgery planned at 8:00 starts at 10:50, thus it has been assumed that for very long delays, a surgery has been replaced as a first case. Analogously, a surgery starting with a consistent but reasonable delay (e.g. 50 minutes) but with a very short duration has been neglected. It has been considered that it could have been replaced by another short surgeries (e.g. 30 minutes) which started on time. There is awareness that these assumptions may lead to a slight bias in the estimation of the first-case delay, but this bias has been considered negligible with respect to a prospective large overestimation of the delay due to the disruption of the schedule. The following hypothesis have been thus formulated:

- First-case delays cannot be larger than 60 minutes
- First-case delays cannot be longer than the duration of the first surgery

Delays have been plotted on a histogram, Figure 6.14, considering six time bins of 10 minutes each.

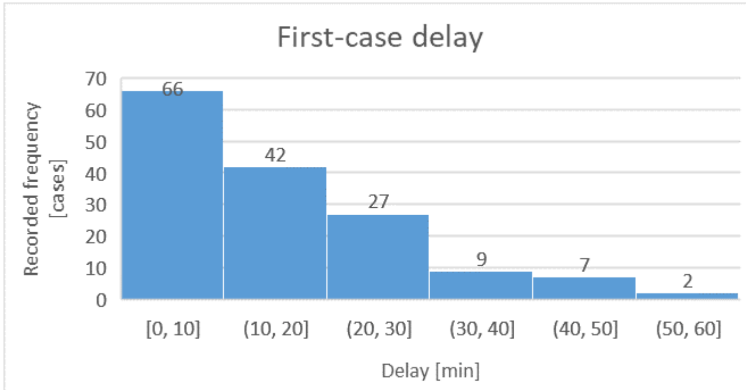


Figure 6.14: Recorded distribution of first case delays

The graph displays a clear monotone decreasing pattern, thus a Weibull distribution has been considered as the candidate to capture the behavior. Since the Exponential distribution is a particular case of the Weibull ($\beta = 1$), if the test rejects the goodness-of-fit of a Weibull distribution, it is sure that the exponential cannot be used.

The Lilliefors test has been used to check the goodness-of-fit. The graphical result of the Weibull probability plot is presented in Figure 6.15.

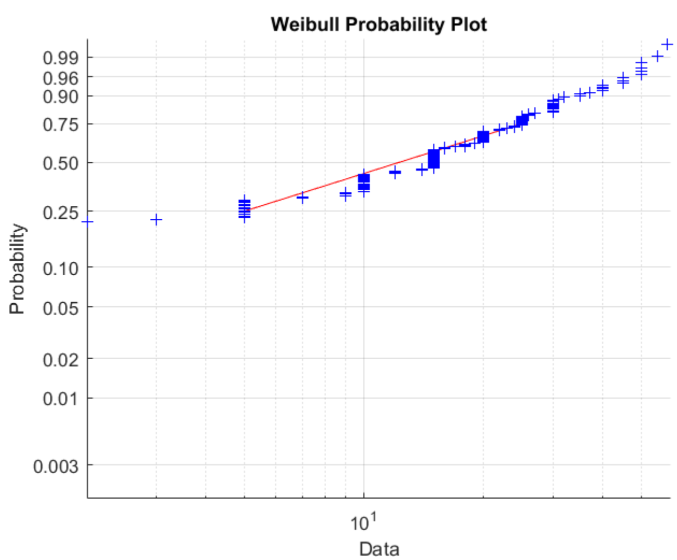


Figure 6.15: Weibull Probability plot

As expected, there is some accordance between the Weibull fit and the recorded data in the middle of the graph, but the high number of outliers on the left and right hand side make the test reject the null hypothesis with a p-value of the order of 10^{-3}. The same test has been conducted removing the zero values with even worse results, as shown in Figure 6.16.

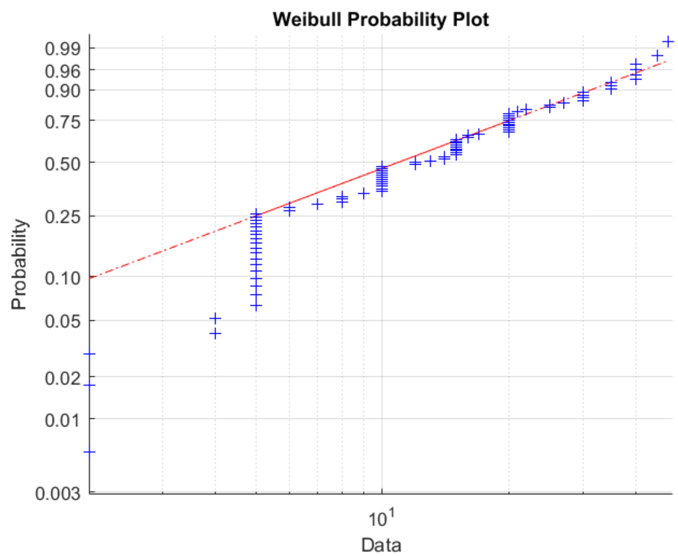


Figure 6.16: Weibull Probability plot of adjusted data

It has been thus decided to adopt an empirical distribution, using the mean values of each delay bins:

- 5 minutes: $p = 0.43$
- 15 minutes: $p = 0.27$
- 25 minutes: $p = 0.18$
- 35 minutes: $p = 0.06$
- 45 minutes: $p = 0.05$
- 55 minutes: $p = 0.01$

Before the application of an incentive program aimed at increasing on-time first cases and reducing the overall makespan, Scalea et al. [90] recorded a on-time first case (delay lower than 6 minutes) rate between 0.3 and 0.33. The value presented above (0.43) is slightly higher, but it takes into account delays up to ten minutes. As shown in graph 6.17, if buckets of 6 minutes are considered, the first bin contains 46 cases which correspond to $p = 0.30$. Accordance with literature findings supports to goodness of the performed analysis. Vitez and Macario [104] found a first case delay rate (computed without a 6 minute margin) around 40%, thus in line with Bichat.

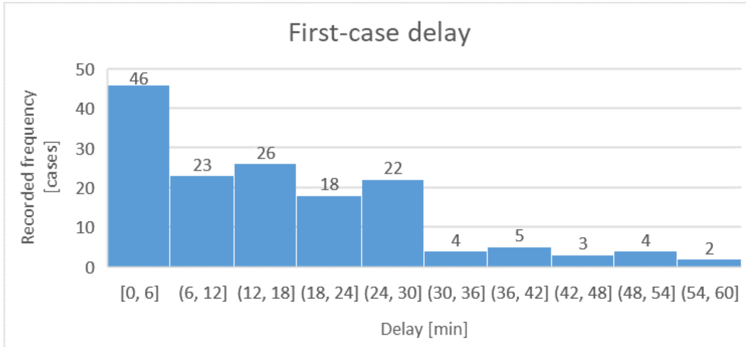


Figure 6.17: Weibull Probability plot

6.1.4 Solicited data

As mentioned at the beginning of Section 6, transportation time and cleaning time are not been recorded by the Hospital. Regarding cleaning time, one could argue that the turnover time could be extracted from the dataset as $Patient_{i+1,IN} - Patient_{i,OUT}$, but that would not take into account of several issues:

- OR cleaning is dependent to the type of surgery performed. It must be specified for each surgery, so this would imply extracting distributions from the dataset for each surgery type, and dealing with unfrequent surgeries.
- OR cleaning would be independent on the sequence, while letting the user decide the duration for each surgery allows for a more resonable representation of the cleaning time.
- turnover time includes waiting time for resources constraints (e.g. cleaning team busy with another operating room or anesthesiologist busy with the anesthesia induction in another operating room).
- due to lack of personnel, there are often long turnover times at lunchtime, which have nothing to do with operating room cleaning.
- Patient transportation can be a driver of increased turnover time.

Through expert judgment, cleaning time has been represented with four modules:

- Very short: Mode = 5 minutes
- Short: Mode = 10 minutes
- Medium: Mode = 20 minutes

- Long: Mode = 30 minutes

For each module, a triangular distribution with 0.7Mode, Mode and 1.3 Mode has been used to represent the stochasticity of the process.

Anesthesia has been solicited with the same principle, using the following modules:

- Short: Mode = 10 minutes
- Medium: Mode = 20 minutes
- Long: Mode = 40 minutes

For patient transportation, a triangular distribution with 5 ± 2 minutes has been used.

6.2 Resources

The following resources are required to run the simulation:

- Number of Anesthesiologists
- Number of Anesthesia nurses
- Number of OR nurses
- Number of PACU beds
- Number of cleaning teams
- Number of "Brancardiers""

PACU beds have been simply counted and the total amount is equal to 14. For the other resources, some additional discussions are required.

6.2.1 Anesthesiologists

Anesthesiologists are not required to be always present in the operating room after the Anesthesia Induction, unless complications arise during the surgery. The minimum allowed ratio $\frac{N_{anesthesiologist}}{N_{OR}} = 0.5$, but analyzing the working schedule of Anesthesiologists in Bichat, it looks clear that some margin is kept from the minimum permitted value.

One week of Anesthesia schedule has been analyzed. Each day is divided into morning and afternoon, and different resources and operating rooms can be deployed in the two parts of the week.

From Monday to Thursday, an average ratio $\frac{N_{anesthesiologist}}{N_{OR}} = 0.63$, has been extracted, while on Friday, $\frac{N_{anesthesiologist}}{N_{OR}} = 0.84$.

6.2.2 Anesthesia Nurses

Prof. Longrois reported that, since the presence of an Anesthesia nurse, is a strict constraint for the beginning of the surgery, a ratio $\frac{N_{anesthesia\ nurse}}{N_{OR}} = 0.1.2$ would be desiderable. However, due to budget constraints, Hospital Bichat works with $\frac{N_{anesthesia\ nurse}}{N_{OR}} = 0.1$.

6.2.3 Number of OR nurses

Each operation requires two OR nurses. However, in case of lack of nurses, one OR nurse can be replaced by a resident or the surgeon may decide to operate in degraded conditions (i.e. with only one assisting nurse). It turns out that OR nurses are not a significant constraint for the hospital, thus a total amount of 2 OR nurses for each active operative room has been assigned (no constraint introduced). This resource has been model to record its utilization and to leave space for prospective follow up projects.

6.2.4 Cleaning teams

Each cleaning team is assigned to two operating rooms, except for Chirurgie Cardiologique, where each cleaning team is assigned only to one surgery room. Since, excluding Chirugie Cardiologique, there are 15 ORs, one surgery room (Mat3) has been assigned to only one cleaning team.

6.2.5 Brancardiers

“Brancardiers”” are working in the whole Hospital, so it is not possible to know their capacity and availability, thus it is not possible to model them as a resource of the Operating Theater. In order to represent congestions in case of high demand, “Brancardiers”” have been modeled with arbitrary capacity.

Chapter 7

Verification and Validation

Law [55] point that a simulation model must pass through a process of verification and validation before it can be used for any decision-making purpose. **Verification** *is concerned with determining whether the assumptions document has been correctly translated into a computer program.* **Validation** *is the process of determining whether a simulation model is an accurate representation of the system, for the particular objectives of the study.*

7.1 Verification

Law [55] suggests 8 techniques to verify a simulation model.

Write and debug, adding complexity gradually The simulation model has been created step by step, one OR at a time, the correct functioning checked after each step. Also, for the coding in VBA, an easy support model has been used to develop and test macros in a clean environment. The tested and working codes have then been applied to the complex model.

Multiple reviewers The project has been set as individual work. Nevertheless, periodic reviews of the simulation model have taken place with Prof. Jouini, who could provide a third person review of the simulation model. The model has been reviewed block by block and the simulation has been run and checked together.

Multiple settings Each input parameter has been set with different values to verify the model reacts correctly to changes. Particular attention has been paid to the variation of:

- Number of surgeries in each operating room, to check that the VBA code loads the proper number of surgeries in each OR

- Duration of the surgeries, to check that VBA attributes correctly the duration to each surgery and changes values at each simulation

- Personnel schedules

Array values are potentially more critical than scalar quantities because of the poor debugging features of VBA. For example, VBA quits a Subroutine if it spots issues with the indexes of an array, without returning errors. This prevents Arena from reading, for example, the updated values of the surgeries following the index error, but it does not necessarily block the simulation. To prevent the occurrance of this issues, two techniques have been used:

1 VBA debugger to check that each line has been read by the compiler.

2 Specific focus on the last items of the code.

Traces Several record blocks have been added to the model to make sure that time intervals return reasonable results. Record blocks include: anesthesia induction, cleaning time, time spent in the operating theatre and in the operating room. In addition, Arena computes by default min-max-avg of all queues and resource utilization.

Test under simplifying assumptions This step has been skipped because of the inherent complexity of the model. To compute by hand an easy model, the original one would be simplified to the point that it would not provide any credible verification.

Animations Some simple animations are included in Arena, which allow to see the progress of entities and the amount of queues at each process module. A blocking state is thus displayed by default by arena with non-served queues on Hold and Seize blocks.

Verification of input distribution See Chapter 6 (data analysis).

Commercial simulation software Arena by Rockwell Automation has been used, leading software for discrete-event simulation.

7.2 Model Validation

The Hospital provided an Excel data set including, for each surgery performed in 2017:

- Operating room of the surgery

- Medical specialty

- Specific type of intervention
- Scheduled begin, date and time
- Actual begin, date and time
- Date and time of patient out
- Surgery duration (patient in - patient out)
- Destination (Reanimation or PACU)
- Class of surgery (scheduled, scheduled today, urgent)

From the Excel sheet, four days of realized schedule of each operating room have been extracted. In order to exclude potential correlations, different weekdays in different periods of the year have been extracted: Wednesday 6 June 2018, Friday 22 June 2018 (data extracted from a file previously submitted by the hospital which includes only June 2018), Monday 25 September and Thursday 23 February.

Validation has been performed comparing the average makespan over 50 replications with the realized makespan, for each OR on each day. In order to enhance the credibility of the model, validation has been performed in two steps:

- Deterministic surgery durations: in this validation step, the actual duration of the surgeries has been used as a deterministic input for the model.
- Full stochasticity: the model has been fed with the computed probability distributions of the surgeries

For both the validation steps and for each day, the following objects have been reported:

- Graphical representation of the average simulated makespan and the realized one
- Average percentage error, computed as:

$$Consistency\ error = \frac{\sum_{i=1}^{N_{ORs}} \overline{MS_{sim,i}} - MS_{real,i}}{N_{ORs} \times \overline{MS_{sim}}} \times 100$$

  This parameter gives an indication of the consistency of the model. The ideally consistent model would return $Consistency\ error = 0$ for $N_{ORs} \to \infty$ and $N_{repl} \to \infty$

- Absolute average percentage error, computed as

$$Average\ Variability = \frac{\sum_{i=1}^{N_{ORs}} |\overline{MS_{sim,i}} - MS_{real,i}|}{N_{ORs} \times \overline{MS_{sim}}} \times 100$$

This value is by definition different from zero, since one realization is in general different from the average of the process beneath it. Nevertheless, a relatively small value for is required by a simulation model which aims at being useful for decision making. An excessively large variability from the actual outcome would prevent the credibility of singular outputs.

