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Multiscale modeling and event tracking wireless technologies to improve efficiency and safety of the surgical flow in an OR suite

Guillaume Joerger

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UNIVERSITÉ DE LA ROCHELLE

École Doctoral Science et Ingénierie en Matériaux, Mécanique, Énergétique et Aéronautique (SI-MMEA)

Laboratoire des Sciences de l'Ingénieur pour l'Environnement (LaSIE)

THÈSE

présentée par :

Guillaume JOERGER

pour obtenir le grade de : **Docteur de l'université de La Rochelle**

Discipline : **Mécanique des fluides**

Multiscale Modeling and Event Tracking Wireless Technologies to improve efficiency and safety of the surgical flow in an OR suite

Soutenue le : 16/06/2017

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"Start where you are. Use what you have. Do what you can."

Arthur Ashe

Abstract

Multiscale Modeling and Event Tracking Wireless Technologies to improve efficiency and safety of the surgical flow in an OR suite

by Guillaume JOERGER

Improving operating room management is a constant issue for modern large hospital systems who have to deal with the reality of day to day clinical activity. As opposed to other industrial sectors such as air civil aviation that have mastered the topic of industry organization and safety, progress in surgical flow management has been slower. The goal of the work presented here is to develop and implement technologies that leverage the principles of computational science to the application of OR suite problems. Most of the currently available models of surgical flow are used for planning purposes and are essentially stochastic processes due to uncertainties in the available data. We propose an agent-based model framework that can incorporate all the elements, from communication skills of the staff to the time it takes for the janitorial team to go clean an OR. We believe that human factor is at the center of the difficulty of OR suite management and should be incorporated in the model. In parallel, we use a numerical model of airflow at the OR suite level to monitor and simulate environment conditions inside the OR. We hypothesize that the following three key ingredients will provide the level of accuracy needed to improve OR management:
1. Real time updates of the model with ad hoc sensors of tasks/stages
2. Construction of a multi-scale model that links all key elements of the complex surgical infrastructure
3. Careful analysis of patient population factors, staff behavior, and environment conditions.
We have developed a robust and non-obtrusive automatic event tracking system to make our model realistic to clinical conditions. Not only we track traffic through the door and the air quality inside the OR, we can also detect standard events in the surgical process. We propose a computational fluid dynamics model of a part of an OR suite to track dispersion of toxic surgical smoke and build in parallel a multi-domain model of potential nosocomial contaminant particles flow in an OR suite. Combining the three models will raise the awareness of the OR suite by bringing to the surgical staff a cyber-physical system capable of prediction of rare events in the workflow and the safety conditions.

Keywords : Multiscale Modeling, Agent-based Model, Operating Room Management, Operating Room Workflow, Safety, Indoor Air Quality, Computational Surgery, Computational Fluid Dynamics.

Résumé

Modélisation multi-échelle assistée d'un système de détection d'évènements : optimisation du fonctionnement et de la sécurité au sein des blocs opératoires

par Guillaume JOERGER

Améliorer la gestion et l'organisation des blocs opératoires est une tâche critique dans les hôpitaux modernes, principalement à cause de la diversité et l'urgence des activités impliquées. Contrairement à l'aviation civile, qui a su optimiser organisation et sécurité, le management de bloc opératoire est plus délicat. Le travail ici présenté abouti au développement et à l'installation de nouvelles technologies assistées par ordinateur résolvant les problèmes quotidiens des blocs opératoires. La plupart des systèmes existants modélisent le flux chirurgical et sont utilisés seulement pour planifier. Ils sont basés sur des procédés stochastiques, n'ayant pas accès à des données sures. Nous proposons une structure utilisant un modèle multi-agent qui comprend tous les éléments indispensables à une gestion efficace et au maintien de la sécurité dans les blocs opératoires, allant des compétences communicationnelles du staff, au temps nécessaire à la mise en place du service de nettoyage. Nous pensons que la multiplicité des ressources humaines engagées dans cette structure cause des difficultés dans les blocs opératoires et doit être prise en compte dans le modèle. En parallèle, nous avons construit un modèle mathématique de flux d'air entre les blocs opératoires pour suivre et simuler la qualité de l'environnement de travail. Trois points sont nécessaires pour la construction et le bon fonctionnement d'un ensemble de bloc opératoire:
1. avoir accès au statut du système en temps réel grâce au placement de capteurs
2. la construction de modèles multi-échelles qui lient tous les éléments impliqués et leurs infrastructures
3. une analyse minutieuse de la population de patients, du comportement des employés et des conditions environnementales
Nous avons développé un système robuste et invisible qui permet le suivi et la détection automatique d'événements dans les blocs. Avec ce système nous pouvons suivre l'activité à la porte d'entrée des blocs, puis l'avancement en temps réel de la chirurgie et enfin l'état général du bloc. Un modèle de simulation numériques de mécanique des fluides de plusieurs blocs opératoires est utilisé pour suivre la dispersion de fumé chirurgicale toxique, ainsi qu'un modèle multi-domaine qui évalue les risques de propagation de maladie nosocomiale entre les blocs. La combinaison de ces trois aspects amène une nouvelle dimension de sensibilisation à l'environnent des blocs opératoires et donne au staff un système cyber-physique capable de prédire des événements rares impactant la qualité, l'efficacité, la rentabilité et la sécurité dans l'hôpital.

Mots clés : modélisation multi-échelle, modèle multi-agent, organisation des blocs operatoires, workflow dans les blocs operatoires, sécurité, qualité de l'air, chirurgie assistée par ordinateur, mécanique des fluides numériques

Résumé substantiel:

Améliorer la gestion et l'organisation des blocs opératoires est une tâche critique dans les hôpitaux modernes, principalement à cause de la diversité et l'urgence des activités impliquées. Contrairement à l'aviation civile, qui a su optimiser organisation et sécurité, le management de bloc opératoire est plus délicat. Le travail ici présenté abouti au développement et à l'installation de nouvelles technologies assistées par ordinateur résolvant les problèmes quotidiens des blocs opératoires. La plupart des systèmes existants modélisent le flux chirurgical et sont utilisés seulement pour planifier. Ils sont basés sur des procédés stochastiques, n'ayant pas accès à des données sures. Nous proposons une structure utilisant un modèle multi-agent qui comprend tous les éléments indispensables à une gestion efficace et au maintien de la sécurité dans les blocs opératoires, allant des compétences communicationnelles du staff, au temps nécessaire à la mise en place du service de nettoyage. Nous pensons que la multiplicité des ressources humaines engagées dans cette structure cause des difficultés dans les blocs opératoires et doit être prise en compte dans le modèle. En parallèle, nous avons construit un modèle mathématique de flux d'air entre les blocs opératoires pour suivre et simuler la qualité de l'environnement de travail. Trois points sont nécessaires pour la construction et le bon fonctionnement d'un ensemble de bloc opératoire:
1. avoir accès au statut du système en temps réel grâce au placement de capteurs
2. la construction de modèle multi-échelles qui lient tous les éléments impliqués et leurs infrastructures
3. une analyse minutieuse de la population de patients, du comportement des employés et des conditions environnementales
Nous avons développé un système robuste et invisible qui permet le suivi et la détection automatique d'événements dans les blocs. Il est constitué de capteurs sans fil placés stratégiquement dans le bloc. Avec ce système nous pouvons suivre l'activité à la porte d'entrée des blocs, puis l'avancement en temps réel de la chirurgie et enfin l'état général du bloc. Le système est installé dans cinq blocs opératoires et a recueilli 1000 opérations sur une période de un an. Ces données peuvent être envoyées au manager des blocs, lui évitant d'interrompre la procédure en entrant dans la salle pour connaître l'état d'avancement, mais aussi peuvent être sauvegardées et analysées. Le système est donc capable de donner une vue globale de l'efficacité d'utilisation de tous les blocs. Par exemple, la détection et l'analyse du temps entre deux procédures est une donnée essentielle pour les hôpitaux, reflétant leurs rendements et est une des valeurs que le système peut calculer en temps réel. Sur un an d'analyse le système a détecté 72% de temps entre deux procédures plus longs que le temps imparti par l'hôpital. Une utilisation optimisée avec un système de vérification est donc possible avec le système mais ne doit pas remettre en question la sécurité des patients ainsi que des professionnels de santé. C'est pourquoi nous avons ensuite construit un modèle de simulation numérique de mécanique des fluides de plusieurs blocs opératoires pour suivre la dispersion de fumée chirurgicale toxique, ainsi qu'un modèle multidomaine qui évalue les risques de propagation de maladie nosocomiale entre

les blocs. L'augmentation de l'utilisation des instruments chirurgicaux électriques produit des quantités de fumée, dues a la combustion de tissue, importante. Cette fumée a été prouvée toxique pour les humains qui la respire et aurait les mêmes effets que la fumée d'une cigarette. Notre simulation 3D prend en compte l'architecture de deux blocs opératoires et le couloir reliant les deux. La pression positive dans les blocs pousse l'air vers le couloir entrainant avec elle, les particules de fumée ainsi que des possibles bactéries ou virus ayant la même taille que ces particules. La simulation suit donc le volume de fumée, représentée par du gaz carbonique, à différents endroits et son évolution dans le temps. Il permet de démontrer qu'il est possible que des particules émises dans un bloc A arrivent après deux minutes devant la porte d'entrée d'un bloc adjacent B. L'activité et la dynamique du monde chirurgical dans cet environnent crée de fort échange d'air au niveau de la porte d'entrée qui peuvent même faire entrer des particules de l'extérieur, probablement toxiques, dans le bloc. Cette dynamique est enregistrée par notre collection de capteurs et peut être utilisée en entrée de notre modèle mathématique compartimental. Ce model prend en compte plus de blocs opératoires, peut suivre la qualité de l'air sur de longues périodes (mois, années) et aussi inclus la dynamique au niveau de la porte d'entrée. Nous avons comparé les valeurs trouvées par nos deux modèles avec des mesures de concentration de particules faites dans les blocs avec des capteurs de fines particules. Le modèle système montre le risque possible de contamination entre deux blocs mais a aussi permis de simuler la qualité de l'air en fonction de l'activité dans le bloc. La combinaison de ces trois aspects amène une nouvelle dimension de sensibilisation à l'environnent des blocs opératoires et donne aux professionnel de santé un système cyber-physique capable de prédire des événement rare impactant la qualité, l'efficacité, la rentabilité et la sécurité dans l'hôpital.