- Percentage mean square error, computed as

$$MSE = \frac{\sum_{i=1}^{N_{ORs}} (\overline{MS_{sim,i}} - MS_{real,i})^2}{N_{ORs} \times \overline{MS_{sim}}} \times 100$$

  This term has no physical meaning but it is largely used by researchers as an error indicator. It has been added to the list of outcomes for the sake of completeness.

In addition, an overview of the number of simulated makespans which differ from the realization by less than 30 minutes, between 30 and 60 minutes and more than 60 minutes, has been reported.

7.3 Deterministic surgery durations model

As mentioned before, at this step each surgery has been treated as a process with deterministic duration, equal to the realized one. Since recorded durations refer to $Patient_{OUT} - Patient_{IN}$, PACU capacity has been arbitrarily increased, to make sure it does not introduce any blocking conditions. The realized durations already include the waiting time for PACU full, so it would be incorrect to introduce further delays. This step, which is in between verification and validation, is useful to gain confidence about two issues:

- To qualitatively verify that the model properly processes inputs without missing entries and bugs.
- To quantitatively validate the model of the whole structure of the operating theater: first case delay, cleaning time, personnel constraints, patient transportation. Decoupling the stochasticity of surgery durations (and PACU) from the stochasticity of the surrounding scenario, and validating the latter first, allows to believe that both blocks are representing reality, not only their combination.

7.3.1 Graphical inspection

Figures 7.1, 7.2, 7.3, 7.4 show the comparison between the average simulated makespan and the realization. Despite a few outliers, a clear accordance between simulation and realization can be spotted on each analyzed workday.

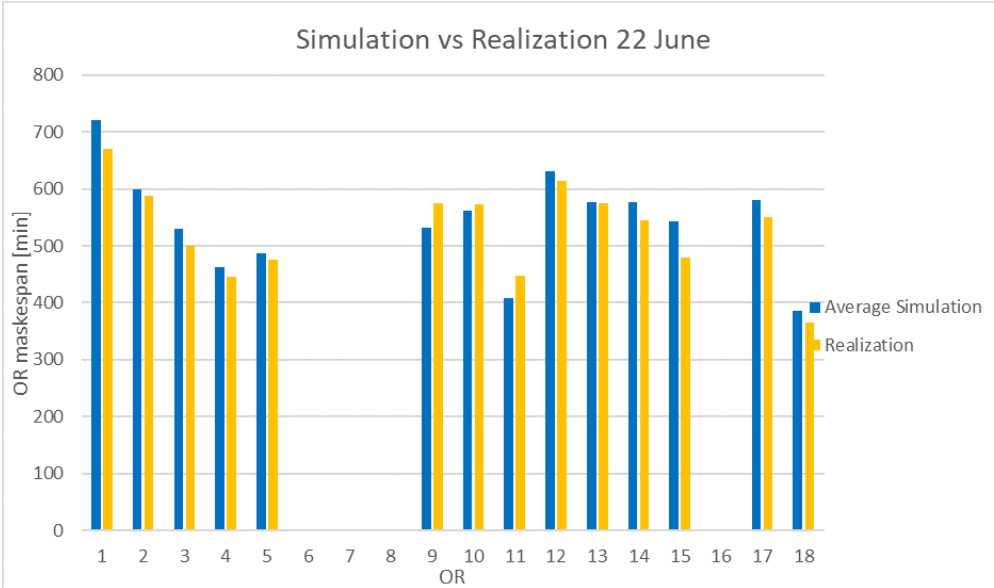


Figure 7.1: Comparison simulation vs realization for 22 June 2018

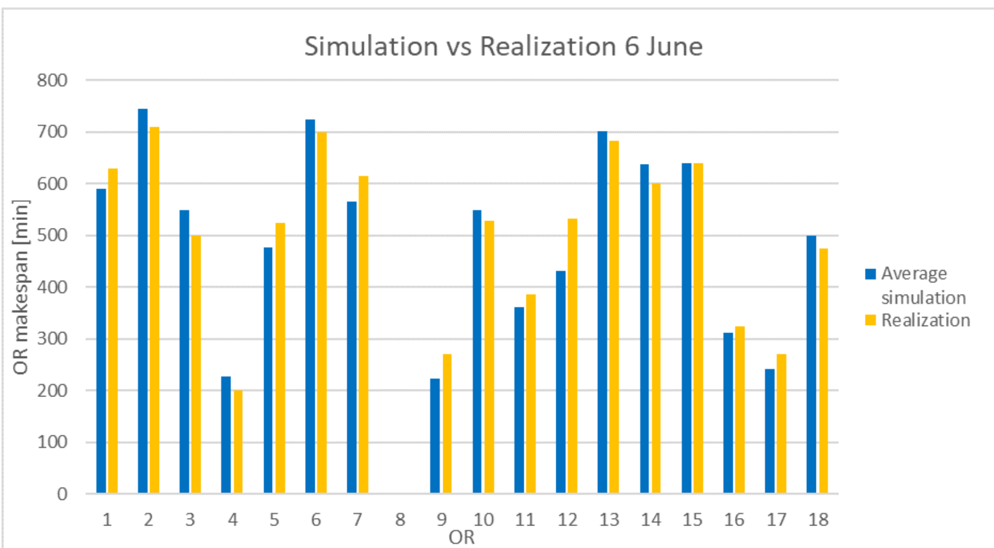


Figure 7.2: Comparison simulation vs realization for 6 June 2018

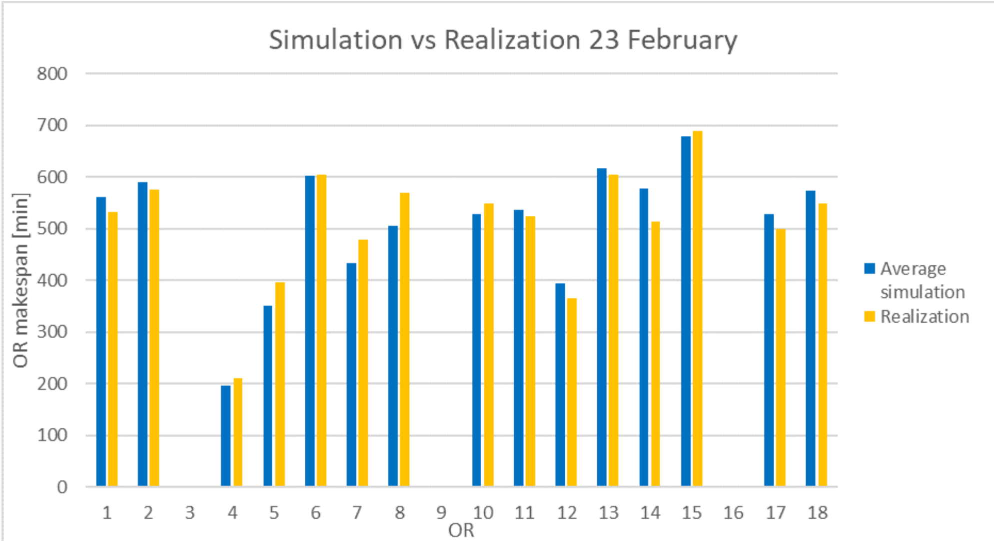


Figure 7.3: Comparison simulation vs realization for 23 February 2017

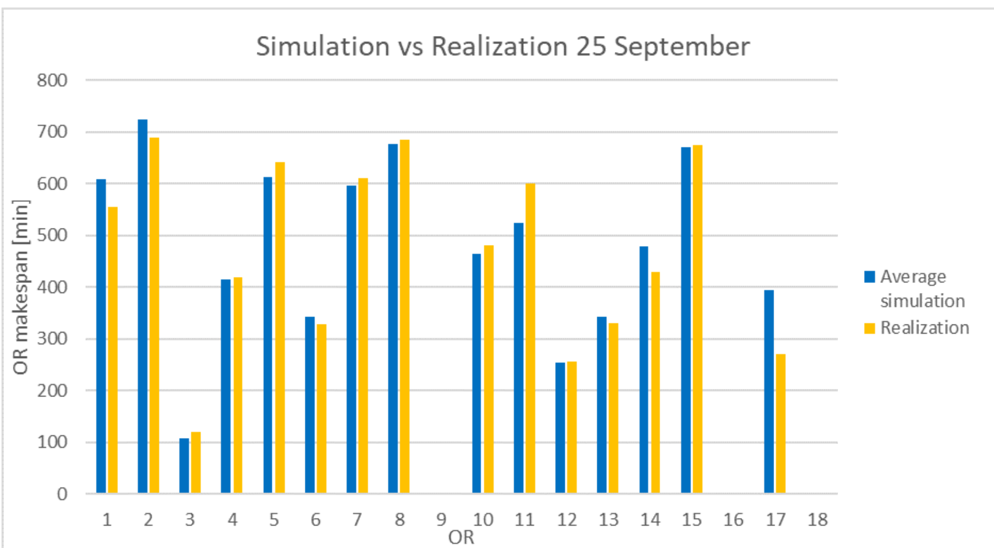


Figure 7.4: Comparison simulation vs realization for 25 September 2017

7.3.2 Numerical analysis

The obtained quality indicators (introduced in Section 7.2) are summarized in Table 7.1.

Indicator	22 June	6 June	23 February	25 September
Bias (%)	2.64	-1.28	1.70	0.08
Absolute average variability (%)	5.15	6.86	6.38	5.48
MSE (%)	0.432	0.472	0.625	0.437

Table 7.1: Numerical analysis of the goodness of simulation results

Data shows the consistency of the model, consistency error is smaller than 2.5% for each analyzed day. At the same time the absolute variability ranges between 5.22% and 6.72%. As mentioned in Section 7.2, this value must be different from zero since the expected average of a process differs from one of its possible realizations. Nevertheless, the average variability interval allows for a local prediction of the makespan.

Considering all four days and active operating rooms, 60 makespans have been simulated. Out of them, 37 differed by less than 30 minutes, 18 between 30 and 60 minutes and 5 simulations produced results which differed by more than 60 minutes.

7.4 Full stochasticity

At this step, the model has been tested applying all the stochastic inputs. In other words, the model tested in this section, is the tool which will be used for decision making.

At this point, the model incorporates the following drivers of stochasticity:

- Surgery durations extracted from the analyzed distributions
- Length of stay in PACU
- Cleaning time
- Transportation from Hospital Wards to the OT
- First case delay

The goal of this validation step is to check consistency and variability of the results with respect to realized workdays. Consistency is expected to be similar to the previous scenario because the fully stochastic model must not introduce a significant bias to the results. Nevertheless, since the surgery duration recorded by the Hospital is obtained as $Patient_{OUT} - Patient_{IN}$, data used to fit the distributions include the waiting time for PACU full. The addition of further delay is thus expected to introduce a slight bias.

Furthermore, the indicator of variability is expected to be larger, since two big sources of variability have been introduced.

7.4.1 Graphical inspection

As for the case of deterministic surgery durations, the graphs of each day and each operating room have been displayed in Figures 7.5,7.6,7.7,7.8.