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Contents

Abstract **v**

Résumé **vii**

Acknowledgements **xi**

1 State of the art **1**
1.1 Introduction . . . 1
1.2 Complexity of OR workflow in modern hospitals . . . 2
1.3 Patient safety . . . 2
1.4 Need to record systematic information . . . 3
1.5 Indoor air quality inside a hospital . . . 5
1.5.1 Generalities and simulation . . . 5
1.5.2 The special case of the OR . . . 5
1.5.3 Propagation of particles . . . 6
1.6 Mathematical modeling in healthcare . . . 6
1.7 Conclusion . . . 7

2 Automatic tracking system of OR workflow **9**
2.1 Introduction . . . 9
2.2 Design of the system smartOR . . . 10
2.2.1 Method . . . 10
2.2.2 Installation and development . . . 10
First phase of implementation . . . 11
Second phase of implementation . . . 14
2.2.3 Software and signal processing . . . 16
2.2.4 Validation . . . 18
2.2.5 Report . . . 19
2.2.6 OR awareness and spread of the information: an introduction to MCPS . . . 20
2.2.7 Preoperative area study . . . 21
First case start time study . . . 22
Patient tracking . . . 23
2.3 Results . . . 24
2.3.1 Generalities . . . 24
2.3.2 Turnover time . . . 24
2.3.3 Elapsed time . . . 25
2.3.4 Detection of outliers and reasons for delays . . . 26
2.3.5 Analysis of specific type of surgeries . . . 27
2.3.6 RFID study for first start case . . . 28
2.3.7 Comparison with data from the EMR . . . 28
2.4 Conclusion . . . 29

3 Monitoring of indoor air quality and link with OR activity **31**
3.1 Introduction on HVAC . . . 31
3.2 Method . . . 33
3.2.1 First test . . . 34
3.2.2 Surgical smoke plume monitoring . . . 35
3.2.3 Air quality in an OR, a way to track airflow . . . 38
3.2.4 Air contamination in the OR suite: can one OR contaminate another one? . . . 39
Door closed: What happens to particles emitted in the hallway? 40
Door closed: What happens to particles emitted on the table during the case? . . . 41
Opening the door . . . 42
Using the plume as a tracker for other particles such as bacteria 44
3.3 Conclusion . . . 44

4 OR Workflow modelization : a multi-scale approach **47**
4.1 Introduction . . . 47
4.2 Methods . . . 48
4.2.1 Acquisition of data . . . 48
4.2.2 Construction of the ABM . . . 49
4.3 Method to retrofit the model to the data and validate input parameters 55
4.4 Verification . . . 56
4.5 Results . . . 57
4.5.1 Comparing the model to data . . . 57
4.5.2 Ask the model "what if?" . . . 59
4.6 Conclusion . . . 63

5 Air quality and safety inside the OR suite, a numerical and system approach **65**
5.1 Introduction . . . 65
5.2 Numerical analysis of airflow in a surgical suite . . . 66
5.2.1 Background . . . 66
5.2.2 Method . . . 68
5.2.3 Boundary conditions . . . 69
5.2.4 Results . . . 70
Steady mode with door closed . . . 70
Steady mode with door open . . . 73
Transient mode and CO_2 phase tracking . . . 74
Injection inside the OR with the door closed . . . 74
Injection outside with the door open . . . 74
5.2.5 Contamination from one OR to another . . . 75
5.2.6 Verification . . . 76
5.2.7 Validation . . . 78
5.2.8 Conclusion . . . 80
5.3 A system approach to assess transport and diffusion of airborne hazard in a large OR suite . . . 82
5.3.1 Methods . . . 82
5.3.2 Experimental set up to asses the source of particles . . . 83
5.3.3 Assimilation of experimental data . . . 84
5.3.4 System model . . . 86
5.3.5 Results . . . 89

5.3.6 Discussion 93
5.3.7 Conclusion of the chapter 93

6 Conclusion **95**

A Introduction to MCPS **99**

B Noticable publications and presentations **101**

Bibliography **103**

List of Figures

1.1 Complexity of the OR 2

2.1 Operating room states and cycle 11
2.2 Implementation in Strasbourg University Hospital 12
2.3 Casing and sensor design 14
2.4 Output of data from the sensors 15
2.5 Positioning of the sensors in the OR 17
2.6 Technical GUI 19
2.7 OR network 20
2.8 Reports 20
2.9 Spread of information 21
2.10 First case start time 22
2.11 RFID system 23
2.12 Patient tracking system 24
2.13 Distribution of turnover time 25
2.14 Distribution of phases total elspased times in the OR 26
2.15 Distribution of elapsed time between different steps 27
2.16 Comparison with EMR data 29

3.1 Size of particulate matters 32
3.2 HVAC in an OR 33
3.3 Comparison of tow sensors placed in the OR 36
3.4 APC instrument particles counting 37
3.5 Experience at MITIE 38
3.6 Comparison IAQ in the hallway and OR 39
3.7 Sensor in the OR 40
3.8 Position of the sensors 41
3.9 Particles counting inside the OR 42
3.10 Experiment to track the impact of the door opening 43
3.11 Detection of particles from one OR to another 45

4.1 Lognormal distribution of time in the OR 49
4.2 Flow Chart of Surgical Procedures 50
4.3 Description of Task Advancement in the Flow Chart 51
4.4 Performance factors 52
4.5 Normalized distribution of cases length 58
4.6 Normalized distribution of turnover time 59
4.7 Impact of the number of anesthesiologists on outcome 61
4.8 Impact of surgeon skills on team performance 62
4.9 Impact of global team skills on outcomes 62

5.1 Multi-scale of OR workflow 66
5.2 3d model 68

5.3 Temperature profile door closed 70
5.4 Path lines in the model 71
5.5 Steady mode results on environment parameters of the model 72
5.6 Buoyancy driven flow 73
5.7 Tracking of a plume of smoke with door closed 75
5.8 Tracking of a plume of smoke with door open 76
5.9 Detection of smoke at the entry of the OR 77
5.10 Examination of spatial grid convergence 78
5.11 Examination of temporal convergence 79
5.12 Measurements of parameters 80
5.13 Volume of gas inhaled by staff from simulation 81
5.14 Map of the OR suite and block system representation 82
5.15 Electrosurgical smoke 83
5.16 Analysis of the source to feed the model 84
5.17 Position of the sensors and sources 86
5.18 Dispersion from the OR table to the hallway 89
5.19 Dispersion in the hallway 90
5.20 Tracking and simulation of particles from one OR to the adjacent one . 91
5.21 IAQ Measurement for laparoscopy surgeries in clinical condition . . . 91
5.22 IAQ simulation of one day in one OR and its adjacent hallway 92

List of Tables

2.1 Sensors targeting key events at each step of the operative procedure . . 13
2.2 Minimized array of sensors targeting each key steps of the operative procedure 16

3.1 Air quality chart for small particles count 34
3.2 Level of particles for different electrosurgical instruments 37

4.1 Ranking the influence of the parameters on key factors of OR efficiency, such as anesthesia time, wake up time and turnover 57
4.2 Solution of the system parameters values 57

5.1 Boundaries conditions 71
5.2 Validation parameters 80
5.3 Comparison of amplitudes and diffusion coefficients of instruments . . 88
5.4 Parameters of the model 89

List of Abbreviations

ABM	**A**gent **B**ased **M**odel
OR	**O**perating **R**oom
EMR	**E**lectronic **M**edical **R**ecord
UTC	**U**niversal **T**ime **C**oordinated
RFID	**R**adio **F**requency **ID**entification
HVAC	**H**eating **V**entilation and **A**ire **C**onditioning
IAQ	**I**ndoor **A**ir **Q**uality
IEQ	**I**ndoor **E**nvironment **Q**uality
CFD	**C**omputational **F**luid **D**ynamic
TCP	**T**ransmission **C**ontrol **P**rotocol
GUI	**G**raphic **U**ser **I**nterface
UTC	**U**niversal **T**ime **C**oordinated
IRB	**I**nstitutional **R**eview **B**oard
MCPS	**M**edical **C**yber **P**ysical **S**ystem
MIS	**M**inimally **I**nvasive **S**urgery
EMR	**E**lectronic **M**edical **R**ecord
SD	**S**tandard **D**eviation
BMI	**B**ody **M**ass **I**ndex
AC	**A**ir **C**onditioning
PM	**P**articulate **M**atter
EPA	**E**nvironmental **P**rotection **A**gency
FMS	**F**acility **M**anagement **S**ervices
ER	**E**mergency **R**oom
RF	**R**adio **F**requency
PDE	**P**artial **D**ifferential **E**quation

Physical Constants

Standard gravity $g = 9.81\,\mathrm{m\,s^{-1}\,s}$

List of Symbols

p	pressure	Pa
v	velocity	$\mathrm{m\,s^{-1}}$
t	time	s
E	energy	J
T	temperature	K
ω	angular frequency	rad
ρ	density	$\mathrm{kg\,m^{-3}}$

Dedicated to my parents, my sister and my grand parents

Chapter 1

State of the art

1.1 Introduction

Suboptimal OR processes make the hospital lose a lot of money. The anesthesia cost of a regularly-scheduled hour was estimated at $100, based on the 2001 median annual United States compensation for academic anesthesiologists [94]. The constant augmentation of patients makes the hospital overloaded and the number of bed is not anymore sufficient in most of the case which brings lots of delays and share of equipment is a huge problem that can bring up to 5 minutes of delay per surgery [139]. It is common nowadays to have to wait to start a case that another one is over because of equipment shortage (CT scan, endoscopes...). The workload of the staff is too high, they have to do too many things at the same time which shift their focusing more on the management and paperwork than on the patient. The use of technology instead of decreasing the amount of work, increases it, and virtualize the patient who is a number now. The majority of hospitals have not been built in one time, it is the addition of multiple parts that makes the whole institution. Their architecture, on the physical part and on the management are completely unconnected. This makes information sharing inexistent or totally non-efficient. This is true at the hospital level but especially at the OR level, for example, today all communication are based on phone calls or people having to go physically in a room to know what is going on inside [137, 63, 23, 58]. All of this raises the amount of workload for the employees and brings a high level of frustration in and between the surgical staff, which at the same time raises the level of stress [5, 130] and can affect patient safety. On another hand, available data are usually entered manually by the nurse or anesthesiologist. These data always carry a personal side. It produces most of the time biased data containing possible errors that management services cannot use as a foundation to make improvements and assessments systems. A robust measurement system to systematically identify, track, report and prevent adverse events is lacking.