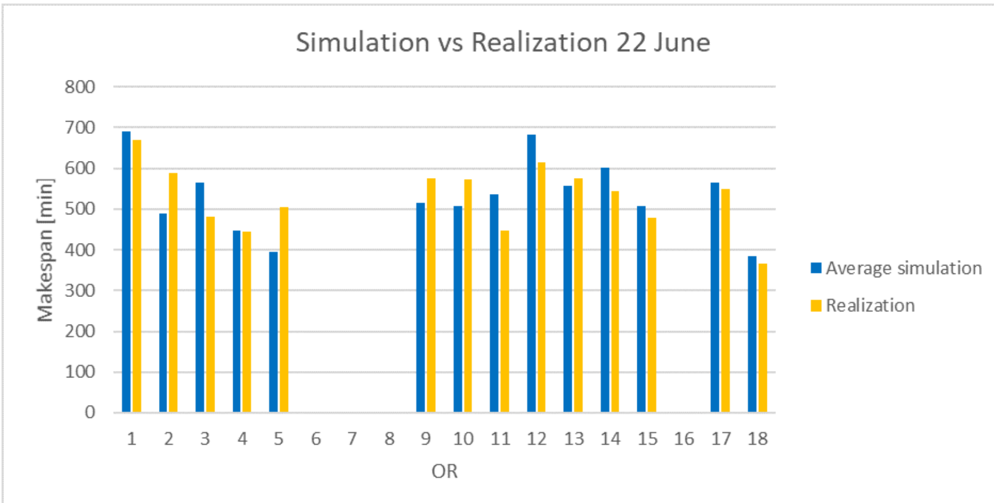


Figure 7.5: Comparison simulation vs realization for 22 June 2018

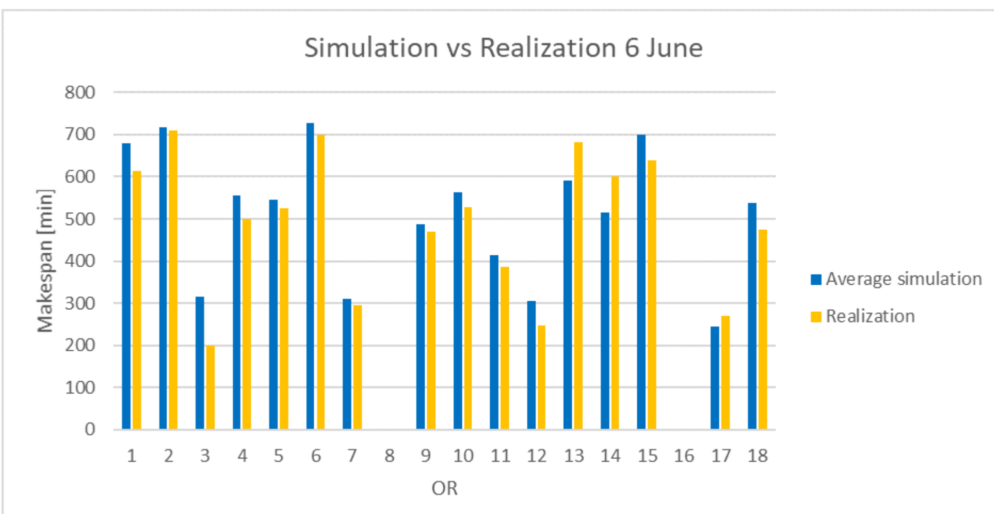


Figure 7.6: Comparison simulation vs realization for 6 June 2018

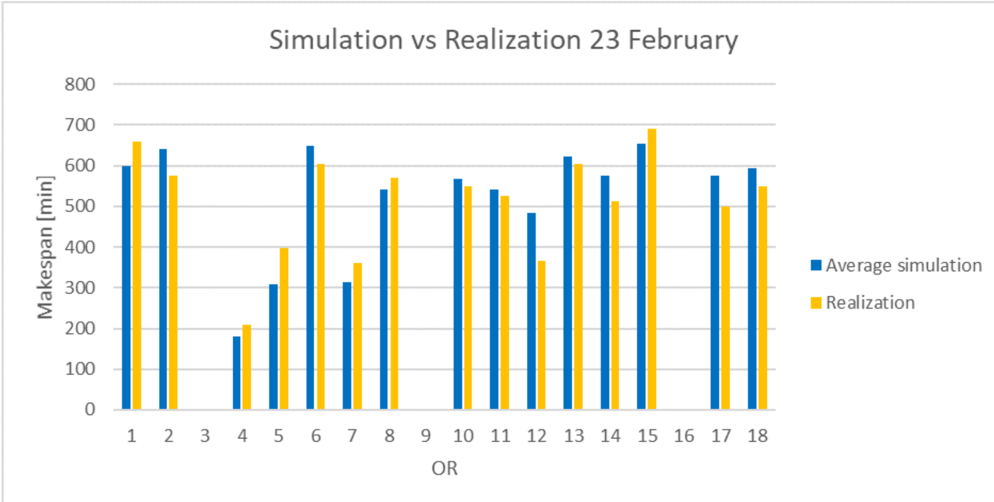


Figure 7.7: Comparison simulation vs realization for 23 February 2017

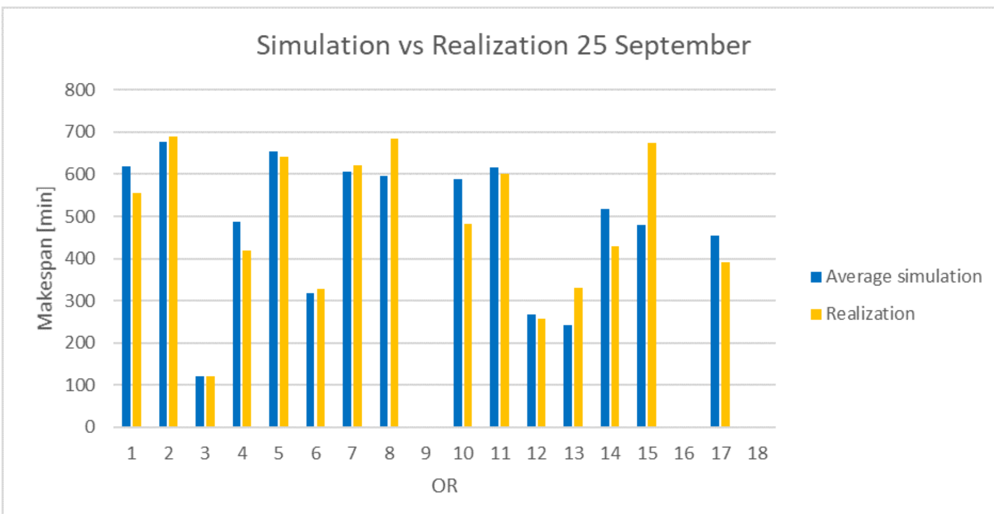


Figure 7.8: Comparison simulation vs realization for 25 September 2017

7.4.2 Numerical analysis

The three measured quality indicators are displayed in Table 7.2.

Indicator	22 June	6 June	23 February	25 September
Bias (%)	0.42	4.60	2.25	0.22
Absolute average variability (%)	9.89	9.78	9.77	11.54
MSE (%)	3.14	3.26	2.89	3.11

Table 7.2: Numerical analysis of the goodness of simulation results

As expected, consistency error is slightly larger than in the previous case, though it remains within an acceptable interval. This result confirms the assumption that the recorded surgery durations ($Patient_{OUT} - Patient_{IN}$) are not significantly different from the duration which would conceptually match the model ($Surgical\ act_{END} - Patient_{IN}$).

Variability increases with respect to the first scenario (range 9.74-11.64 %) and it can be stated that roughly 50% of the variability is due to the system and roughly 50% to the surgical act.

Out of the 60 simulated makespans, 22 differed by less than 30 minutes, 18 between 30 and 60 minutes, 20 differed by more than 60 minutes.

Chapter 8

Heuristics

One of the opportunities enabled by simulation modeling is the testing, in stochastic conditions and including all the main resources, of different scheduling scenarios.

The optimization of the schedule has been performed by considering couples of ORs. Operating rooms are coupled two by two for cleaning and anesthesia, but they are all coupled together for PACU. An effective heuristic, which rigorously tackles PACU congestions, would require to take into account all 18 operating rooms at the same time. This would add extra complexity and computational burden and it would not be possible to compare the results with the ideal solution.

Assuming four surgeries for 15 active operating rooms, it turns out that the ideal best solution (which is the best of all the possible combinations), would require to check: $4!^{15} \approx 5 \times 10^{20}$ combinations.

Furthermore, even considering pairs of operating rooms, evaluating all combinations does not result in a meaningful option, since for example, a couple of operating rooms with 9 and 7 surgeries (reasonable situation for some specialties) would imply the evaluation of $9! \times 7! = 1.8 \times 10^9$ combinations.

8.1 Targets and description

Targets The goal of this part of the project is to develop a heuristic which incorporates the following goals:

1 low computational burden: the algorithm must converge within 10 seconds at most for each pair of operating rooms, using a commercial processor.

2 the obtained schedule should push a short surgery to PACU early in the morning, to smooth its utilization

3 surgeries ending at the same time should be prevented as much as possible, in order to avoid blocking states and reduce the makespan

4 the sequence should stick as much as possible to a decreasing pattern, in order to prevent long surgeries at the end of the day (personnel satisfaction constraint). The internal policy of the hospital includes weekly meetings of all care givers of the operating theater, aimed at achieving consensus about the schedule. Schedules with long surgeries at the end of the day would hardly be accepted.

To summarize the four items, the goal of this section is to obtain a schedule which minimizes the occurrence of surgeries ending together, including constraints of computational burden and personnel satisfaction.

Description of the heuristic The designed heuristic works in the following way:

- The room with the shorter expected makespan starts with the shortest surgery (for PACU). This is the initial condition of the algorithm.
- At each round, the algorithm adds a surgery to the OR to which a shorter expected duration has been assigned. When one operating room has completed the filling of the schedule, the other one proceeds alone.
- At each iteration, the heuristic assigns the longest surgery which does not end within a ± 30 minutes interval with the *last assigned surgery* of the other operating room. If no surgery fulfills this requirement, the longest available surgery (i.e. the longest not yet allocated) is scheduled.

Example Considering the following two vectors:

$$OR_1 = \begin{bmatrix} 96 \\ 45 \\ 21 \\ 120 \\ 55 \\ 110 \end{bmatrix} \qquad OR_2 = \begin{bmatrix} 140 \\ 30 \\ 70 \\ 135 \\ 120 \end{bmatrix}$$

$$MS_1 = 441$$
$$MS_2 = 495$$

The first operating room has a shorter makespan, thus the algorithm places the shortest surgery of OR_1 first. At this point, OR_2 has a shorted assigned total duration, thus a surgery is assigned to

OR_2. The algorithm tries with the longest available surgery (140). Since it does not fall in a ± 30 minutes interval with OR_1, 140 is assigned as the first surgery of OR_2. The algorithm proceeds with OR_1, since a shorter duration has been assigned to it. The longest available surgery lasts 120 minutes, thus it cannot be chosen ($21 + 120 = 141$, too close from the end of the first surgery in OR_2). The second longest available surgery cannot be assigned either, so the algorithm chooses 96. The algorithm proceeds with these rules. Considering that, if there are no available surgeries which can prevent a contemporary completion, the longest one is selected, the resulting schedule is the following one:

$$OR_1 = \begin{bmatrix} 21 \\ 96 \\ 120 \\ 110 \\ 55 \\ 45 \end{bmatrix} \qquad OR_2 = \begin{bmatrix} 140 \\ 135 \\ 120 \\ 70 \\ 30 \end{bmatrix}$$

For this specific case, only one contemporary completion occurs, a short surgery has been pushed early to PACU, and a reasonably decreasing pattern has been followed.

8.2 Benchmarking the heuristic

A preliminary testing of the heuristic has been conducted, considering pairs of realized schedules. The goal of this preliminary testing is to evaluate whether is to check whether the heuristic manages to reduce the number of contemporary completions.

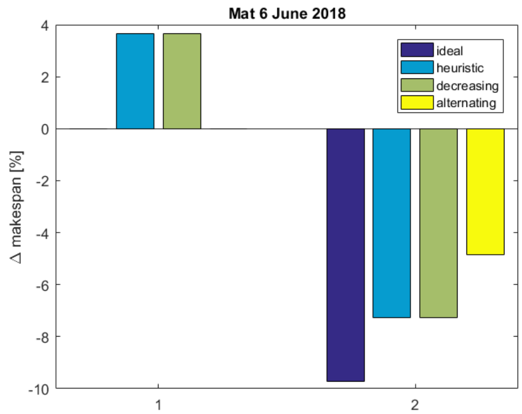
The competing schedules are the following ones:

- Original schedule
- Ideal schedule (all combinations tested)
- Schedule produced by the heuristic
- Surgeries scheduled by decreasing duration
- Surgeries scheduled alternating the duration (shortest, longest, second shortest, second longest, ...)
- Shortest surgery scheduled first, then a decreasing pattern is followed

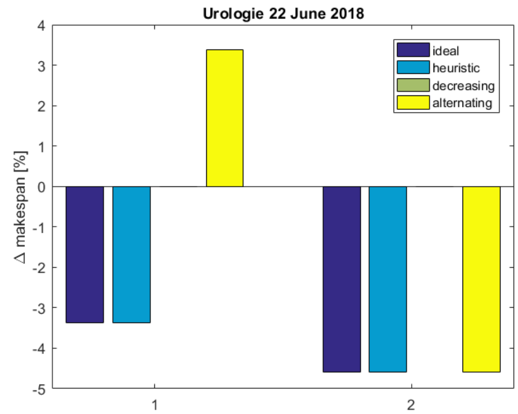
The preliminary benchmarking has been conducted using deterministic durations. Both realized surgery durations and mean values of the distributions have been used as inputs. The two analysis have been carried out to check the consistency of the results in a realized scenario (realized durations) and to verify it may be useful from a more general perspective (mean values of the distributions).

The makespan of each operating room has been computed as the total duration of the surgeries, adding 15 minutes to surgeries ending immediately after (within 15 minutes) a surgery in the other operating room. The computed makespans are thus not representative of the real system, but rather a method to assess whether the algorithm may be useful for a purpose and gather a rough estimation of how much time can be saved through a proper rescheduling.

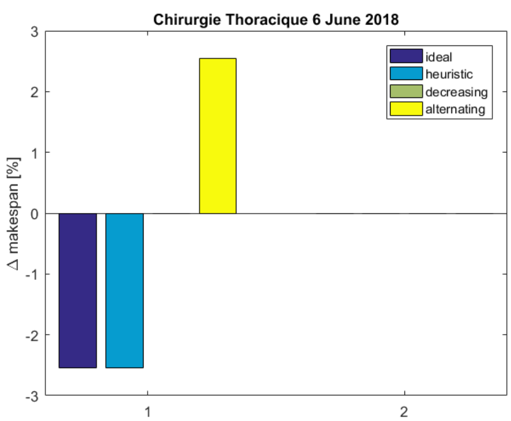
In Figure 8.1 results of the realized scenario are displayed, in Figure 8.2, results coming from the mean duration of the distributions. The first observation is that in no case, the heuristic produces worse results than the original schedule. In 4 cases, the schedule coincides with the ideal one, in 4 cases it is slightly worse.



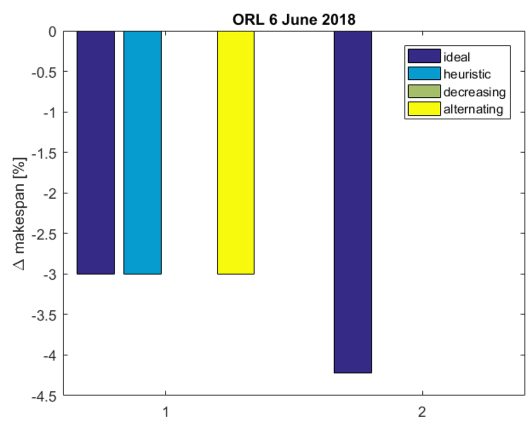
(a) Mat 1 and 2



(b) Urologie

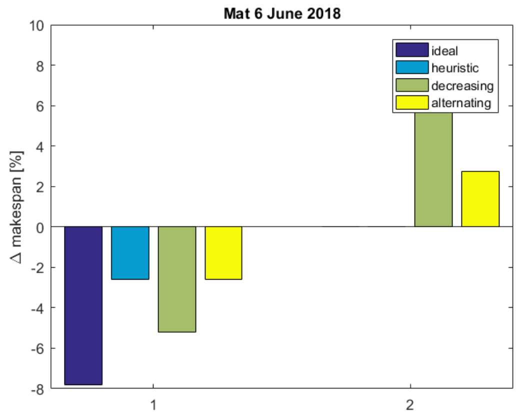


(c) Chirurgie Thoracique

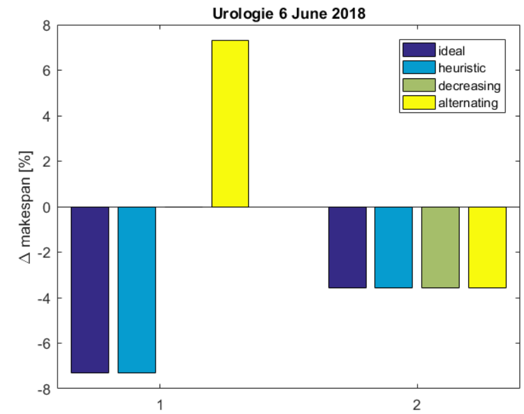


(d) ORL

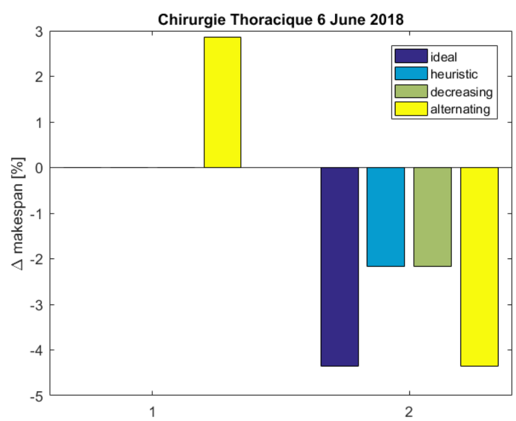
Figure 8.1: Percentage makespan difference between the original schedule, the ideal schedule, the heuristic, a decreasing pattern and an alternating pattern with the shortest first - Mean values of the distributions



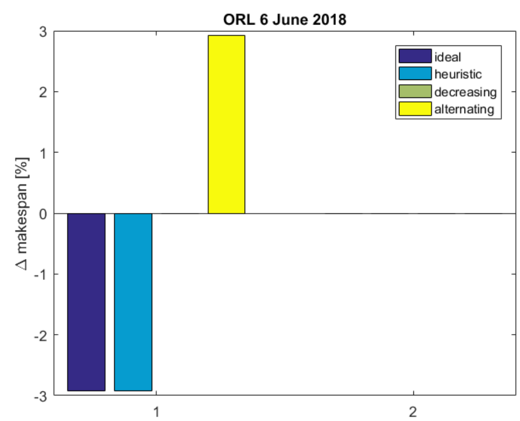
(a) Mat 1 and 2



(b) Urologie



(c) Chirurgie Thoracique



(d) ORL

Figure 8.2: Percentage makespan difference between the original schedule, the ideal schedule, the heuristic, a decreasing pattern and an alternating pattern with the shortest first - realized surgery durations

8.3 DOE

The proposed heuristic has been tested in stochastic conditions. The heuristic has been applied on two Operating Rooms, removing the capacity constraint on PACU and synchronizing the first case. The heuristic thus only takes into account the contemporary endings of the cleaning in the Operating Rooms.

8 different scheduling scenarios have been considered, combining three instances:

- Mean value: M (long surgeries) and m (short surgeries). A short surgery has been defined as a surgery which lasts less than 90 minutes. A long one lasts between 90 and 240 minutes.

Surgeries longer than 4 hours have been excluded because they would not allow an actual sequencing in the Operating Room.

- Variance: V (large variance) and v (small variance). For the case of long surgeries, long variance has been considered larger than one third of the mean value and small variance, smaller than one fourth of the mean value. For long surgeries, smaller and higher than one third.

- Loading: L (high loading) and l (low loading). In the former case, surgeries have been added until the sum of the expected duration is larger than 500 minutes, in the latter one until 250 minutes.

A pool of 10 surgeries with the four possible characteristics (MV,Mv,mV and mv) has been created. From each pool of surgeries, 10 schedules have been extracted, both in the full-load and half-load scenario. Each schedule has been tested with 20 replications.

To summarize: 8 scenarios, 10 schedules for each scenario, 20 replications for each schedule. In the Appendix, Table D.1 includes, for each one of the 80 schedules:

- Average makespan with the original schedule

- Average makespan after the application of the heuristic

- Average gain

Results in Table D.1 have been summarized in Table 8.1 to provide an overview of the experiments.

Configuration	Total average gain	Percentage gain
MVL	-102	-0.758
MvL	-88	-0.656
mVL	-129	-0.801
mvL	-184	-1.137
MVl	-17	-0.221
Mvl	-25	-0.350
mVl	67	0.816
mvl	-111	-1.311

Table 8.1: Aggregate data of the experiments. Results in minutes

Table 8.1 shows that the average improvement is more interesting when the loading of the Operating Room is greater. This result has two intuitive explanations:

1 The more the surgeries, the wider the pool, the easier to find proper synchronization

2 The more the surgeries, the higher the number of turnovers, thus the more likely to save time

To summarize and interprete the results numerically, an ANOVA General Linear model has been performed on the dataset, to evaluate the effectiveness of the heuristic. Table 8.3 summarizes the results of the test.

Factor Information

Factor	Type	Levels	Values
Mean	Fixed	2	1, 2
Variance	Fixed	2	1, 2
Loading	Fixed	2	1, 2
Heuristic	Fixed	2	0, 1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Mean	1	1341769	1341769	159.30	0.000
Variance	1	9063	9063	1.08	0.301
Loading	1	18746242	18746242	2225.57	0.000
Heuristic	1	2173	2173	0.26	0.612
Error	155	1305582	8423		
Lack-of-Fit	11	349682	31789	4.79	0.000
Pure Error	144	955901	6638		
Total	159	21404830			

Figure 8.3: Results of the the General Regressive Model

Figure 8.3 shows that Mean and Loading have a significant impact on the makespan, while Variance and Heuristic do not. Mean as an impact because the longer the Mean duration of the surgeries, the less turnovers have to be performed, thus the result was expected. The significance of Loading is trivial: less loaded Operating Rooms complete their activity earlier. Regarding the heuristic, the non significance was expected, because of the very poor results (and even negative in the mVl scenario) of the heuristic in case of low loading.

Focusing on the most promising scenarios, namely schedules with short surgeries and high loading (both small and large variance), with 80 schedules for each configuration and 50 replications (to ensure accurate average makespans), significance of the heuristic has been found. Figure 8.4 reports the results of the ANOVA General Linear Model. The variance remains non significant. Results of the simulations are displayed in the Appendix, Figure D.2.

General Linear Model: MS versus Variance, Heuristic

Method

Factor coding	(-1, 0, +1)

Factor Information

Factor	Type	Levels	Values
Variance	Fixed	2	1, 2
Heuristic	Fixed	2	0, 1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Variance	1	1289	1288.9	0.35	0.555
Heuristic	1	14532	14531.5	3.95	0.048
Error	317	1167447	3682.8		
Lack-of-Fit	1	908	907.7	0.25	0.620
Pure Error	316	1166539	3691.6		
Total	319	1183268			

Figure 8.4: Results of the the General Regressive Model, focusing on schedules with short surgeries

8.4 Limitations

The heuristic has been presented to Prof. Longrois, who has expressed his appreciation for the idea and positively valued implementation opportunities. Nevertheless, he has pointed that the heuristic presented above, neglects two constraints of the Operating Theater:

1. Some surgeries require equipment with limited availability (e.g. two surgeries may require a machine which is shared by two Operating Rooms, thus it is not possible to perform them both at the same time)

2. Some patients require to receive surgeries early in the morning. Prof. Longrois has mentioned the issue of children: since patients have to fast the whole day until surgery, children have the priority to avoid them fasting for a long time span.

Incorporating in the model the abovementioned constraints would require several work with the Hospital, to define for each surgery the required machinery. Therefore, even if they would not introduce significant theoretical issues, limitations have been neglected in this project. Awareness could lead to prospective future improvements.

Chapter 9

Results and Managerial Insights

The verified and validated simulation model can be now used to gather a quantitative overview of the system and to test new scenarios aimed at providing decision aiding insights to Hospital Managers.

In the following Chapter, the following three topics have been tackled:

1. Overview of the system, aimed at understanding bottlenecks and sources of inefficiency.
2. Cost-free “What-If” scenarios: the effect of scheduling following the heuristic proposed in Chapter 8.
3. Sensitivity analysis of different resource allocations

9.1 System Overview

This Section includes first the computed utilization rate of each Operating Room over each workday, the average value over the 18 Operating Rooms and some description of the wasted time in the Operating Theater, extracted from the simulation results.

9.1.1 Operating Room Utilization

Table 9.1 displays the utilization of each Operating Room, computed as:

$$U_{OR} = \frac{Surgery\ time}{OR\ makespan}$$

Surgery time includes Anesthesia induction, Incision and Patient Awakening, in other words, the sum of the value adding activities during which the patient is obliged to occupy the Operating Room. Everything else does not add value to the Hospital and it can be considered as *waste*.

	Utilization			
	06-Jun	22-Jun	23-Feb	25-Sep
THO1	0.847	0.827	0.817	0.791
THO2	0.867	0.809	0.887	0.838
RYT1	0.885	0.886		0.776
RYT2	0.728	0.715	0.808	0.720
CAR1	0.879	0.829	0.859	0.888
CAR2	0.882		0.880	0.868
CAR3	0.871		0.861	0.875
ORT1			0.837	0.816
ORT2	0.817	0.720		
ORL1	0.825	0.735	0.860	0.762
ORL2	0.779	0.747	0.816	0.785
DIG1	0.864	0.802	0.832	0.766
DIG2	0.846	0.765	0.862	0.790
MAT1	0.741	0.646	0.804	0.690
MAT2	0.796	0.721	0.830	0.802
MAT3				
URO1	0.748	0.768	0.839	0.753
URO2	0.777	0.775	0.868	

Table 9.1: Computed average OR utilization over 50 replications

As expected, CAR1, CAR2 and CAR3 present the highest values of occupation, since there is one cleaning team fully dedicated to each OR (thus no blocking for cleaning) and since patients are discharged in ICU (thus no time is wasted for PACU blocked).

The average utilization of each workday is displayed in Table 9.2.

	Utilization			
	06-Jun	22-Jun	23-Feb	25-Sep
OT	0.822	0.768	0.844	0.795

Table 9.2: Computed average OT utilization over 50 replications

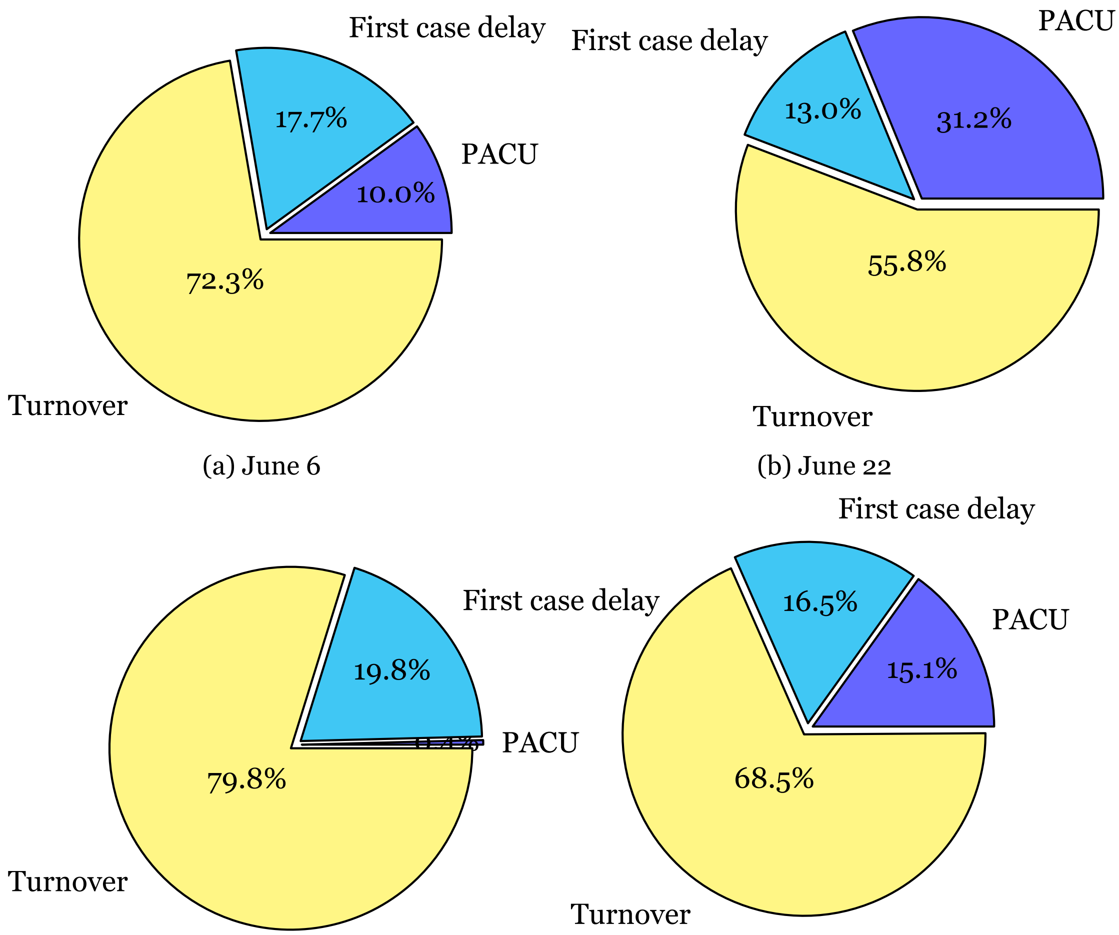
9.1.2 Sources of inoccupancy

The modeled sources of inoccupancy are the following ones:

1. Turnover time: cleaning time + waiting for cleaning + wating for anesthesiologist
2. Waiting time for a free bed in PACU (when PACU is full it is not possible to discharge the patient)
3. First case delay

First case delay is an input of the model, it has been analyzed from the dataset (see Chapter 6). It turns out that the average first case delay corresponds to 16 minutes.

Pie charts in Figure 9.1 show the impact of each one of the three factors for each workday.



(a) June 6 (b) June 22

(c) February 23 (d) September 25

Figure 9.1: Impact of the three sources of inefficiency over the overall inoccupation

Figure 9.1 shows that the major driver of inoccupancy is *Turnover*, ranging between 55.8% and 79.8% while *First case delay* is a relevant but secondary issue, ranging between 13.0% and 19.8%. PACU is the most variable source of inoccupancy, ranging from 0.4% (practically negligible) on February 23rd to 31.2% on June 22nd.

9.1.3 Discussion

Figure 9.1 clearly shows that the highest effect of non-operating time comes from turnover. Part of it can be avoided by increasing the performance of the system but it cannot be completely erased, since *cleaning* is a mandatory operation after each surgery. PACU waiting time could be theoretically lead to zero by increasing PACU capacity and properly scheduling surgeries. Scheduling is cost-free (this topic will be analyzed in the next section), and it cannot completely prevent PACU waiting time. PACU waiting time can be nullified only by adding beds. The actual cost effectiveness can be evaluated by Hospital managers, based on the presented results. First case delay cannot be tackled by simulation; the most intuitive approach to reduce first case delays is the introduction of incentive programs. Scalea et al. [90] and St Jacques et al. [96] propose incentive programs which turned out to be successful in terms of reduction of first case delays.

9.2 Cost-free “What-If” scenarios

Following the assumption N.8 of the assumptions document (see Section 4.4), surgeries have been assumed to be black boxes, time and sequence independent, thus performance improvements can be reached only through two different methods:

- Choosing the best surgeries to plan each workday of each Operating Room: unfeasible because of the block scheduling approach of Hospital Bichat. The list of surgeries of each operating room is a constrained input of the model
- Reducing congestions by redesigning some structures of the system and/or rescheduling surgeries

Regarding congestions, two main issues have been gathered by the conceptual modeling of the Operating Theater:

- Cleaning Teams work on two parallel Operating Rooms, thus contemporary or near terminating times make one Operating Room wait for the Cleaning Team.
- Analogous issue with Anesthesiologists working on two different rooms at the same time. Two surgeries cannot begin at the same time because the presence of one Anesthesiology in the Operating Room during Anesthesia induction is required for safety reasons by law
- PACU saturation leads to patient recovery in the Operating Room, thus reducing the productivity of the system

The developed heuristic in Chapter 8 is aimed at tackling the abovementioned issues, reducing the probability of contemporary begins of surgeries in coupled ORs and trying to smooth PACU utilization by pushing short surgeries at the beginning of the day.