The increase of the size of healthcare facilities as well as an increase in the number of healthy, infectious and immunocompromised individuals sharing the same space bring also unique challenges to air distribution and contaminant control [41]. The hospital HVAC should assure and maintain a comfortable environment for its employees as well as for its patients but also safe and clean air as a means of preventing the spread of infection. Before any HVAC design decisions are made, it is important to first understand how viruses or bacteria and other agents are spread inside the building before their propagations impact the surgical workflow as well.

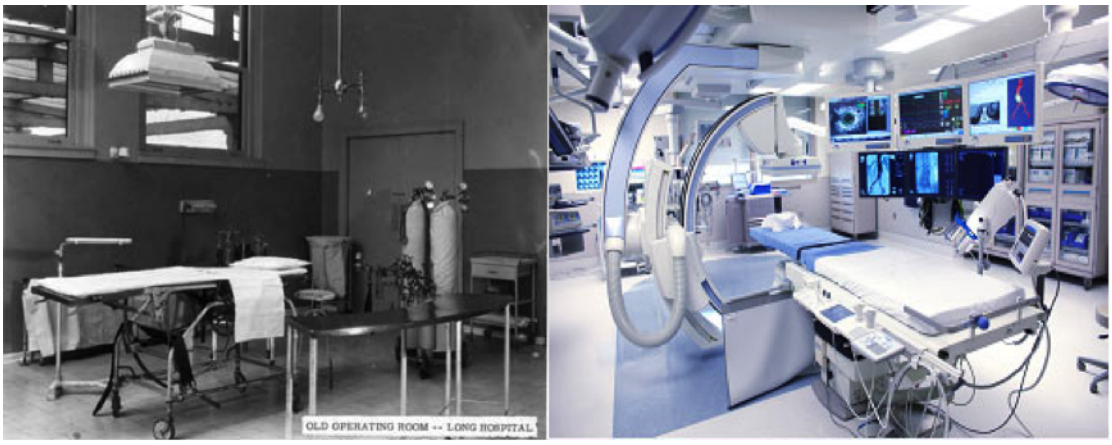


FIGURE 1.1: Complexity of the OR is rising with the appearance of technologies

1.2 Complexity of OR workflow in modern hospitals

Compared with other industries, hospitals have to deal with very diverse situations such as patient conditions, diseases, and emergencies. This brings a level of complexity that makes hospital management challenging. The number of patients is increasing every year and on top of that, the continuous increase of new technologies (see Fig. 1.1) bring with them more complexity and new technics to learn and deal with [38, 22, 133, 2]. If it gives new data and more possibilities, it can also very quickly get overwhelming, uncontrollable or even worst, impossible to predict [28]. The OR suite, which includes a large number of ORs where multiple types of surgeries are performed as well as the pre and post-operative areas, is not an exception and is probably the most complex of this industry. Because of this, huge effort and high interest are seen to improve its efficiency. Even though it is the most expensive part of a hospital, surgery is also the one that brings the most earnings [45, 28]. Standards and requirements are at that point impossible to avoid for such a critical place. The pressure on its stakeholders can be very heavy and impact the whole process. Their goal is to make sure the patient experience in the hospital stays effortless and without interruption [38] as well as maintaining patient and staff safety at all time. During his/her stay the patient is passing through different steps; they, first, have to be admitted and then prepared in the preoperative area. The nurses have to be sure that patients are ready to be wheeled to the OR in a timely manner. Then, the whole surgical crew has to be ready to start on time, nurses have cleaned and prepared the room for this specific surgery with this specific surgeon for this specific patient. On his side, the anesthetist is in the room ready to intubate and finally, the surgeon can start the procedure. This requires communication at every steps and exchange of information with the rest of the hospital to avoid any kind of delays. This workflow is an infinite loop that restarts for every procedure, understanding all the steps and needs to pass from one to the next is necessary to hope improving it.

1.3 Patient safety

Patient safety strongly depends on surgical staff ability to deal with the technological, hierarchical and social complexity of their working environment. The efficiency

of the overall process is the key to improving quality of care [38, 61]. Due to the dynamic environment of the OR, patient safety can be put at risk if it is not managed carefully. One of the solutions found by hospital management is to put in place automation and standardizations [50, 75, 119]. However, unfitted solutions, to emergency cases, for example, can put more pressure on the staff and unsafe situation might rise from them and be the cause of considerable avoidable medical error [28]. Some progress has been made with the implementation of guidelines such as hand hygiene program or pre-surgery checklists [134, 62]. But acceptability rates are still very low, nobody uses them on the long run. The causes are multiple, guidelines can be very time consuming and usually, they do not totally fit to the situation and are too rigid [132, 135]. The same problematic applies to scheduling. Due to the large diversity of situation that can happen in the OR, a rigid scheduling is unreliable and not adaptable to unplanned events [33, 42]. What happens, in reality, is the proliferation of workaround, staff find other solutions that they feel are more efficient in urgent situations. Unfortunately, these improvisations, based on the experience of the employees, can be seen as deviations and shortcuts for the management [29] making any kind of assessments almost impossible. Healthcare system is more an exception than the normality and simple cause and effect assumption here is not sufficient to explain mistakes [119, 104]. Of course, surgical staff need guidelines and help through automation or guidelines, but they also need a part of liberty in decision making. This concept is explained in the guidelines call *Safety-II*, where the importance of flexibility to the health professionals is explained because they are one who really take care of patient safety, usually following their experiences to unexpected events [119]. Finally, there is a big team dimension in this organization. Team effort is key for a fluent workflow. Employees need training on communication, situation awareness, leadership and monitoring [136]. But at the end, it is still impossible, even with the medical knowledge acquired to be prepared for every possible situation. Some events or consequences to action cannot be overseen all the time. Guedon et al. brings the concept of "adaptive support" where it explained the need to have a standard system that makes everything rolling in an efficient and cost effective way when there are no emergencies and still leave some flexibility to the staff in case they have to take a decision on something out of the regular system. You cannot always reduce complexity but you can embrace it to limit it as much as possible [57]. By putting the user at the center of the design, the system presented here is supposed to serve the safety of the patient without increasing the complexity for the staff.

1.4 Need to record systematic information

In his paper, Deming [31] explains his principle of continuous improvement. He explains that a process is stable when performance variations remain within a regular range. The missing link in today's hospital system is that there is no rigorous way of automatically collecting information on what is occurring in the OR and the perioperative space [1]. Other industries showed how measurement systems are important to assess efficiency, and bring organizations to a higher level of performance. The measurement system will give the ability to keep track of any improvements. Two kinds of measurement systems can be put in place: using already existing technologies or adding sensors in the OR. Previous work on workflow analysis systems showed usefulness on assessment of new management rules, such as Rotondi et al. [111] who put in place a real-time patient routing system. Although their system

focuses only on the perioperative area and needed some manual data entry, they were able to assess the improvements of building multidisciplinary teams. On the same way some other researches have been made following sound and video, or usage of the surgical tools [103, 57, 110]. Some systems rely completely on RFID technology, as well which is expensive and requires complex installation and tag deployment [84]. Most current systems are error prone because they require a fairly large amount of tedious human work and intervention while health care personnel are usually already very busy with their duties [35].

Same results have been found with systems using already existing technologies like for example: following vital signs [140] or following OR measurement systems like anesthesia management systems [44, 79]. Another direction is to use both, already existing and adding sensor like the idea of a black box in the OR [24, 60, 124]. Also, acceptation rate of this kind of system is usually very low. First staffs think that they are tracked, especially with systems requiring their intervention or involving cameras [101, 59, 16, 103].

Finding the reason of late surgery start times is a very difficult task. Even if surgeons appear to be the main cause of delays, it has been shown [79] that effort to improve their on-time performance alone is not sufficient to improve on-time performance. In his paper, Caulkins et al. [21] explain on-time performance for arrival times of commercial airline flights. Taking into account that pilots can adjust flight speed to reduce delays (which surgeons cannot) he showed that any delays at any step would be seen in all remaining steps. In other words, the Pareto principle does not apply to healthcare (i.e. the most apparent cause is not mandatory the one you have to focus on) and, it is more a snowball effect that you see: people arrive late in reaction to other people being late.

This brings in the idea of cognitive bias. E. Dexter [33] shows that OR staff demonstrate a clear lack of understanding of the effects and subsequent impacts of late first case start time has in regards to how the rest of the cases of the day progress. We can also see in the paper of F. Dexter [34] that many of the steps currently taken to decrease unused OR time are done on the actual day of the scheduled cases as that is when actual utilization of the rooms is understood. As such, current methods of optimization require close collaboration between OR team members and directors. There are constant, real-time changes required throughout a day to ensure OR optimization. Finally, McIntosh [94] adds that scheduling cases and making decisions on the day of operation(s) to increase OR efficiency are worthwhile. However, the most important step is the appropriate refinement of OR allocation (staffing) 2-3 months before the day of surgery.

This system produces a lot of data that has to be processed and stored by a robust IT infrastructure. Every system implemented in a healthcare facility have to meet standards and present a high level of accuracy. To be used in the real clinical world, a system has to be thought for and with their users. Putting the medical team in the design loop of the system is the key to high acceptation rate and impact on efficiency. The system needs to be scalable and adaptive. Machine learning is one of the solutions where the system would recognize an event that already happened through the detection of specific patterns, this could even apply to complex and emergency situation and could help the staff to take a decision, but never takes it for them.