Furthermore, a new configuration has been tested: grouping cleaning teams into a single resource instead of having them allocated to couples of Operating Rooms leads for sure to performance improvements, but the quantitative advantages due to this configurations are unknown to the Operating Theater manager.

To summarize and introduce the results, five different scenarios have been tested:

1. Same allocation of cleaning teams, applying the scheduling heuristic presented in Chapter 8
2. Same allocation of cleaning teams, applying a similar heuristic, but imposing the shortest surgery first in all Operating Rooms
3. Cleaning teams grouped into a single resource, with the original schedule (i.e. the realized one)
4. Cleaning teams grouped into a single resource, applying the scheduling heuristic presented in Chapter 8 Cleaning teams grouped in a single resource, applying a similar heuristic, but imposing the shortest surgery first in all Operating Rooms

For the sake of clarity, full Tables containing the makespans of the each Operating Rooms have been attached to Appendix C.

Conversly, the aggregation and the analysis of the results has been included in this Chapter.

9.2.1 Average makespans

Table 9.3 shows that in no case the current configuration corresponds to the optimal one. Different scheduling approaches and configurations do not produce prominent improvements due to both constraints (i.e. sticking as much as possible to a decreasing duration pattern to create an acceptable schedule) and assumption declared in Section 4.4.

	Original Cleaning Configuration			Grouped Cleaning Teams		
Date	Original	Heuristic 1	Heuristic 2	Original	Heuristic 1	Heuristic 2
06-Jun	513	507	504	508	505	501
22-Jun	519	520	519	518	521	517
23-Feb	321	321	316	318	318	317
25-Sep	342	338	340	342	338	339

Table 9.3: Average simulated makespans with different scheduling and cleaning teams allocation over the four simulated operating days

9.2.2 Aggregate makespan reduction

To provide quantitative data about the overall prospective time saving in the whole Operating Theater, the sum of the difference between new makespan and original one over the 18 Operating Rooms has been displayed in Table 9.4.

In formulas, each of the cells of Table 9.4 has been computed as follows:

$$\sum_{i=1}^{N_{ORs,active}} MS_{new} - MS_{original} = \overline{MS}_{OT} * N_{ORs,active}$$

	Original Cleaning Configuration			Grouped Cleaning Teams		
Date	Original	Heuristic 1	Heuristic 2	Original	Heuristic 1	Heuristic 2
06-Jun		-86	-148	-70	-124	-189
22-Jun		20	1	-10	35	-19
23-Feb		-2	-76	-48	-58	-61
25-Sep		-70	-35	-11	-68	-49

Table 9.4: Average simulated makespans with different scheduling and cleaning teams allocation over the four simulated operating days

Before discussing results, it must be pointed that on June 6th there are 16 active Operating Rooms, on June 22nd, 14 active Operating Rooms, and on September 25th and February rd, 15 active Operating Rooms.

The effect of improving cleaning time is thus substancial, while on June 22nd, with 14 active ORs, it does not affect much the system. Furthermore, considering Figure 9.1, it can be noticed that on June 22nd, a significant congestion in PACU has been experienced. PACU is positioned downstream the Operating Rooms, thus most of the improvements generated in the Operating Rooms are absorbed by the blocking PACU. This statement is also supported by Table 9.4: on June 22nd, Heuristic 2, which is designed to prioritize PACU smoothing, performes significantly better than Heuristic 1, which prioritizes cleaning and caregivers' satisfaction (by introducing one constraint less than Heuristic 1).

9.2.3 Overtime

Overtime is a crucial KPI related to the economic effectiveness of the Operating Theater [30, 17]. Considering as Overtime anytime a makespan is longer than 10 hours (elective surgeries, except for Cardiology which anticipates by 30 minutes, are supposed to take place between 8 am and 6 pm), it has been computed how each configuration affects the overtime.

	Original Cleaning Configuration			Grouped Cleaning Teams		
Date	Original	Heuristic 1	Heuristic 2	Original	Heuristic 1	Heuristic 2
06-Jun		-37	8	-47	-20	-43
22-Jun		11	-3	17	32	3
23-Feb		37	-14	-2	23	26
25-Sep		17	24	11	4	24

Table 9.5: Average simulated overtime with different scheduling and cleaning teams allocation over the four simulated operating days

Table 9.5 shows the simulated difference between between Overtime in original conditions and with different configurations. Overtime can be significantly reduced on June 6th, while no significant improvements can be achieved with the other configurations. Fortunately, it can be spotted a correspondence between the best performing configurations in terms of makespan reduction and overtime.

9.2.4 Required cleaning teams

In the original configuration, 11 cleaning teams are used: cleaning teams coupled 2 by two in 14 ORs and cleaning teams allocated singularly to 4 ORs.

The box plot in Figure 9.2 shows the required Cleaning Teams at peak conditions (i.e. the moment of the day, in which the maximum number of cleaning teams are working at the same time) in case of grouping teams into a single resource. Quartiles have been calculated over 50 replications.

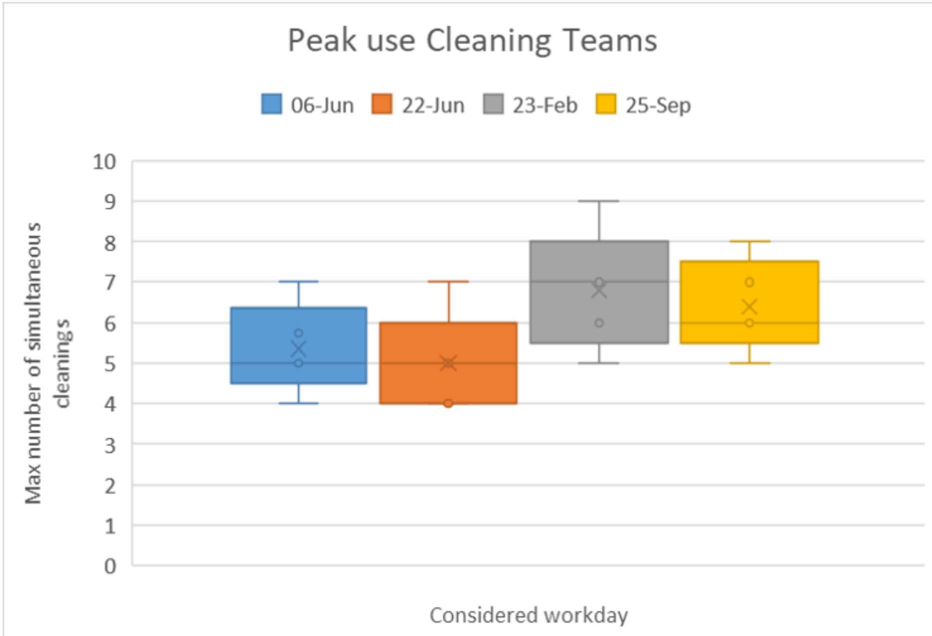


Figure 9.2: Number of simultaneous cleanings at peak condition for each of the four considered days. Boxplots created over 50 replications.

Cleaning Teams are overstaffed, since at peak condition, no replication requires more than 9 cleaning teams to work at the same time. Considering median values, no workday requires more than 7 Cleaning Teams at the same time.

9.2.5 Discussion

Results show that, despite the application of scheduling approaches which take into account care givers' satisfaction, it is possible to not penalize, and even slightly improve the overall performance of the Operating Theater. In terms of performance, shifting longer interventions before the last one (which is the outcome of the heuristic) reduces the measured performance of the Operating Theater, because the last cleaning is not included in the OR makespan. Makespan has been measured as $Patient_{N,OUT} - Patient_{1,IN}$, thus pushing long surgeries (which are coupled to long cleaning duration) at the end of the list, improves the measured performance. Despite this penalization, by reducing congestions due to contemporary cleaning and anesthesia induction, as well as pushing short cases to PACU at the beginning of the day, an overall reduction in Hospital's makespan has been achieved. As expected, improvements are prominent when there are more active Operating Rooms, and less significant when the PACU generates abundant congestions.

In terms of overtime, non significant improvements have been achieved, except for June 6^{th}, when the overall Operating Theater is benefiting from a rigorous scheduling. With regards to cleaning teams, simulation has clearly shown that the Hospital, by coupling them two by two rooms in

14 ORs and having 4 teams allocated to a single OR, instead of grouping them into a single resource and having them work in the all operating theater, is both penalizing the performance and overstaffing the resource.

9.3 Sensitivity analysis

One of the results of Section 9.1.2 is that PACU blocking ranges from being an absolutely negligible issue to accounting for almost one third of the overall inoccupancy. Since PACU is sometimes used as a backup for ICU (which must not block for safety reasons), a smaller amount of beds can be available. Also, it has been tested the effect of adding PACU beds on the overall performance of the Operating Theater.

9.3.1 Makespan original configuration - Sensitivity PACU

The increase/reduction of time wasted because of PACU blocking by adding 1 and 2 beds (prospective investment) and subtracting 1 and 2 beds (ICU saturated) has been analyzed, considering the original resource allocation (cleaning teams allocated two by two) and original schedule.

Results have been plotted on Figure 9.3.

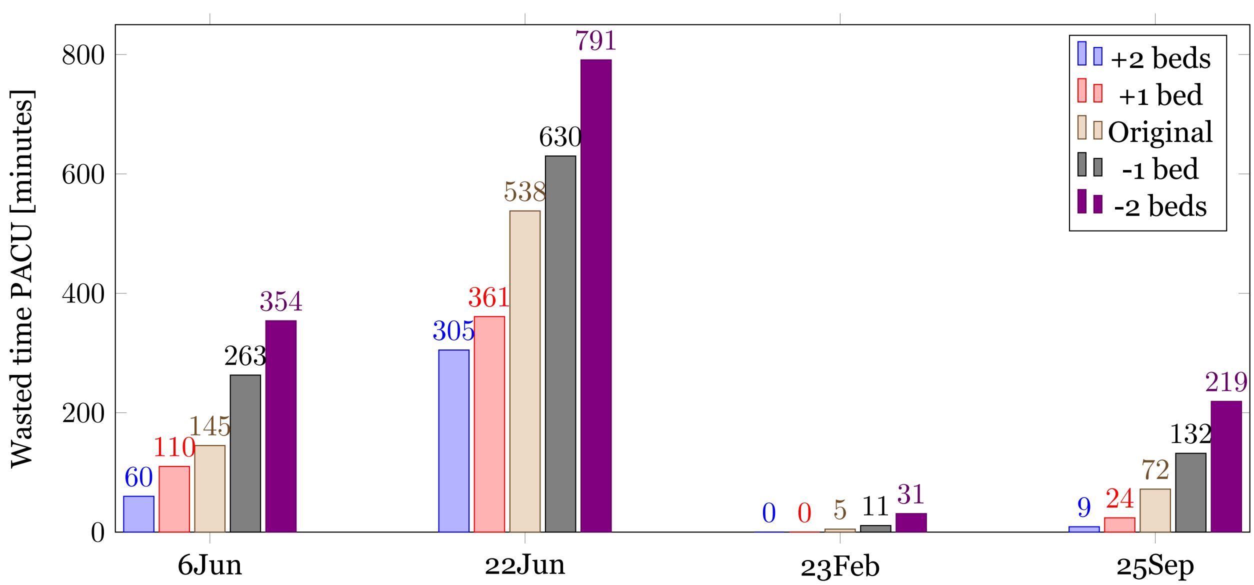


Figure 9.3: Sensitivity of time wasted in the Operating Theater due to PACU blocking

Histograms in Figure 9.3 show that the addition of the first bed in PACU has a greater effect than the addition of a second one. As expected, on February 23rd, when the effect of PACU blocking is negligible, the system is not sensitive to changes, while on June 22nd, which experiences prominent congestions in PACU, subtracting two beds to PACU would increase by 258 minutes the congestion and adding two beds would reduce congestions by 235 minutes.

9.3.2 Heuristics with variations in PACU beds

	Original Cleaning Configuration			Grouped Cleaning Teams		
Configuration	Original	Heuristic 1	Heuristic 2	Original	Heuristic 1	Heuristic 2
Original		20	1	-10	35	-19
+1 bed		-66	-25	-41	-54	-55
+2 beds		12	-14	-9	-17	-58

Table 9.6: Effect of applying heuristics and grouping cleaning teams with reduced congestions in PACU

As expected, by adding PACU beds, thus reducing congestions created by PACU saturation, there is a twofold effect:

- Reduction of time wasted for congestions (quantified in Figure 9.3)
- More relevant effect of the Heuristics: considering a highly overloaded PACU, which is a bottleneck positioned downstream with respect to the Operating Rooms, not much optimization can be carried out in the Operating Rooms. Any improvement upstream is canceled by PACU. Also, even pushing short surgeries at the beginning produces slight effect in an overloaded system.

9.3.3 Discussion

In section above, it has been shown the effect of allocating more PACU beds and having some ICU urgency in the system. The analysis has been performed with fixed capacity, while patients coming from ICU are hospitalized temporarily in PACU, until an ICU bed is available. The effect shown in Figure 9.3 is thus extremely more moderate. The Operating Theater is sensitive to the addition of one PACU bed, less to the addition of a second one, and as presented in Table 9.6, in case of highly congested system, the addition of PACU beds, increases the effect of rescheduling and grouping cleaning teams.

9.4 Conclusions, Limitations and Future Outlooks

The problem of allocating one cleaning team over two parallel operating rooms has been proved to produce significant time losses, although not vital. According to Prof. Longrois, the reason why they have not been grouped into a single resource with large capacity lies in the lack of managerial culture in Public Hospital. To the extent of his knowledge, there is no technical barrier to this change of approach, but pure indifference towards performance improvements. Nevertheless, the proposed heuristic, would provide slight improvements, by sequencing surgeries taking this issue into account. As shown in Figure 9.2, grouping cleaning team would also lead to redundance, which could be exploited to smooth the workload or progressively save money by not replacing future vacancies.

The second major reason of performance losses, namely PACU blocking states, could be faced by smoothing patients' inflow or by increasing the number of available beds. As shown in Figure 9.3, the addition of just one bed would provide large savings in three of the four considered workdays.