1.5 Indoor air quality inside a hospital

1.5.1 Generalities and simulation

Indoor air quality in health care facility must be carefully designed before installation and maintained in good working order. Healthcare facilities serve a vulnerable population as well as the comfort of their employees. That is why expert design and maintenance guidance are essential. A reference in standards for air quality in the building can be found in the guidelines of the American institute of architects. For a hospital, these guidelines exist in ASHRAE and give all the recommendation on IAQ and HVAC specifically in ORs [41]. With the development of CFD software and the better understanding of heat transfer, it is now easier and easier to model the airflow in a room, a floor or an entire building. This was applied first to find the best characteristic of an indoor airflow for comfort [64, 65]. The introduction of the compressible Navier-Stokes equations and the possibility to take into account the buoyancy effect was quickly applied to the numerical calculation for heat transfer [128]. But we have to wait the 90's to see the first study on contaminant tracking with the work of Lage *et al.* [78] and their results on the effect of orientation of inlet and outlet on the removal of contaminant. Going deeper in the analysis, Kato *et al.* [72] found using to finite difference methods applied to diffusion fields that having inlet and outlet in the ceiling brings a lot of advantage in the removal of contaminant. Sieber *et al.* [118] published his work in ASHRAE on the relationship between health outcomes and IAQ in the building and presented his notion of Relative Risk which put a statistical scale on this relationship. Finally, lots of research has been made following the risk of deposition in the surgical site and the effect on the different type of ventilation systems. Memarzadeh *et al.* [95] proves the necessity of different air changes rates depending on the air quality you are looking for. Following the same direction, Loomans *et al.* [85] introduce his notion of Colony Forming Units (CFU). It is a parameter that he uses to classified the level of cleanness in an OR. For example, the class 1 is an OR used for very intrusive surgery and is <10 CFU/m3 The CFU value has a direct relationship with the infection rate possible in the OR.

1.5.2 The special case of the OR

The use of electrosurgical instrument is very common now and helps a lot the work of surgeons as well as leave less scar tissue. Unfortunately, surgical smoke plume produced by thermal destruction of tissue during the use of laser or electrosurgical units can be very dangerous for the health, not only for the patient but of the surgical staff. Surgical smoke plumes content is similar to other smoke plumes, including traces of toxic gasses. Particles smaller than 0.3 microns can bypass the lungs filtration and reach the vascular system through the alveoli. Not only this can be inhaled by the staff working on top of the body but it has been showed that the smoke components gets distributed in the whole room as well as in the anesthesia machine airflow [142]. The air that the patient is inhaling is very important to be filtered and controlled. Not only this can affect the airway of the patient and surgical staff, the presence of smoke in the belly of the patient is known to augment the level of benzene and toluene present in the body after surgery [37]. Also due to positive pressure in the room all these particles are pushed out of the room in the hallway where the A/C and traffic control the airflow. It has been showed by Mousavi *et al.* [98] those very small particles (size of most of the viruses and bacteria) can migrate

up to 14.5 meters from a patient room to a nurse area in less than 14 minutes, with concentration 2 to 5 times higher than the ambient particles already present. Another approach than particle count is bacterial active count [115]. They found that small air dust <2.5 microns particles were strongly correlated with operation length but not with surgical techniques. On the other hand particles bigger than 5 microns, surgical techniques were a good predictor of the particles level with a higher level found during open surgery than MIS ones. They did not find a strong correlation between the door opening and air dust particles but bacterial counts was a good predictor of high human activity at the door. Indeed, directional airflow, due to positive pressure can be disrupted or even reversed due to door opening dynamics coupled with the movement of the staff entering or exiting [99]. Finally, the way the door is opened and the time it stays open are linearly related to the exchange volume and can reverse the positive pressure during a certain amount of time, letting the air from the outside getting inside [125].

1.5.3 Propagation of particles

Source of contamination and infection may be endogenous (already on the patient when entering the room) or exogenous (outside of the patient) [105]. Ventilation systems are rarely the source of pathogens but can become a reservoir. A large source of contamination is people coming from the outside of the room as well as the air that comes along them. Indeed in their paper, Lynch*et al.* [87] observed the foot traffic in the operating room and realized that not only the number of opening is proportional to case length but also that it has an exponential relationship with the number of people in the OR, all of them compromising the sterility of the OR environment. Also, every time someone opens the door of the OR it can reverse the gradient of pressure between the room and the hallway. Indeed, the velocity of the door create a vortex around it and exchange of air with the outside air can happen. Not only contaminated air from the inside can go out even easily and affect the whole hallway air quality but also outside can enter because of the vortex. A second parameter affect air exchange at the door, it is the gradient of temperature between inside and outside [74]. This gradient can create a two-way buoyancy flow and air can enter the room like it has been shown in a case of nosocomial transmission to a nurse in the paper of Tang *et al.* [125]. They showed with a tank of water and dyed fluid the exchange due to door opening's vortex. Last but not least, surgical smoke plume produced by thermal destruction of tissue during the use of electrosurgical instruments can be dangerous for the health, not only of the occupants of the OR but for every person present in the perioperative suite [12]. Surgical smoke plumes include traces of toxic gasses and can contaminate the whole room but also can be diffused outside without any kind of monitoring. Our aim is to show that diffusion of smoke in the OR can help understand OR suite airflow and explain airborne infection in the OR suite. In that context, we address how the source of particles can be dispersed in the OR and beyond due to OR traffic and its architecture.

1.6 Mathematical modeling in healthcare

Our lab has extensive experience with several multi-scale models combining differential equations with agent-based models has demonstrated that it can describe key feedback mechanisms back and forth between agents and environmental conditions.

These predictive models have been applied to the field of plant ecology [96, 14], biological systems describing vascular adaptation [68, 51] and clinical problems such as breast conservative therapy [53, 113]. Casarin *et al.* [20], describe the development of several mathematical models, with an escalating level of complexity, to be applied to the field of medicine. In particular, they addressed the improvement of a machine used to repopulate lung scaffolds, the study of the post-surgical vein graft restenosis phenomenon, and the prediction of the outcome of targeted therapies for vascular diseases. The new challenge here is to come up with a model that integrates enough knowledge from socio-psychology, industrial organization and the surgical field to predict dynamics of a complex organization [91, 19, 48]. In the work of Urban *et al.* [131], a generic agent-based framework for human behavior has been proposed. We are going to base the construction of our model on his results.

Surgical flow is a very complex process involving multiple levels and teams across the hospital system. Most of the currently available models of surgical flow are used for planning purposes, and relies on some form of discrete combinatorial mathematical optimization. These models link the set of surgical procedures to be completed with the set of operating room resources that can be allocated in time. Due to uncertainties in the data, it is essentially a stochastic process and rely on some form of discrete combinatorial mathematical optimization. These models link the set of surgical procedures to be completed with the set of operating room resources that can be allocated in time. Even though this problem formulation is very complex, it does not account for the human factors, the number of agents within the surgical team and their interactions between them or with the environment, as well as the different surgical procedural steps that may all influence the final outcome. As it is rather rare for an operation to proceed exactly as planned secondary to the variations in patient disease, surgical team performance, and staff availability, we propose an agent-based model framework that can incorporate all of these elements. In parallel, we will use a mechanical model of airflow at the OR level, as well as the surgical suite level (around 10 ORs) to support the analysis of air contamination between rooms.

1.7 Conclusion

The increase in the number of patients comes with the raising number and size of hospitals. This implies new management decisions and the needs of controlling and monitoring the workflow as well as the environment to ensure efficient use of time and maintaining safety at all time. Sharing of resources and equipment are the largest source of delays and frustration in the OR. While other large industrial sectors followed the implementation of new technologies and achieved remarkable reliability and consistency in their procedure flow and safety, healthcare stayed behind in term of adaptation and acceptance rate. This is very understandable, as any changes in the normal workflow can have drastic impacts on outcomes or patient satisfaction. If more and more hospitals are starting to use fully EMR, these solutions are usually very singular and totally different between institutions without any kind of possible communication. Lots of solutions seen today brought into hospitals are designed without taking into account the user needs. Because of this, surgical staff see technology more like a slowing down process than anything else. Worst, technologies take the focus of the surgeons out of the patient as they are now only numbers in a system and can communicate with their medical doctor through text messages. There is today a need for communication between surgeons and surgical

staff and computer scientists. It is indeed observed that engineers do not realize the issues that surgical staff have to face every day and on the other hand, most of the staff do not know the new capabilities of bringing the power of computation inside the OR. With the solution presented here, we want to tackle the gap in the literature and in the clinical field by creating a specific OR/perioperative-area management system including an array of sensors and different technologies that are able to catch inefficiencies as well as the lack of safety in an automatic, unbiased, accurate and robust way. We want to integrate and develop technologies in and around the OR, helped by mathematical modeling, to support surgical staff in improving the overall safety and efficiency of the hospital. This will embrace an automatic surgical steps detection system to catch the workflow and the efficiency of the OR suite, while air quality sensors monitor the safety of the environment and give us access to the airflow of the OR suite. All this data are then used in mathematical models where different scenarios of workflows can be simulated, difficult cases can be detected in advance, the exposure to toxic gasses can be monitored and the design of OR suite can be rethink to avoid possible nosocomial disease spread. This thesis is designed following this reasoning, the two first paragraph are going to present the installation of different types of sensors inside the OR in order to gather clinical data on workflow and air quality, the results are going to be presented as well as the link between these two domains. The last tow chapters are going to present the use of these data as parameters of different mathematical model aiming at modeling and simulating the reality of clinical data in order to prevent and detect issues and lack of safety as well as try to simulate different scenarios, and their impact on the efficiency and safety of the OR suite. The final goal is to be able to implement the best scenarios in the clinical world and assess their success or failure through their output on readmission rate and money saved by the hospital.

Chapter 2

Automatic tracking system of OR workflow

2.1 Introduction

Most current OR management methods cannot achieve more than 70% efficiency, and it is not even clear (in the absence of an efficient automatic tracking system) that this estimation is accurate [122]. To date, all of these systems require manual input of each data point by a member of the surgical staff. From the time the patient enters the OR on through the critical points of the operation (intubation, first incision, initiation of laparoscopic portion of the procedure, etc.), the time points must be entered by a staff member into the system before it is projected on the digital screen [35]. This creates a burdensome workflow for the OR team which detracts from patient care and leads to inaccurate data collection [7]. We started the smart operating room (OR) concept to aid surgeons, OR staff, as well as patients and patient family members that have expressed their frustration in excessive waiting times as well as delays in and out of the OR. Difficulties in efficient communication between OR staff and those team members responsible for organizing and managing the OR suite activities also exists in every hospital across the nation [36]. An OR suite at a hospital is a system constantly in flux. Cases are added and canceled regularly, rooms need to be reallocated, and a significant amount of coordination is required to know current room statuses for each OR in order to guide staff and patient movement in the perioperative space. The hospital management is constantly struggling to improve the efficiency of OR usage, as it is becoming a major issue to provide high quality affordable health care. At a cost of approximately $100 per min, OR time is incredibly expensive and even small delays compounded over the course of multiple ORs and multiple days result in a significant impact [122]. By just increasing overall efficiency by 5 min per case per day, a 20 OR suite that averages two cases per room per day can save upwards of 5.2 million dollars per year (assuming 260 business days per year). We have assembled an interdisciplinary team of surgeons, applied mathematicians, and computer scientists to focus on two key aspects and needs to improve OR efficiency:

1. How do we close the information loop between the surgical team and the OR system, so the OR system can add computational intelligence to deliver the procedures with allocation of OR time and resources in an optimal way?

2. Can we provide context information on patient status from patient registration to patient discharge, since it is well known that inefficiency and safety issues may come from miscommunications with the OR team at both the preparation and

recovery stage?

2.2 Design of the system smartOR

We endeavor to propose a modern solution that would work for any operation but would be most efficient for large volume procedures. The major steps of an OR cycle (Fig. 2.1) from the patient entering the OR through the cleaning after a case is completed can be segmented, with at least one specific event occurring at each step that can be targeted with a simple, dedicated sensor.

2.2.1 Method

The first step we took at the beginning of this project was to section the activities in the OR into defined segments as a way of understanding the cycle of the OR (Fig. 2.1). After this, we further identified a key action or activity that indicated when each part began and/or concluded. Once this was done, we determined what type of dedicated sensor could be used to capture that action or activity (Table 2.1). Continued feedback from hospital administration, nursing staff as well as surgeons allowed us to refine the system. The goal was to ensure that the system was robust enough to build a timeline of events during a day in the OR and to be able to collect and transmit these data wirelessly to a centralized computer for consolidation and analyses. These sensors allow the system to capture and define the procedure steps and room states listed in Fig. 2.1. The focus of our sensors choices and placement was to collect data on aspects of the operation that are regularly discussed and evaluated for OR efficiency, but also as a way to detect delays/statistical outliers and ultimately build statistical models on total case lengths and particular procedure times. One of the first targets was to follow turnover time (the time between a patient leaves the OR and the next one enters) as this is one of the key metrics of efficiency for the OR staff and administration. The cornerstone of this system design method is a set of time series with discrete values that correspond to the state value for each action of interest (Table 2.1).

2.2.2 Installation and development

Each designed sensors were built with custom communication software protocols as well as being Wi-Fi-enabled to allow for wireless connectivity, ease of installation and remote maintenance. The complete sensor system was installed in each OR in under 30 min and did not affect the flow of the operation. Finally, the system was running and collecting data on a dedicated Wi-Fi 4G server that allowed us to perform software maintenance and data downloading from the system without having to physically enter the ORs. We started the project with a large number of different sensors detecting a multitude of steps. On table 2.1, we show the initial sensors and what they were targeting. After starting to analyze the data from the sensors and putting them into the context of the clinical realities we realized that a lot of them were redundant or were not bringing any new information. For example, the information coming from the sensor under the mattress' bed was very close to the information coming from the pressure sensor at the door. Continued feedback from hospital administration, nursing staff as well as surgeons on our multidisciplinary team allowed us to further refine the system to the minimum number of sensors placed in the OR while maximizing the collection of relevant data (Table 2.2). We

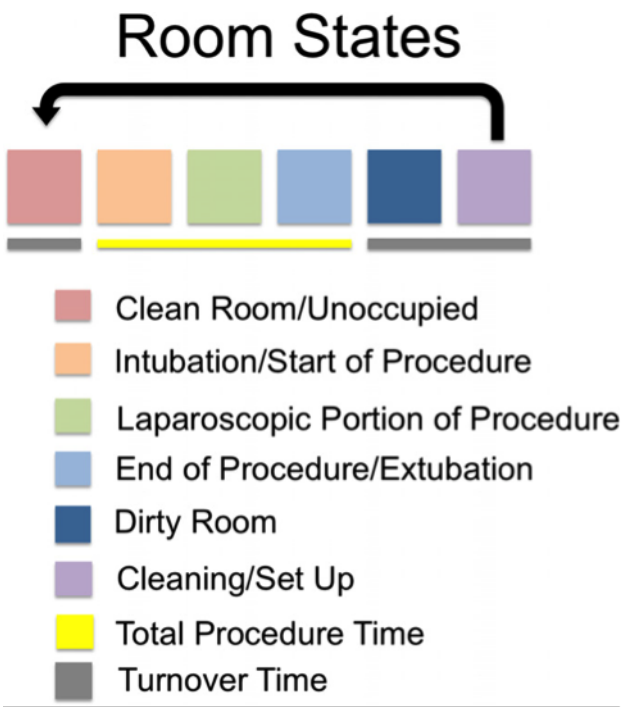


FIGURE 2.1: Operating room states and cycle

realized that the sensor for the scalpel needed a training period for the scrub nurse and needed special attention during the cleaning of the room. We want our system to be very modular and have a solution to any kind of needs from the surgical team or the procedure itself. For example, we built the scalpel sensor in order to detect the first incision, which is an important step for the surgery itself and makes timing possible of how long the patient is kept open -very important for contamination rates and transplant cases. Due to the detection of this characteristic, this sensor has been used during cases where the timing is important such as living donor nephrectomy (kidney ablation from a living donor). It is used at the vascular department of the University Hospital of Strasbourg, France where the first deployment and tests in clinical environment of the smartOR were made. It helped them in one of their research project where they wanted to correlate the size of the kidney along with other patient characteristics, with the length of the surgery. Our system was able to give them the data they previously had to enter manually and do the statistic automatically after each case. The results were very encouraging and we showed, first, that our system was fitting their previous data then that the volume of the kidney, that can be found on CT scans, is a good predictive characteristic for the length of the case but finally that the volume of fat around it is also a good indicator, see Fig. 2.2. After different runs of test in our lab and the first results from Strasbourg's Hospital we were able to prove the usefulness of the system and refine the sensors used to be ready to install a unobtrusive system that would run 24/7, not anymore for one specific case, in ORs of the Houston Methodist Hospital. The installation went through different phases.

First phase of implementation

The goal of this phase was to understand the minimum number of sensors in order to still detect all our key steps and to find the best position of these in the OR

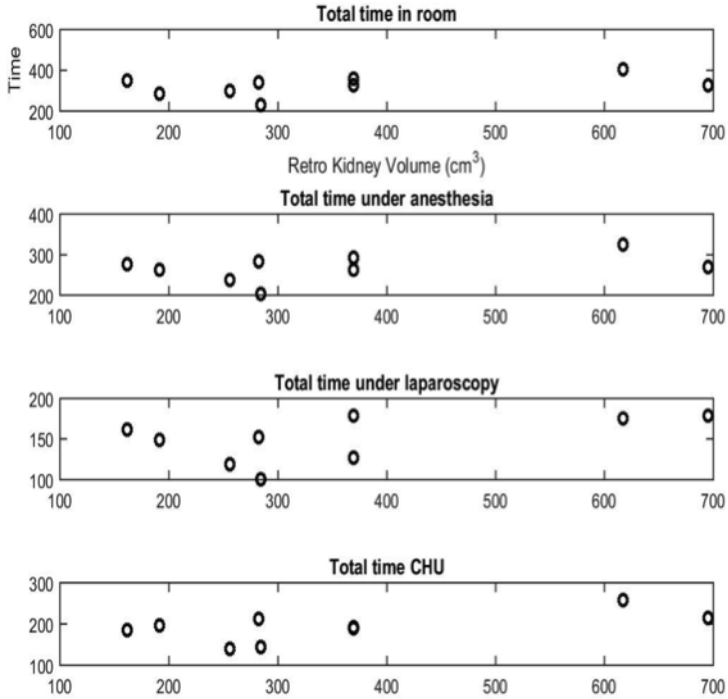


FIGURE 2.2: Result from operation at the University Hospital of Strasbourg and comparison between the size of the kiddney and the length of different parts of the procedure.

for full efficiency. With sensors placed around the OR doorway, on the anesthesia machine and an infrared motion detector in one corner of the room (Fig. 2), we were able to capture critical data regarding the case with extreme accuracy. Three sensors were placed at Dunn OR suite at key locations of the rooms to capture the targeted events while remaining out of the way and unobtrusive to the OR team. For this phase of the study, two ORs adjacent to each other were outfitted with the three sensors array (Fig. 2) and both communicated via a secure wireless network to the central computer that not only projected the sensor outputs in real-time but also captured the data for retrospective analyses. The system was installed and running 24 hours a day for 7 days a week beginning at the end of 2014. At the beginning, the bed detection sensor was constituted of two parallel pressure sensor stripes taped between two rubber matts. It was placed at the doorway of the OR and whenever a bed is rolling on it, the wheel is detected through a very specific pattern of $2x2$ spikes due to the crossing of two wheels on two pressure sensor. This sensor had the most number of versions because, first, of its busy location and second because we were using pressure sensors that could only handle around 30 pounds of pressure on them. They are using a bilayer system, also called FSR (Force Sensitive Resistor) with a spacing of air in between the printed interdigitated electrodes and the base layer of uniform printed semi-conductor. The issue is that at weights at the upper of their limit, the sensors are not able to continue to function effectively over long periods of time. The failure is due to a compression of the two layers together and over time the materials cease to have their original shape. The result is a near-constant (or constant) contact between the top electrodes layer and the bottom conductive layer resulting in a noisy signal. We needed a novel device that allows for extremely heavy weight measurements to be detected and quantified while remaining robust

TABLE 2.1: Sensors targeting key events at each step of the operative procedure

Procedure	Event Target	Sensor Type
Instrument/Back Table Setup	Instrument Racks Placed On Table	Pressure Sensing Strip
Patient Brought Into OR	Stretcher Crossing Door Threshold	Pressure Sensing Strip
Patient Transferred to OR Table	Patient Weight Transferred From Stretcher to Table	Pressure Sensing Strip
Induction of Anesthesia	Ventilation Initiation	Motion Detection Camera
Operation Starts	First Incision	Scalpel Pick Up Detection
Reversal of Anesthesia/Extubate	Ventilator Cessation	Motion Detection Camera
Patient Transferred to Stretcher	Patient Weight Transferred From Table to Stretcher	Pressure Sensing Strip
Patient Taken to Recovery Room	Stretcher Crossing Door Threshold	Pressure Sensing Strip
Occupancy of the OR	Movement in the OR	Infrared sensor

over longer periods of time. We designed a new system comprised of three layers (Fi. 2.3 bottom left) where the top and bottom layers are the same than on the former one. The center layer is a non-conductive mesh-like material that serves as a physical barrier between the top and bottom layers. No matter the weight of compression on the sensor as a whole, the center layer prevents electrical connectivity between the two conductive layers through a physical barrier. It presents geometric shapes cut out of it to provide a controlled opportunity for the top and bottom layers to contact each other under the right weights and pressures while reducing the risk of long-term failure due to the remainder of the non-conductive layer serving as support to physically keep the top and bottom layers separate. This made the detection of the bed possible on a long-term period and with less noise in the data as lightweight pressure are not anymore detected. The second sensor is a camera placed on top of the bellow of the anesthesia machine and works as a motion detections sensor. Whenever the patient is intubated the bellow of the anesthesia machine starts moving to act as a pump and give oxygen to the patient. We can catch this movement by applying motion detection on the images coming from the camera.