The large number of assumptions adopted for the development of this project limits its accuracy and leads to significant deviations between realized and simulated makespans. Assumptions have been forced into this project by lack of data collected by the hospital, scarce integration among different data sets, lack of funds and time to produce more accurate analysis.

The implementation of this simulation model has been pushed early in the system, which was not able to support it with sufficient transparency. Length of stay in PACU is collected manually, thus a small-sized sample has been extracted, data about patients' routing is dirty and often clearly corrupted (Patient N.2 cannot enter the Operating Room before patient N.1 leaves it). Intervention IDs are often mistyped, thus an excessive number of records has been processed, thus reducing sample size and accuracy of data analysis. No measures of cleaning time, anesthesia induction and time wasted for blocking states are collected by the Hospital. There is no tracking of the "Brancardiers", and no data about waiting times. Barjis [7] support the thesis that Simulation should be supported by a complete and effective data collection infrastructure.

Future outlooks for this project lie in empirical analysis performed on input data. As stated in the Assumptions Document (Section 4.4), surgeries have been treated as black boxes. There is extensive literature showing that predictive models based on empirical data analysis improve the accuracy of surgery durations.

Gillespie et al. [35] find evidence that communication failures explain 4.5% of the variance of the distribution of surgery durations. Shahabikargar et al. [92] point and test several predictors of surgery duration: patient characteristics, operation characteristics, specialty and team composition. Strum et al. [100] find that type of anesthesia, age, gender of the patient and ASA class are factors affecting variability of surgery duration. Dexter et al. [23] carried out a systematic review to identify predictors of surgery durations of General Thoracic Surgery.

Feeding the model with predictive analysis of durations, based on historical data, would enhance the accuracy of the results and increase the possibility of improvements at the same time.

Also, ICU, roughly modeled but not explored rigorously, could be integrated in future simulation models, and the model could be expanded to the Ambulatory and to Urgent patients. Taking inspiration from Mielczarek and Zabawa [69], a forecasting of the future demand, based on population aging, could be carried out to test how the system will perform in 5, 10, 20 years and plan future resources.

Bibliography

[1] (2016). Health at a Glance: Europe 2016. Technical report, OECD.

[2] Alvarez, R., Bowry, R., and Carter, M. (2010). Prediction of the time to complete a series of surgical cases to avoid cardiac operating room overutilization. *Canadian Anesthesiologists' Society*, 57:973–9.

[3] Ang, W. W., Sabharwal, S., Johannsson, H., Bhattacharya, R., and Gupte, C. M. (2016). The cost of trauma operating theatre inefficiency. *Annals of Medicine and Surgery*, 7:24–29.

[4] Asamoah, D., R. Sharda, R., Rude, H., and Doran, D. (2018). Rfid-based information visibility for hospital operations: exploring its positive effects using discrete event simulation. *Anesthesiology*, 21:305–316.

[5] Azari-Rad, S., Yontef, A., Aleman, D., and Urbach, D. (2013). Reducing elective general surgery cancellations at a canadian hospital. *Canadian Journal of Surgery*, 56(2):113–118.

[6] Bai, M., Storer, R. H., and Tonkay, G. L. (2017). A sample gradient-based algorithm for a multiple-OR and PACU surgery scheduling problem A sample gradient-based algorithm for a multiple-OR and PACU surgery scheduling problem. *IISE Transactions*, 49(4):367–380.

[7] Barjis, J. (2011). Healthcare Simulation and its Potential Areas and Future Trends. Technical report, Department of Systems Engineering, TU Delft.

[8] Begen, M. A. and Queyranne, M. (2011). Appointment Scheduling with Discrete Random Durations *. *Mathematics of Operations Research*, 36(2):240–257.

[9] Bosch, P. M. V. and Dietz, D. C. (2000). Minimizing expected waiting in a medical appointment system. *IIE Transactions*, 32(9):841–848.

[10] Brailsford, S. (2005). Overcoming the barriers to implementation of operations research simulation models in healthcare. *Clinical and Investigative Medicine*, 28(6):312–315.

[11] Busby, C. R. and Carter, M. W. (2017). Data-Driven Generic Discrete Event Simulation Model of Hospital Patient Flow Considering Surge. Toronto, Canada.

[12] Campbell, D. A., Sonnad, S. S., Eckhauser, F. E., Campbell, K. K., and Greenfield, L. J. (2001). Burnout among american surgeons. *Surgery*, 130(4):696 – 705.

[13] Cardoen, B., Demeulemeester, E., and Beliën, J. (2009). Operating room planning and scheduling: A literature review. *European Journal of Operational Research*, 201:921–932.

[14] Chan, W. K. V., D'ambrogio, A., Zacharewicz, G., Mustafee, N., Wainer, G., Khoshkenar, A., Taaffe, K., Muhs, M., Fredendall, L., Ferrand, Y., Joseph, A., and San, D. (2017). Proceedings of the 2017 Winter Simulation Conference SIMULATION-BASED DESIGN AND TRAFFIC FLOW IMPROVEMENTS IN THE OPERATING ROOM. Charleston, South Carolina, USA.

[15] Choi, S. and Wilhelm, W. E. (2012). An analysis of sequencing surgeries with durations that follow the lognormal, gamma, or normal distribution An analysis of sequencing surgeries with durations that follow the lognormal, gamma, or normal distribution. *IIE Transactions on Healthcare Systems Engineering*, 2(2):156–171.

[16] Chou, H., Hecker, R., and Martin, A. (2012). Predicting nurses well-being from job demands and resources: a cross-sectional study of emotional labour. *Journal of Nursing Management*, 20:502–511.

[17] Courpron, J. and Krief, J. (2011). Démarche de benchmarking des blocs opératoires. Technical report, Agence Régionale de Santé Bretagne.

[18] Darawad, M. W., Nawafleh, H., M. M., Hamdan.Mansour, A., and Azzeghaiby, S. (2015). The relationship between time pressure and burnout syndrome: A cross-sectional survey among jordanian nurses. *Scientific Research Publishing, Health*, 7:14–22.

[19] Denton, B. and Gupta, D. (2003). A Sequential Bounding Approach for Optimal Appointment Scheduling. *IIE Transactions*, 35(11):1003–1016.

[20] Denton, B., Nelson, H., Rahman, A., and Bailey, A., editors (2006). *Simulation of a Multiple Operating Room Surgical Suite*.

[21] Denton, B. T., Care, H., Sci, M., Denton, B., Viapiano, J., Vogl, A., Denton, B., Viapiano, J., Vogl, ☐. A., and Allen, F. (2007). Optimization of surgery sequencing and scheduling decisions under uncertainty. *Health Care Manage Science*, 10(1):13–24.

[22] Denton, B. T., Fitts, E. P., Miller, A. J., Balasubramanian, H. J., and Huschka, T. R. (2010). Optimal Allocation of Surgery Blocks to Operating Rooms Under Uncertainty. *OPERATIONS RESEARCH*, 58(4):802–816.

[23] Dexter, F., Dexter, Elisabeth U. Masursky, D., and Nussmeier, N. A. (2008). Systematic review of general thoracic surgery articles to identify predictors of operating room case durations. *Anesthesia Analgesia*, 106(4):1232–1241.

[24] Dexter, F., Marcon, E., Aker, J., and Epstein, R. H. (2009). Numbers of Simultaneous Turnovers Calculated from Anesthesia or Operating Room Information Management System Data. *Anesthesia & Analgesia*, 109(3):900–905.

[25] Dexter, F., Marcon, E., Epstein, R., and Ledolter, J. (2005). Validation of statistical methods to compare cancellation rates on the day of surgery. *Anesthesiology*, 82:94–101.

[26] Dexter, F. and Traub, R. (2002). How to schedule elective surgical cases into specific operating rooms to maximize the efficiency of use of operating room time. *JAMA Surgery*, 94:933–42.

[27] Dunn, P., Arnetz, B., Christensen, J., and Homer, L. (2007). Meeting the imperative to improve physician well-being: Assessment of an innovative program. *Journal of General Internal Medicine*, 22(11):1544–1552.

[28] Díaz-López, D., López-Valencia, N., González-Neirab, E., Barrerab, D., Suárezc, D., Caro-Gutiérrezb, M., and Sefair, C. (2018). A simulation-optimization approach for the surgery scheduling problem: a case study considering stochastic surgical times. *International Journal of Industrial Engineering Computations*, 9:409–422.

[29] F., D. and J.H., T. (1995). Modeling and prediction of surgical procedure times. *Anesthesiology*, 82:94–101.

[30] François, H. (2012). Vers des blocs opératoires plus sûrs et plus performants. Technical report, AP-HP.

[31] Freeman, N., Zhao, M., and Melouk, S. (2017). An iterative approach for case mix planning under uncertainty. *Omega*, 9:160–173.

[32] Gaba, D., Howard, S., and Jump, B. (1994). Production pressure in the work environment. *Anesthesiology*, 81(2).

[33] Ghanes, K., Wargon, M., Jouini, O., Jemai, Z., Diakogiannis, A., Hellmann, R., Thomas, V., and Koole, G. (2015). Simulation-based optimization of staffing levels in an emergency department. *Simulation*, 91(10):942–953.

[34] Gifford, E., Galante, J., Kaji, A., and et al (2014). Factors associated with general surgery residents' desire to leave residency programs: A multi-institutional study. *JAMA Surgery*, 149(9):948–953.

[35] Gillespie, B. M., Chaboyer, W., and Fairweather, N. (2012). Factors that influence the expected length of operation: results of a prospective study. *BMJ Quality and Safety*, 21(3):3–12.

[36] Guest, R. S., Baser, R., Li, Y., Scardino, P. T., Brown, A. E., and Kissane, D. W. (2011). Cancer surgeons' distress and well-being, i: The tension between a culture of productivity and the need for self-care. *Annals of Surgical Oncology*, 18(5):1229–1235.

[37] Gul, S. (2018). A Stochastic Programming Approach for Appointment Scheduling Under Limited Availability of. *Surgery Turnover Teams*. *Service Science*, 10(3):277–288.

[38] Gunal, M. and Pidd, M. (2010). Discrete event simulation for performance modelling in health care: a review of the literature. *Journal of Simulation*, 4:42–51.

[39] Hancock, W., Walter, P., More, R., and Glick, N. (1988). Operating room scheduling data base analysis for scheduling. *Journal of Medical Systems*, 12(6):397–409.

[40] Hariharan, S. and Chen, D. (2015). Costs and Utilization of Operating Rooms in a Public Hospital in Trinidad, West Indies. *Perm J 2015 Fall*, 19(4):128–132.

[41] Harper, P. R. and Pitt, M. A. (2004). On the Challenges of Healthcare Modelling and a Proposed Project Life Cycle for Successful. *Source: The Journal of the Operational Research Society*, 55(6):657–661.

[42] Henderson, S. G., Biller, B., Hsieh, M.-H., Shortle, J., Tew, J. D., Barton, R. R., Huschka, T. R., Denton, B. T., Fitts, E. P., and Fowler, J. W. (2007). Proceedings of the 2007 Winter Simulation Conference BI-CRITERIA EVALUATION OF AN OUTPATIENT PROCEDURE CENTER VIA SIMULATION. Technical report, Department of Industrial Engineering, Arizona State University.

[43] Houdenhoven, van, M. (2007). *Healthcare Logistics: the art of balance*. PhD thesis, Erasmus University Rotterdam.

[44] Jacobson, S. H., Swisher, J., and Healthcare, M. W. (1999). Application of Discrete-Event Simulation in Health Care Clinics: A Survey. *Article in Journal of the Operational Research Society*.

[45] Jean-Marcel, M. (2017). Atlas de la demographie médicale en france. Technical report, Ordre National des Medecins.

[46] Jenkins, K. and Wong, D. (2001). Survey of professional satisfaction among canadian anesthesiologists. *Canadian Journal of Anesthesia/Journal canadien d'anesthésie*, 48:637–645.

[47] Khowaja, K., Merchant, R., and Hirani, D. (2005). Registered nurses perception of work satisfaction at a tertiary care university hospital. *Journal of Nursing Management*, 13:32–39.

[48] Komashie, A. and Mousavi, A. (2005). Modeling Emergency Departments Using Discrete Event Simulation Techniques. Uxbridge, Middlesex, U.K.

[49] Koppk, L., Wiesche, L., Schacht, M., and Werners, B. (2017). Optimal distribution of operating hours over operating rooms using probabilities. *European Journal of Operational Research*, 267:1156–1171.

[50] Kougias, P., Tiwari, V., and Berger, D. H. (2016). Use of simulation to assess a statistically driven surgical scheduling system.

[51] Lamiri, M., Xie, X., and Zhang, S. (2008). Column generation approach to operating theater planning with elective and emergency patients. *IIE Transactions*, 40(9):838–852.

[52] Larrsson, J. and Sanner, M. (2010). Doing a good job and getting something good out of it: on stress and well-being in anaesthesia. *Bristish Journal of Anesthesia*, 105(1):34–37.

[53] Larsson, J., Rosenqvist, U., and Holmstrom, I. (2007). Enjoying work or burdened by it? how anesthetists experience and handle difficulties at work: a qualitative study. *British Journal of Anaesthesia*, 99(4):493–499.

[54] Latorre-Nùnez, G., Luer-Villagra, A., Marianov, V., Obreque, C., Ramis, F., and Neriz, L. (2016). Scheduling operating rooms with consideration of all resources, post anesthesia beds and emergency surgeries. *Computer Industrial Engineering 97*, 97:248–257.

[55] Law, A. M. (2015). *Simulation Modeling and Analysis*. McGraw-Hill Education, 2 Penn Plaza, New York, NY 10121.

[56] Lederer, W., Kinzl, J., Trefalt, E., Traweger, C., and Benzer, A. (2005). Significance of working conditions on burnout in anesthetists. *Acta Anaesthesiologica Scandinavica*, 50:58–63.

[57] Lin, R.-C., Sir, M. Y., Sisikoglu, E., Pasupathy, K., and Steege, L. M. (2013). Optimal nurse scheduling based on quantitative models of work-related fatigue Optimal nurse scheduling based on quantitative models of work-related fatigue. *IIE Transactions on Healthcare Systems Engineering*, 3(1):23–38.

[58] Liu, L., Lee, S., Chia, P., Chi, S., and Yin, Y. (2012). Exploring the association between nurse workload and nurse-sensitive patient safety outcome indicators. *The Journal of Nursing Research*, 20(4):300–309.

[59] Liu, Y., Chu, C., and Wang, K. (2011). A new heuristic algorithm for the operating room scheduling problem. *Computers & Industrial Engineering*, 61:865–871.

[60] Lowery, J. and Davis, J., editors (1999). *Determination of operating room requirements using simulation*, Ann Arbor, MI, USA. Center for Practice Management and Outcomes Research.

[61] Macario, A. (2006). Are your operating rooms 'efficient'? *Anesthesiology*, 105:237–240.

[62] Macario, A. (2010). What does one minute of operating room time cost?

[63] Macario, A., Vitez, T., Dunn, B., and McDonald, T. (1995). Where are the costs in perioperative care? - analysis of hospital costs and charges for inpatient surgical care. *Anesthesiology*, 93:1138–1144.

[64] Malberg, B., Persson, R., Jonnson, B., Erfurth, E. Flisberb, P., Ranklev, E., and Ørbaek, P. (2007). Physiological restitution after night-call duty in anaesthesiologists: impact on metabolic factors. *Acta Anaesthesiologica Scandinavica*, 51:823–830.

[65] Mancilla, C. and Storer, R. (2012). A sample average approximation approach to stochastic appointment sequencing and scheduling. *IIE Transactions*, 44(8):655–670.

[66] Marcon, E., Dexter, F., Marcon, E., and Dexter, F. (2006). Impact of surgical sequencing on post anesthesia care unit staffing. *Health Care Manage Sci*, 9:87–98.

[67] Master, N., Zhou, Z., Miller, D., Scheinker, D., Nicholas Bambos, □., Glynn, □. P., Bambos, N., and Glynn, P. (2017). Improving predictions of pediatric surgical durations with supervised learning. *International Journal of Data Science and Analytics*, 4:35–52.

[68] May, H., Strum, and Vargas, D. (2000). Fitting the lognormal distribution to surgical procedure times. *Decision Sciences*, 30(1):129–148.

[69] Mielczarek, B. and Zabawa, J. (2017). *Simulation Model for Studying Impact of Demographic, Temporal, and Geographic Factors on Hospital Demand*. Wroclaw, Poland.

[70] Molina-Pariente, J. M., Fernandez-Viagas, V., and Framinan, J. M. (2015). Integrated operating room planning and scheduling problem with assistant surgeon dependent surgery durations. *Computers & Industrial Engineering*, 82:8–20.

[71] Nyssen, A., Hansez, I., Baele, P., Lamy, M., and De Keyser, V. (2003). Occupational stress and burnout in anesthesia. *British Journal of Anaesthesia*, 90(3):333–337.

[72] of Societies of Anesthesiologists, W. F. (2018). Workforce Map. https://www.wfsahq.org/workforce-map.

[73] Ozen, A., Marmor, Y., Rohleder, T., Balasubramanian, H., Huddleston, J., and Huddleston, P. (2015). Optimization and Simulation of Orthopedic Spine Surgery Practice at Mayo Clinic. *Manufacturing & Service Operations Management*, 18(1):157–175.

[74] Ozkarahan, I. (2000). Allocation of Surgeries to Operating Rooms by Goal Programing. *Journal of Medical Systems*, 24(6).

[75] Paoletti, X. and Marty, J. (2007). Consequences of running more operating theatres than anesthetists to staff them: a stochastic simulation study. *British Journal of Anaesthesia*, 98(4):462–469.

[76] Peltokorpi, A. (2011). How do strategic decisions and operative practices affect operating room productivity? *Health Care Management Science*, 14:370–382.

[77] Pham, D.-N. and Klinkert, A. (2006). Surgical case scheduling as a generalized job shop scheduling problem. *European Journal of Operational Research*, 185:1011–1025.

[78] Pontone, S., Brouard, N., Hubin, J., and Nivoche, Y. (2014). La démographie des anesthésistes réanimateurs à l'horizon 2019 : plus favorable en France, déficitaire en Île-de-France avec persistance d'une inadéquation à la demande de soins. *Annales francaises d'anesthesie et de reanimation*, 33:A263.

[79] Raft, J., Millet, F., and Meistelman, C. (2015). Example of cost calculations for an operating room and a post-anaesthesia care unit. *Anaesthesia Critical Care & Pain Medicine*, 34:211–215.

[80] Rajaram, K. and Rath, S. (2017). Managing the operating room suite at ucla ronald reagan medical center. *Impact*, 3(2):31–35.

[81] Rama-Maceiras, P., Parente, S., and Kranke, P. (2012). Job satisfaction, stress and burnout in anaesthesia: relevant topics for anesthesiologists and healthcare managers? *European Journal Anesthesiology*, 29:311–319.

[82] Rath, S., Rajaram, K., and Mahajan, A. (2017). Integrated Anesthesiologist and Room Scheduling for Surgeries: Methodology and Application Forthcoming, Operations Research. *Operations Research*, 65(6):1460–1478.

[83] Robinson, L. W. and Chen, R. R. (2003). Scheduling doctors' appointments: optimal and empirically-based heuristic policies. *IIE Transactions*, 35(3):295–307.

[84] Rosenthal, T. (2018). What Is a Minute Worth in the OR? - OR Management News. https://www.ormanagement.net/Clinical-News/Article/06-18/What-Is-a-Minute-Worth-in-the-OR-/48791.

[85] Roshanaei, V., Luong, Curtiss Aleman, D. M., and Urbachb, D. R. (2017). Collaborative operating room planning and scheduling. *INFORMS Journal on Computing*, 29(3):14–22.

[86] Ruiz-Patiño, A., Acosta-Ospina, L. E., and Rueda, J.-D. (2017). Solving the negative impact of congestion in the postanesthesia care unit: a cost of opportunity analysis. *Journal of Surgical Research*, 210:86–91.

[87] Saadouli, H., jerbi, B., Dammak, L., Masmoudi, L., and Bouaziz, A. (2015). A stochastic optimization and simulation approach for scheduling operating rooms and recovery beds in an orthopedic surgery department. *Computers & Idustrial Engineering*, 80(2):72–79.

[88] Saleh, K., Quick, J., Conaway, M., Sime, W., Martin, W., Hurwitz, S., and Einhorn, T. (2007). The prevalence and severity of burnout among academic orthopaedic departmental leaders. *Journal of Bone and Joint Surgery*, 89:896–903.

[89] Šárka, P. and Michaela, Z. (2016). Example of cost calculation for operating rooms in the hospital. *Economics and Management Systems*, 1:201–207.

[90] Scalea, T., Carco, D., Reece, M., Fouche, Y., Pollak, A., and Sushruta, S. (2014). Effect of a novel financial incentive program on operating room efficiency. *JAMA Surgery*, 149(9):920–4.

[91] Schmid, V. and Doerner, K. F. (2012). Examination and Operating Room Scheduling including Optimization of Intra-hospital Routing. *Transportation Science*, 48(1):59–77.

[92] Shahabikargar, Z., Khanna, S., Sattar, A., and Lind, J. (2017). Improved Prediction of Procedure Duration for Elective Surgery. *Integrating and Connecting Care*, 239:133–138.

[93] Shanafelt, T., Balch, C., Bechamps, G., Russell, T., Dyrbye, L., Satele, D., Collicott, P., Novotny, P., Sloan, J., and Freischlag, J. (2009). Burnout and career satisfaction among american surgeons. *Annals of Surgery*, 250(3):463–470.

[94] Siciliani, L. and Hurst, J. (2003). Explaining Waiting Times Variations for Elective Surgery across OECD Countries.

[95] Simwita, Y. and Helgheim, B. (2016). Simulation analysis of resource flexibility on healthcare processes. *Journal of Multidisciplinary Healthcare*, 9:519–528.

[96] St Jacques, P. J., Patel, N., and Higgins, M. S. (2004). Improving Anesthesiologist Performance Through Profiling and Incentives. *Journal of Clinical Anesthesia*, 16:523–528.

[97] Stepaniak, P., Pieter, S., Heij, C., and De Vries, G. (2010). Modeling and prediction of surgical procedure times. *Statistica Neerlandica*, 64:1–18.

[98] Strum, D., May, J., and Vargas, L. (2010). Modeling and prediction of surgical procedure times. *Statistica Neerlandica*, 64:1–18.

[99] Strum, D. P., Sampson, A., and May, J.H., V. L. (2000a). Surgeon and type of anesthesia predict variability in surgical procedure times. *Anesthesiology*, 92:1454–66.

[100] Strum, D. P., Sampson, A. R., May, J. H., and Vargas, L. G. (2000b). Surgeon and type of anesthesia predict variability in surgical procedure times. *Anesthesiology*, 92:1454–1456.

[101] Ta-Chung, W. and Cheng-Che, L. (2014). Optimal work shift scheduling with fatigue minimization and day off preferences. *Hindawi Publishing Corporation*.

[102] Tyler, P. and Cushway, D. (1992). Stress, coping and mental wellbeing in hospital nurses. *Stress Medicine*, 8:91–98.

[103] Utriainen, K., Ala-Mursula, L., and Kingas, H. (2015). Hospital nurses' wellbeing at work: a theoretical model. *Journal of Nursing Management*, 23:736–743.

[104] Vitez, T. S. and Macario, A. (1998). Setting Performance Standards for an Anesthesia Department. Technical report, Department of Anesthesia, Stanford University Medical Center, Stanford, CA, USA.

[105] Volpin, A., Orth, F., and Haddad, F. S. (2016). Theater Cost Is £16/Minute So What Are You Doing Just Standing There? *Journal of Arthroplasty*, 31:22–26.

[106] Wang, J., Li, C., Kao, S., Yeh, T., Arens, J., and Ho, S. (2015). Factors associated with taiwan anesthesiologists' intention to leave anesthesia practice. *Journal of the Formosan Medical Association*, 114:509–516.

[107] Wilson, J. C. T. (1981). Implementation of Computer Simulation Projects in Health Care. Technical Report 9.

[108] Wong, A. (2011). From the front lines: a qualitative study of anesthesiologists' work and professional values. *Canadian Journal of Anesthesia/Journal canadien d'anesthésie*, 58:108–117.

[109] Wright, I., Kooperberg, C., Bonar, B., and Bashein, G. (1996). Statistical modeling to predict elective surgery time: Comparison with a computer scheduling system and surgeons-provided estimates. *Anesthesiology*, 85:1235–45.

[110] Zhang, X. (2018). Application of discrete event simulation in health care: a systematic review, healh services research. *Journal of Simulation*, 18:687.

[111] Zhang, Z. and Xie, X. (2015). Simulation-based optimization for surgery appointment scheduling of multiple operating rooms Simulation-based optimization for surgery appointment scheduling of multiple operating rooms. *IIE Transactions*, 47:998–1012.

[112] Zhou, J. and Dexter, F. (1998). Method to assist in the scheduling of add-on surgical cases – upper prediction bounds for surgical case durations based on the log-normal distribution. *Anesthesiology*, 92:1160–7.

Appendix A

Conceptual Model

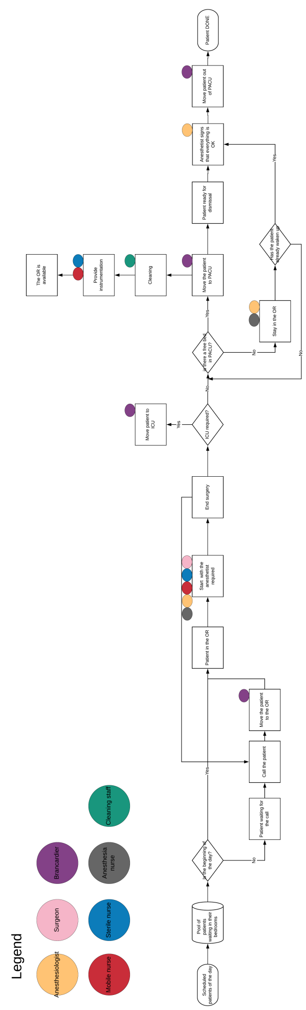


Figure A.1: Full conceptual model of the Operating Theater

Appendix B

Data Fitting Code

```
%MATLAB CODE USED FOR FITTING SURGERY DURATIONS

[~, list , listfull]=xlsread('IPOP 2017 Dan','E2:F16103'); %import excel file

[~,idx] = sort(list(:,1)); % sort just the first column
sortedlist = listfull(idx,:);   % sort the whole matrix using the sort indices

data=sortedlist;

uniquelist=unique(data(:,1)); %sort in alphabetical order and merge equal surgeries

analyzed_data=zeros(size(uniquelist,1),5); %initialize the output matrix

jj=1;
ii=1;

while ii< size(data,1)

    temp=list(ii);
    counter=0;

    while ii+counter<=size(data,1) & strcmp(num2str(cell2mat(data(ii+counter,1))),num2str(cell2mat(da

        counter=counter+1;
    end

    analyzed_data(jj,1)=counter;

    if counter >=12 %surgery repeated at least once per month
```

```
        parmhat=lognfit(cell2mat(data(ii:ii+counter-1,2)));
        [M,V]=lognstat(parmhat(1),parmhat(2));
        analyzed_data(jj,2)=1; %surgery class
        analyzed_data(jj,4)=M; %mean
        analyzed_data(jj,5)=sqrt(V); %sigma
    end

    if counter>5 & counter<12 %surgery repeated at least once every two months

        min_surgery=min(cell2mat(data(ii:ii+counter-1,2))); %set min
        max_surgery=max(cell2mat(data(ii:ii+counter-1,2))); %set max
        avg_surgery=mean(cell2mat(data(ii:ii+counter-1,2))); %set average

        analyzed_data(jj,2)=2; %surgery class
        analyzed_data(jj,3)=min_surgery; %min
        analyzed_data(jj,4)=avg_surgery; %mean
        analyzed_data(jj,5)=max_surgery; %sigma

    end

    if counter<=5 %surgery repeated less than once every two months

        avg_surgery=mean(cell2mat(data(ii:ii+counter-1,2))); %set average

        analyzed_data(jj,2)=3; %surgery class
        analyzed_data(jj,3)=avg_surgery*0.65; %min
        analyzed_data(jj,4)=avg_surgery; %mean
        analyzed_data(jj,5)=avg_surgery*1.6; %sigma
    end

    ii=ii+counter;
    jj=jj+1;


end
```

Appendix C

Tables Makespan

	Original Cleaning Configuration			Grouped Cleaning Teams		
	Original	Heuristic 1	Heuristic 2	Original	Heuristic 1	Heuristic 2
THO1	658	642	661	657	651	642
THO2	720	722	729	730	728	727
RYT1	324	301	290	318	300	288
RYT2	547	549	555	546	546	531
CAR1	587	566	557	584	558	563
CAR2	675	685	679	682	685	694
CAR3	308	313	313	308	313	314
ORT1						
ORT2	489	470	477	485	470	474
ORL1	573	557	505	568	533	542
ORL2	401	399	391	402	396	390
DIG1	298	302	298	299	301	291
DIG2	633	604	631	596	602	599
MAT1	513	523	511	498	518	508
MAT2	702	697	696	676	700	683
MAT3						
URO1	246	238	232	248	235	236
URO2	532	554	534	541	545	535