By looking back at the data after couple of surgeries we realized a specific pattern on the raw data from motion detection algorithm during minimally invasive surgery. We could see, when plotting the data, 3 different phases during the action of the bellow, see Fig. 2.4 bottom graph. By checking what was happening during the case, we realized that this change in the pattern was linked to a change of the general luminosity in the room. During a laparoscopic case, surgeon deemed the lights in the room to have a better contrast on the screen where they are looking the images from the endoscope, they call this “going green”. We were then able to add a detectable step to our system. Finally the last sensor is an IR sensor placed in a corner of the room to catch general activity of the room and know when there is no

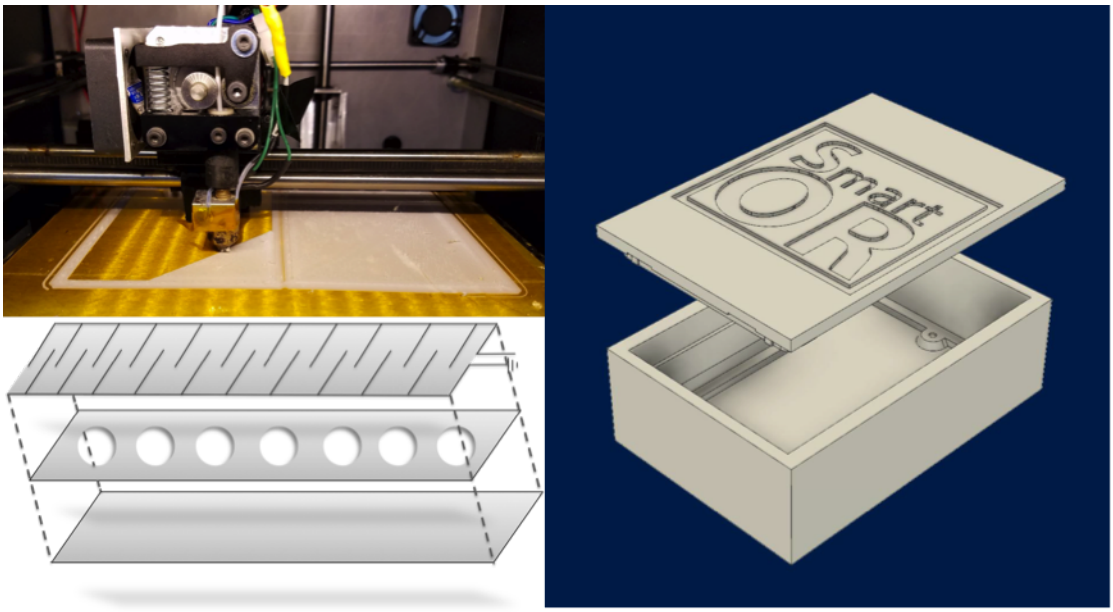


FIGURE 2.3: Different parts and sensors built in our lab. We had to custom made sensors and 3D print cases to fit electrinic parts.

activity between cases for example which would be aproof of inefficient use of OR time.

All the sensors were remotely controllable for fast and noninvasive potential system repairs or updates. All components were easily acquired on the shelf, customized of needed and assembled with 3D printed cases. Only a small white box and the sensor are visible in the installed system, and all sensors were plugged into the emergency power outlets in the OR as these had dedicated uninterrupted power. We tried to avoid as much as possible to use batteries in our system to reduce the amount of on site maintenance and build a 24/7 system. Although this is our choice for installation in our hospital, we do not totally suppress the idea of battery powered sensors, like some of them are in the system used in Strasbourg. The collected data are always anonymous as they centered around case types and perioperative setting movements and functions and not on individuals. The data stream was stored on an on-site secure server, and prior to installation, all our sensors and common wireless communication methods were evaluated and cleared by the hospital administration and the information technology department.

Second phase of implementation

Unfortunately, even after the changes in design we applied on the pressure sensor at the doorway some issues were still present on this specific sensor. First, it was the only sensor that needed maintenance every 3 months because of use deterioration. Second, it was the only sensor in the way of the staff and that needed to be cleaned after every case. All of this pushed us to find another solution that was not on the way and without the need to be cleaned. Since a long time we had this idea to follow the life of the door and not anymore only the activity at the doorway's floor. We started by putting a 9-degrees of freedom sensor on the door in parallel of the pressure sensor. This new sensor includes an accelerometer, a gyroscope and a magnetometer. After looking at the data from these 3 sensors, we realized that, of

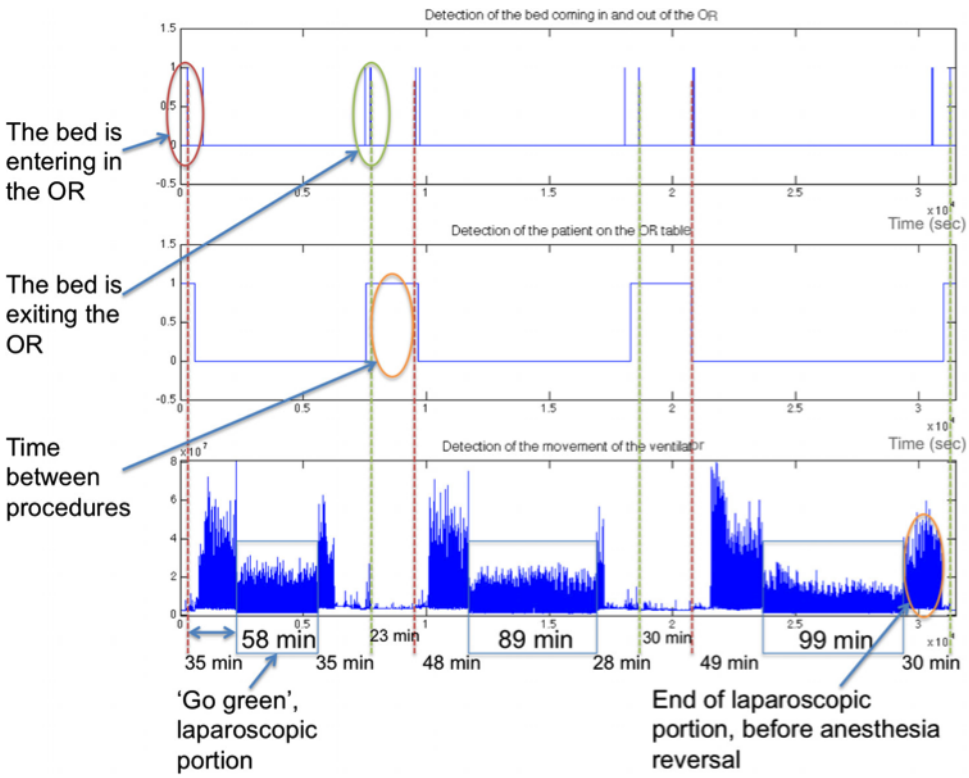


FIGURE 2.4: First type of data received from the sensors. The 2 first plots on the top are processed and cleaned after signal processing segmentation to detect specific steps. The one on the bottom is the raw motion detection from the camera on the anesthesia machine. It is easy to detect the begin and end of the anesthesia portion of the surgery, but we also detected the beginning and end of the laparoscopic portion of the surgery.

course we could have access to the activity of the door with the accelerometer and gyroscope which can give very good information on number of openings and track possible risk of contamination but on top of this, it appeared that the magnetometer was able to easily detect the bed passing through the door. The bed being very heavy, with a lot of metal parts and motors to help its displacements, it actually changes the magnetic field around it. We are able to segment this from the rest such as changes of magnetic field due to moving the door or staff passing with smaller metal parts, due to the size of the bed and the time it takes to pass it though the door with a patient on it. The rest of the sensors stayed unchanged, only some design changes were done like printing new cases for better integration in the room. Acceptance of these sensors was not trivial. We presented the system to the management of the OR suite who then presented it to their staff before it was installed. Even with these precautions they did not embrace right away the advantages of such a system and would unplug it or remove the sensor from their specific places. The reasons were multiple, it is true that plugs in the OR is a very precious resource and the system is not more important than other systems but also it took some times for us to prove that we were not tracking them but only the steps of the procedure. This made gathering of continuous data almost impossible at the beginning and required a lot of manual maintenance. But passing some time in the OR to check the status of the system or to install new sensors with one of the resident working in our lab

TABLE 2.2: Minimized array of sensors targeting each key steps of the operative procedure

Procedure	Event Target	Sensor Type
Patient Brought Into OR	Stretcher Crossing Door Threshold	Accelerometer - Gyroscope - Magnetometer
Induction of Anesthesia	Ventilation Initiation	Small Motion Detection Camera
Laparoscopic portion of procedure	OR Lights Dimming (Going Green)	Motion Detection Camera
Reversal of Anesthesia/Extubate	Ventilator Cessation	Motion Detection Camera
Patient Taken to Recovery Room	Stretcher Crossing Door Threshold	Accelerometer - Gyroscope - Magnetometer
Occupancy of the OR	Movement in the OR	Infrared sensor

who knew more people working there, the staff started to get interested, involved and was aware of why we were doing this. They started to accept this new system in their own environment to the point of using it to hold cables for examples on the camera box. No arm was done to the system anymore and they started to work with it, decreasing quickly the amount of maintenance and increasing the percentage of data gathered. Also a very important action from us was to deliver to the staff and the management department of the OR suite the results we were finding (or not) and to present it to them to compare but also to be very transparent on what the system can really provide without any intrusion in personal data or in everyday workload.

For technology acceptance, it was essential to have sensors targeting tasks and not necessarily specific staff members. The system of distributed sensors also requires as little maintenance as possible, no sterilization, and most importantly, does not change the overall flow of the OR. With the creation of the center of computational surgery in the Houston Methodist Hospital maintaining a translational dialog in the hospital and its stakeholder, it was easier to fully understand the needs of the clinical world and avoid to come with a solution impossible to realize in practice. Not only combining engineers, programmers, and user interface designers but also having dedicated surgeons on the team ensured that the project design can be smoothly implemented while remaining cognizant of the complex functions and the " culture" of the operating room and perioperative space. Just as importantly, we have now nurse managers and OR staff members as regular consultants that can describe the issues they encounter on a daily basis in the perioperative space.

2.2.3 Software and signal processing

The overall complexity of the computer system should not be underestimated. The system's software is divided into different parts of a common TCP network, a client and a server, and our signal processing algorithm plus the database. Here is the presentation of this different parts, their goals and developement. The clients: they are the micro controller attached to the sensors. We are using raspberry pies with USB dongle for Wi-Fi capabilities. A specific software for every sensor written in python is running on them. They have the same architecture for the 3 sensors, the pi read the digital data from the sensor, if needed analyzed them (we use the library openCV for motion detection on the camera's images for example) and send the information with time information on the network. The algorithm takes care to

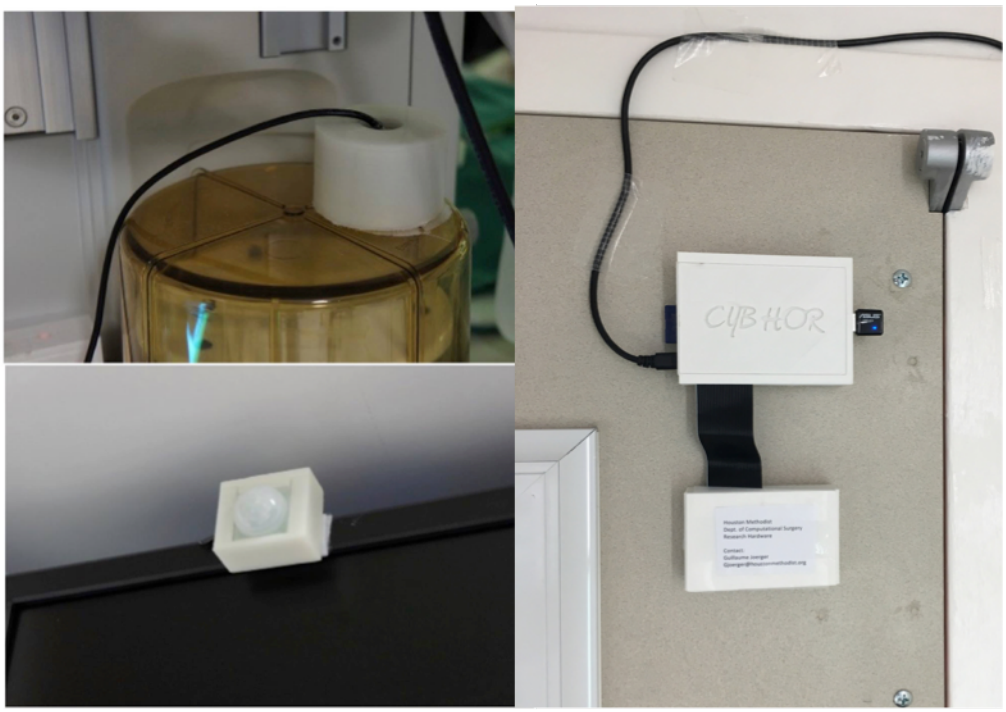


FIGURE 2.5: Final array of sensors installed in 5 ORs of the hospital. On the top left you can see the camera placed on top of the bellow of the anesthesia machine with Velcro. On the bottom left there is the IR motion sensor placed in a corner of the room. Finally, placed on the door you can see the 9-DOF sensor connected to the raspberry pi with its Wi-Fi dongle.

continuously check that the system is connected to the right Wi-Fi network otherwise alerts are sent to prevent lost of data on an extended period. The server: it is a computer and a router placed in one of the OR. It takes care of handling the TCP network to receive the information from the clients. The clients connect to the server, they both confirm the connection and the then server ask the clients of they have to send. If they do, the clients send the information and ask a confirmation of reception to the server. He then saves the raw data and analyze them in order to binarized them, see below the signal processing part. This processed data is plotted in real time on a technical GUI where one can see the status of the sensor, their binarized data, change the different thresholds, scan for new sensors... The software saves this analyzed data too in a file and we can do post analysis on these data like for example statistics on the elapsed time between two steps, see Results. We calculated that it would take 1Tb per year per hospital to save the data from the system everyday in all their ORs. We used a TCP based system because it is known to be reliable and well documented. We added a checksum error check to the algorithm to make sure no data are lost in the transmission process. With the wireless communication protocols clearly established as those being industry standard and proven to not interfere with any medical/surgical equipment in the OR, and all sensors away from active and/or sterile areas of the OR, the smartOR was proven to be safe and harmless. The network allows us to build a real network not only of sensors but also of ORs and be able to control all the OR suite on one plateform like we can see in a air traffic control room, see Fig. 2.7.

The different steps of the procedure are detected by applying thresholds on the

raw data from the sensors. These thresholds come form the manual analysis done on a large number of procedure at the beginning of the study, Different patterns of detection as well as value of threshold were extracted from this preliminary phase to detect then the events automatically and bring real time OR awareness to the whole OR suite without any human action. The unique signal signature of various events enables differentiation of these events by the same sensor. In order to detect the different steps we needed to binarized the raw data using different level of thresholding set during the preliminary analysis. For instance, a footfall on the door threshold sensor has a different signal signature from the wheel of a gurney or the bed as a different magnetic signature than other electronic devices passing through the door and caught by the magnetometer. By mathematically analyzing the signature of the time series signal from each sensor, a time portrait of events in that operating room can be constructed. Finally, the detection of events and the computation of the elapsed time between each steps is what make possible alerts sent to OR managers if these times start to last too long. In post processing, data were consolidated and spreadsheets generated to be able to match sensor data with OR case data including procedure type and nursing/anesthesia notes and then processed using MATLAB. We analyzed the data of the three sensors case by case. We start by narrowing down using the detection of the bed entry and exit. The pressure matt at the doorway was the trickiest part with the detection and segmentation of the pattern from the wheels compare to other detection like footstep or other equipment. But, now the data coming from the magnetometer is clearer and real time detection as well as more robust detection is possible.

Context for detection:
Last but not least, the detection would almost not be possible without taking into account the context of the surgery. For example, there is no reason to try to detect the bed entering or exiting as long as the anesthesia machine is on. Also, all the steps we are trying to detect are happening in a specific order, which also helped a lot the detection. Because of this, the system is only a close to real time system, once a value is detected above or under the threshold we have to gather a little bit of data until being able to confirm this as an event or just noise. For example, it happens that the surgeons asks the anesthesiologist to stop the automatic breathing system when he has to do short but very precise movements. This can be detected as the extubation if taken out of the context of the medical world. To avoid this we keep watching the data and confirm the detection 2 minutes after if nothing else happened since.

With our collaboration with experts in air traffic software design, we started to draw from the field of air transport operation to implement best software practices. Our system requires a 100 % automatic detection in an ever-moving and dynamic environment to ensure accuracy. We intend to continue improving our hardware and software to minimize or altogether eliminate noise and fast positives/negatives in the system. Data security as well as patient (and staff) privacy is also paramount as the system is scaled up.

2.2.4 Validation

When building a system that is going to be installed and used everyday in the most complex place of a hospital, accuracy and robustness are keys for acceptance and usage. Our system is relying on the accuracy provided by the different off-the-shelf parts we are using, the validation part of both the hardware and the software was crucial. First, synchronization between all the parts was needed to put everything on the same reference frame. As any Internet of Things system this was easier with the

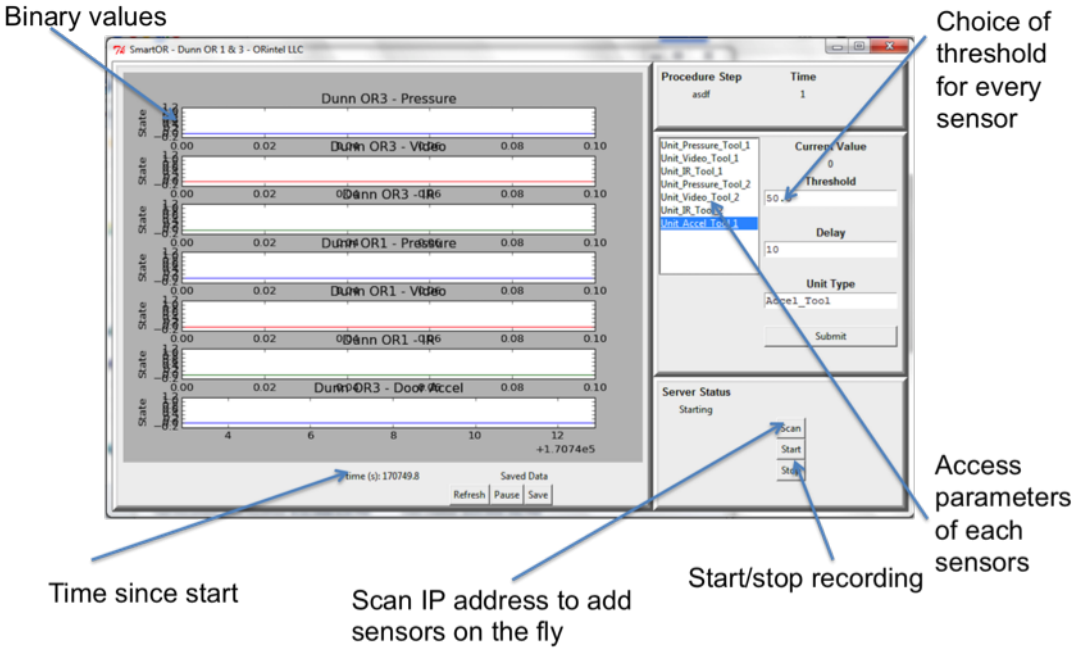


FIGURE 2.6: Technical GUI to access different parameters of the system and check the status of every sensors as well as their values.