Table C.1: Simulated makespans with the three different schedules and the two different cleaning configurations - 6 June 2018

	Original Cleaning Configuration			Grouped Cleaning Teams		
	Original	Heuristic 1	Heuristic 2	Original	Heuristic 1	Heuristic 2
THO1	670	693	668	684	694	686
THO2	464	468	480	474	474	469
RYT1	543	550	534	542	544	531
RYT2	443	431	442	447	446	443
CAR1	400	397	389	392	390	395
CAR2						
CAR3						
ORT1						
ORT2	503	511	504	502	502	495
ORL1	521	505	481	522	512	483
ORL2	514	515	529	514	526	537
DIG1	679	667	677	682	687	665
DIG2	536	555	547	534	559	553
MAT1	562	573	557	557	563	547
MAT2	482	488	491	468	483	490
MAT3						
URO1	575	560	570	555	550	563
URO2	372	371	393	380	371	388

Table C.2: Simulated makespans with the three different schedules and the two different cleaning configurations - 22 June 2018

	Original Cleaning Configuration			Grouped Cleaning Teams		
	Original	Heuristic 1	Heuristic 2	Original	Heuristic 1	Heuristic 2
THO1	606	641	619	602	632	621
THO2	660	649	628	652	642	657
RYT1						
RYT2	241	231	236	234	231	227
CAR1	322	306	318	316	313	318
CAR2	646	659	651	655	661	660
CAR3	323	317	319	315	323	325
ORT1	227	188	198	232	195	192
ORT2						
ORL1	193	202	208	191	195	212
ORL2	268	271	268	254	269	266
DIG1	211	209	208	206	200	214
DIG2	215	215	209	213	206	217
MAT1	273	285	282	272	272	272
MAT2	235	259	245	234	258	235
MAT3						
URO1	217	188	178	207	183	173
URO2	186	201	179	190	182	172

Table C.3: Simulated makespans with the three different schedules and the two different cleaning configurations - 23 February 2017

	Original Cleaning Configuration			Grouped Cleaning Teams		
	Original	Heuristic 1	Heuristic 2	Original	Heuristic 1	Heuristic 2
THO1	642	632	636	627	632	644
THO2	668	685	690	677	683	683
RYT1	148	145	146	155	144	147
RYT2	509	513	505	499	521	521
CAR1	653	657	647	647	654	644
CAR2	315	318	323	325	320	316
CAR3	603	610	618	626	602	620
ORT1	207	193	189	211	192	199
ORT2						
ORL1	302	304	310	289	299	295
ORL2	249	249	256	258	251	251
DIG1	103	75	79	80	70	72
DIG2	43	43	43	43	43	43
MAT1	332	307	307	318	301	296
MAT2	139	127	136	139	138	136
MAT3						
URO1	221	207	215	230	215	218
URO2						

Table C.4: Simulated makespans with the three different schedules and the two different cleaning configurations - 25 Semptember 2017

Appendix D

Conceptual Model Heuristic

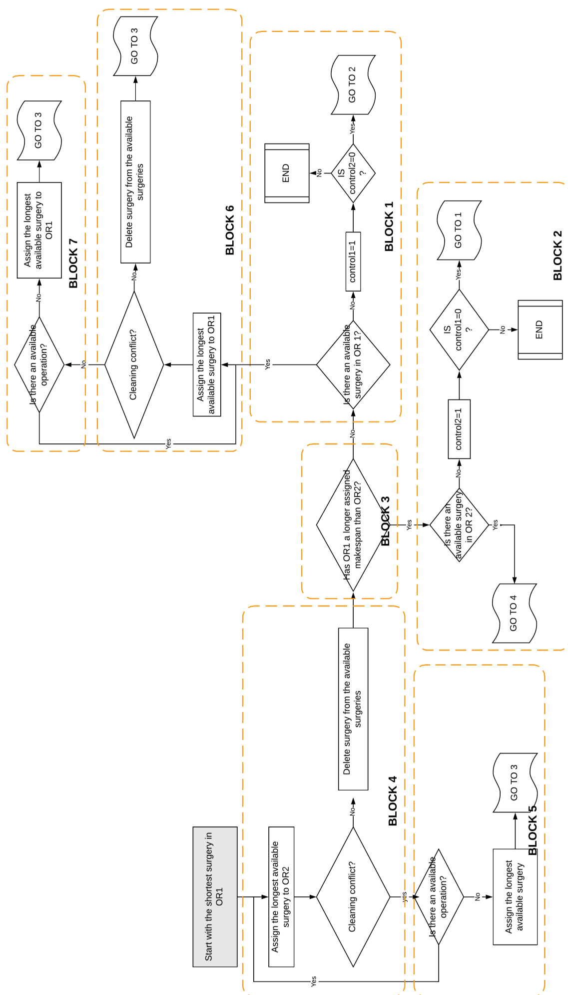


Figure D.1: Quick graphical overview of the system

Configuration	MS original	95% confidence	MS heuristic	95% confidence	Gain
MVL	1261	102	1159	86	-102
MVL	1223	90	1240	95	18
MVL	1342	76	1281	68	-61
MVL	1204	100	1262	103	58
MVL	1385	91	1410	94	25
MVL	1344	75	1364	89	19
MVL	1319	102	1306	79	-13
MVL	1382	106	1483	105	101
MVL	1614	76	1544	92	-70
MVL	1437	118	1359	100	-78
MvL	1317	36	1283	30	-34
MvL	1281	44	1233	30	-49
MvL	1374	47	1357	24	-17
MvL	1330	35	1309	40	-20
MvL	1273	34	1280	25	7
MvL	1416	54	1441	31	26
MvL	1353	38	1327	36	-26
MvL	1239	40	1274	37	36
MvL	1498	45	1522	49	24
MvL	1277	33	1243	34	-34
mVL	1606	60	1628	64	22
mVL	1621	55	1613	39	-9
mVL	1729	61	1685	73	-44
mVL	1639	56	1652	59	13
mVL	1609	44	1602	62	-7
mVL	1589	67	1537	55	-51
mVL	1561	57	1540	42	-21
mVL	1675	44	1670	63	-5
mVL	1510	52	1493	53	-17
mVL	1578	45	1567	48	-11
mvL	1650	26	1677	43	27
mvL	1722	33	1690	28	-32
mvL	1537	24	1529	33	-8
mvL	1510	33	1504	33	-6
mvL	1705	36	1686	26	-20
mvL	1763	28	1766	35	3

mvL	1604	32	1526	35	-78
mvL	1609	43	1578	32	-31
mvL	1559	40	1536	28	-23
mvL	1564	28	1548	28	-16
MVl	799	46	796	50	-2
MVl	837	87	837	87	0
MVl	1035	68	1021	62	-15
MVl	668	62	668	62	0
MVl	791	56	729	52	-62
MVl	809	85	812	84	3
MVl	665	71	671	73	7
MVl	692	61	692	61	0
MVl	735	77	735	77	0
MVl	732	56	784	58	52
Mvl	643	25	649	22	6
Mvl	644	22	644	22	0
Mvl	677	32	661	26	-15
Mvl	796	24	803	27	6
Mvl	707	25	707	25	0
Mvl	694	30	674	23	-20
Mvl	753	31	754	24	1
Mvl	728	25	728	25	0
Mvl	707	30	704	30	-3
Mvl	739	28	739	28	0
mVl	747	36	769	42	22
mVl	888	37	874	46	-15
mVl	865	37	885	43	20
mVl	796	34	816	35	20
mVl	762	35	783	39	21
mVl	799	47	803	43	4
mVl	879	45	893	50	15
mVl	841	30	823	30	-18
mVl	836	32	832	37	-4
mVl	854	40	857	44	3
mvl	961	24	933	31	-28
mvl	856	27	854	22	-2
mvl	924	36	901	28	-23
mvl	888	26	874	25	-13

mvl	857	25	888	38	31
mvl	757	23	749	23	-8
mvl	807	25	812	21	5
mvl	878	32	859	26	-20
mvl	822	33	771	25	-51
mvl	749	29	747	27	-2

Table D.1: Results of the DOE, all results presented in minutes

Configuration	MS original	95% confidence	MS heuristic	95% confidence	Gain
mVL	1556	34	1538	32	-18
mVL	1568	29	1557	34	-11
mVL	1579	34	1595	28	16
mVL	1663	26	1702	28	39
mVL	1555	29	1539	30	-16
mVL	1592	29	1565	35	-27
mVL	1667	34	1655	31	-11
mVL	1555	36	1559	34	4
mVL	1583	29	1614	39	31
mVL	1578	36	1552	34	-26
mVL	1693	36	1669	34	-24
mVL	1541	29	1532	33	-9
mVL	1674	37	1656	39	-19
mVL	1587	32	1583	33	-4
mVL	1588	32	1569	27	-19
mVL	1691	35	1645	26	-47
mVL	1627	32	1594	36	-34
mVL	1583	32	1592	37	9
mVL	1532	25	1560	32	28
mVL	1609	37	1603	40	-5
mVL	1460	36	1474	30	14
mVL	1674	34	1657	29	-18
mVL	1618	29	1589	35	-29
mVL	1672	35	1644	38	-28
mVL	1655	30	1643	30	-12
mVL	1634	33	1648	37	13
mVL	1668	39	1605	34	-63
mVL	1668	40	1645	36	-23

mVL	1550	36	1535	35	-15
mVL	1700	29	1703	30	4
mVL	1623	38	1625	41	2
mVL	1562	29	1551	27	-10
mVL	1490	27	1497	30	7
mVL	1501	28	1519	36	18
mVL	1519	36	1512	35	-7
mVL	1556	30	1522	37	-34
mVL	1667	39	1667	41	0
mVL	1649	35	1661	45	12
mVL	1564	34	1555	30	-9
mVL	1678	27	1694	33	16
mVL	1486	33	1468	40	-18
mVL	1613	34	1602	37	-11
mVL	1537	30	1550	37	12
mVL	1621	34	1565	37	-56
mVL	1538	34	1542	27	3
mVL	1660	36	1668	29	7
mVL	1649	32	1633	33	-17
mVL	1697	25	1705	32	8
mVL	1754	34	1711	31	-43
mVL	1684	39	1668	38	-16
mVL	1594	38	1571	38	-23
mVL	1613	33	1562	35	-50
mVL	1506	33	1505	32	-1
mVL	1610	33	1587	36	-23
mVL	1640	36	1626	26	-14
mVL	1590	33	1577	34	-13
mVL	1563	27	1560	30	-2
mVL	1582	28	1571	30	-10
mVL	1572	33	1526	31	-45
mVL	1509	31	1487	37	-22
mVL	1612	33	1631	31	19
mVL	1629	30	1626	33	-3
mVL	1612	43	1614	36	1
mVL	1655	43	1617	33	-38
mVL	1522	27	1493	28	-30
mVL	1627	31	1615	33	-12

mVL	1597	36	1576	33	-21
mVL	1597	27	1581	30	-17
mVL	1601	27	1604	32	2
mVL	1548	29	1535	25	-13
mVL	1644	34	1640	37	-4
mVL	1625	37	1593	35	-32
mVL	1607	35	1614	28	7
mVL	1538	33	1546	36	7
mVL	1552	22	1581	33	29
mVL	1589	35	1593	30	4
mVL	1588	30	1564	35	-25
mVL	1559	32	1536	38	-23
mVL	1638	30	1622	36	-16
mVL	1575	33	1563	34	-11
mvL	1596	19	1568	24	-28
mvL	1574	21	1566	26	-8
mvL	1490	22	1500	24	10
mvL	1623	18	1587	26	-36
mvL	1551	24	1526	19	-25
mvL	1605	21	1579	20	-26
mvL	1701	23	1696	18	-4
mvL	1682	21	1686	22	4
mvL	1625	24	1603	21	-23
mvL	1565	23	1548	23	-17
mvL	1656	21	1618	21	-38
mvL	1665	23	1654	23	-10
mvL	1614	23	1602	19	-12
mvL	1643	20	1638	19	-5
mvL	1527	22	1528	18	1
mvL	1657	24	1653	26	-5
mvL	1648	22	1633	25	-15
mvL	1590	19	1566	23	-24
mvL	1626	22	1614	24	-13
mvL	1555	23	1555	21	0
mvL	1558	17	1538	20	-20
mvL	1594	25	1551	22	-43
mvL	1621	20	1594	19	-27
mvL	1684	23	1668	21	-15

mvL	1543	23	1534	21	-9
mvL	1527	24	1506	17	-21
mvL	1653	22	1667	20	14
mvL	1474	22	1456	25	-18
mvL	1682	17	1663	24	-19
mvL	1689	18	1661	19	-28
mvL	1596	19	1568	24	-28
mvL	1574	21	1566	26	-8
mvL	1490	22	1500	24	10
mvL	1623	18	1587	26	-36
mvL	1551	24	1526	19	-25
mvL	1605	21	1579	20	-26
mvL	1701	23	1696	18	-4
mvL	1682	21	1686	22	4
mvL	1625	24	1603	21	-23
mvL	1565	23	1548	23	-17
mvL	1656	21	1618	21	-38
mvL	1665	23	1654	23	-10
mvL	1614	23	1602	19	-12
mvL	1643	20	1638	19	-5
mvL	1527	22	1528	18	1
mvL	1657	24	1653	26	-5
mvL	1648	22	1633	25	-15
mvL	1590	19	1566	23	-24
mvL	1626	22	1614	24	-13
mvL	1555	23	1555	21	0
mvL	1558	17	1538	20	-20
mvL	1594	25	1551	22	-43
mvL	1621	20	1594	19	-27
mvL	1684	23	1668	21	-15
mvL	1543	23	1534	21	-9
mvL	1527	24	1506	17	-21
mvL	1653	22	1667	20	14
mvL	1474	22	1456	25	-18
mvL	1682	17	1663	24	-19
mvL	1689	18	1661	19	-28
mvL	1683	23	1651	25	-33
mvL	1572	21	1562	20	-11

mvL	1680	22	1686	24	5
mvL	1487	22	1480	25	-6
mvL	1672	24	1606	27	-66
mvL	1687	21	1656	22	-31
mvL	1741	20	1710	24	-31
mvL	1463	25	1486	25	23
mvL	1657	19	1619	19	-39
mvL	1663	23	1637	18	-26
mvL	1607	19	1582	23	-24
mvL	1492	18	1485	20	-7
mvL	1546	22	1511	21	-35
mvL	1671	17	1658	22	-13
mvL	1636	22	1611	21	-25
mvL	1653	18	1647	21	-6
mvL	1577	20	1537	21	-40
mvL	1604	19	1599	23	-6
mvL	1586	23	1568	21	-18
mvL	1539	21	1502	18	-37

Table D.2: Results of the experiments focusing on fully loaded Operating Rooms with short surgeries, all results presented in minutes