possible connection to the Internet and the use of UTC. Then, creation and plotting of real time data from the sensor on the server helped to put in place controlled validation session, with a timeline of event generated and its comparison with sensors output. We built in our lab a system reliable and robust, even to short lose of connection and were ready to face the clinical world. The first step after installing the system in the clinical world was to compare sensor-triggered events with what was documented in the chart by the nursing staff. In comparing the smartOR acquired times that the patient entered the room and exited the room to the nurse's manual-entry time, the Pearson's coefficient was 0.8 indicating that there was a consistent positive correlation between the sensor-acquired data and what was manually entered into the medical record, see Fig. 2.16 at the end of the Result section. To do this validation we got granted an IRB authorization to get access to all the anonymized cases reported in the record of the hospital during 2015, see Comparison with EMR section.

2.2.5 Report

The advantage of our system is that all the data are saved in a database using Microsoft SQL database and visual studio. This database can be accessed with credential (using Secure Sockets Layout) through a ASP.NET web app. The database is ordered in such a way we can use Report Viewer 2015 to build reports. These reports can provide mean times according to different variables such as surgeon, procedure or room... The reports are very modular with different level of access (basic, advance, detailed) and can be pull out for one day, one week, one month etc... It gives also the possibilities to detect the outliers and go back to the information of what happened during this special case. We think that it would be very useful to have this kind of information available to everyone under the form of a touchscreen in the perioperative area. People can have access to all this statistics, play with them

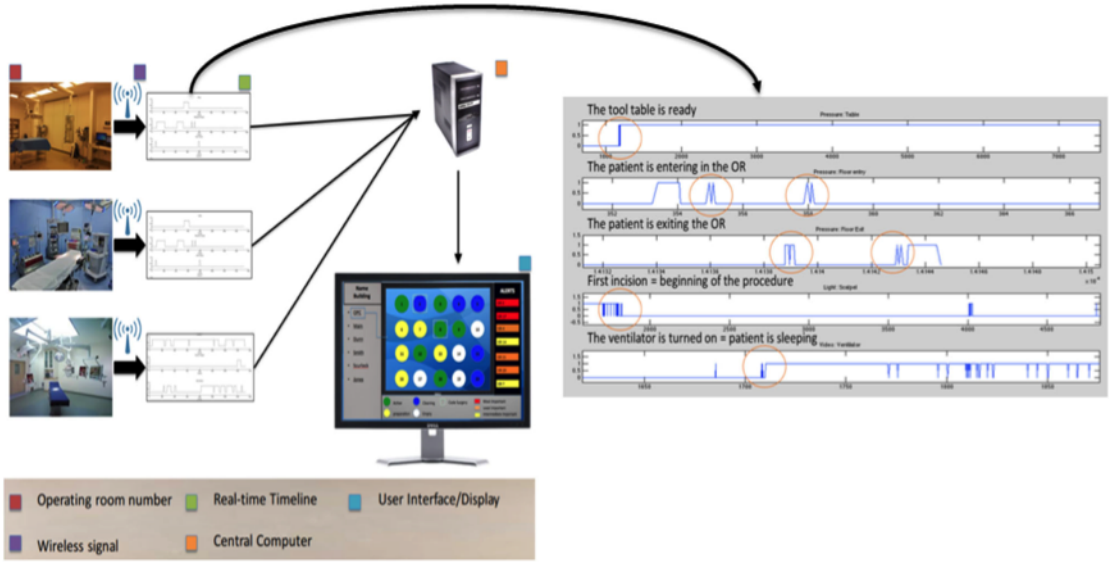


FIGURE 2.7: Creation of a network of ORs and communication through Wi-Fi.

and take part into making the OR suite more efficient. Also, this data will be used to feed our predictive model that is going to be explained in Chapter 4.

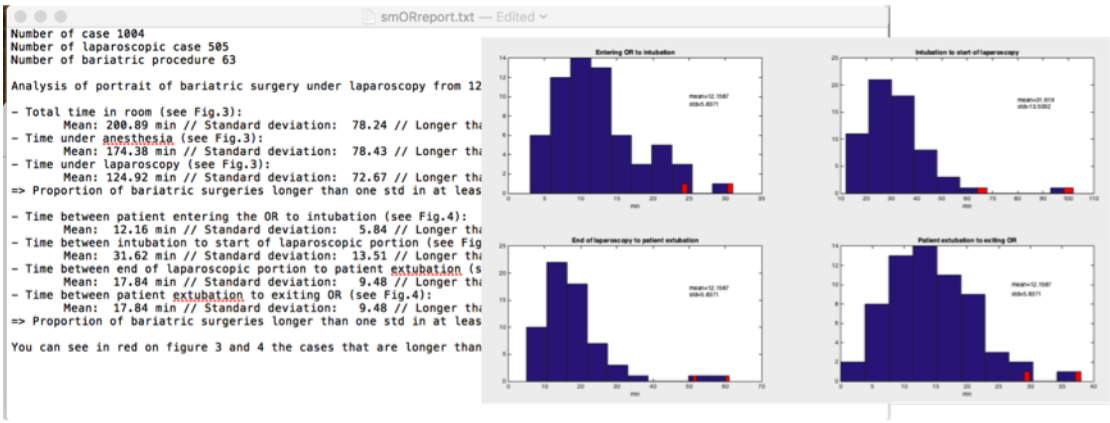


FIGURE 2.8: Example of reports that the management depratement can pull from the OR with a focus on outliers detection here (red).

2.2.6 OR awareness and spread of the information: an introduction to MCPS

Most of the surgical suites data acquired and transmitted to the staff using different technologies - OR status, surgery steps, patient and staff location etc., consists in manual inputs that proved themselves to be usually different from the reality. These unreliable and often biased data make visualization and interaction tools not adapted, which prevent the staff to take optimum organizational decisions. We believe that staff situation awareness is the key to make the right decisions that lead

to better control of the surgical suite, reduce frustration of the staff and better patient outcomes. Li et al. [83] identified two specific challenges for MCPS: context-awareness: how staff interactions with the system and study of staff activity & incertitude of the captured data. With the data from our sensor we have the power of spreading the information in RT to anyone and anywhere in the hospital. This requires more insight from the GUI and human interface world that our lab has now experience in due to the work of Rambourg [108], as well as MCPS world that we started to tackle in s system presented in [70], see annex. In a first version of a GUI for just the smartOR, we imagined to place different screens all around the OR suite and the perioperative area with different access and different level of information, see Fig. 2.9. There would be screens in front of each OR with the actual status of the OR for local awareness and screens in the pre/post-operative area with information about the advancement of cases and the availability of beds in the preoperative area for global awareness in the whole OR suite. Finally, our knowledge on previous procedures analyzed and using the power of machine learning as well as a mathematical model for prediction of OR workflow that is going to be presented later on, we imagine a system of alert every time a part of a procedure would be too long or that the turnover time over pass the institution threshold.

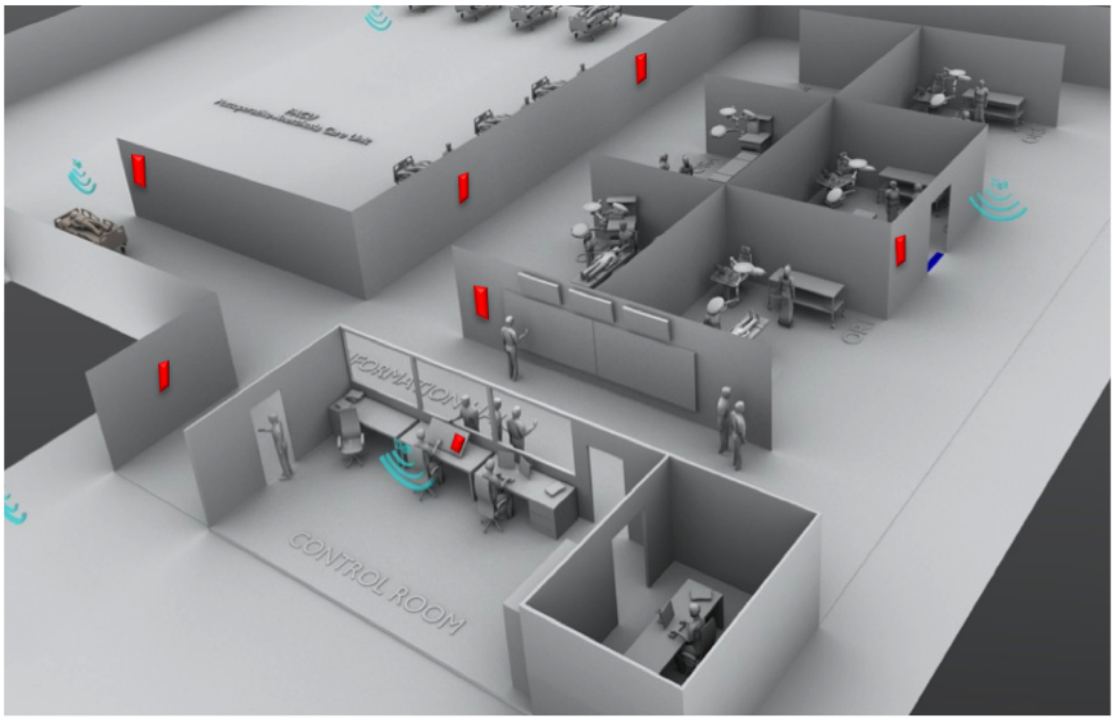


FIGURE 2.9: Placement of local and global screen of information aroun the OR suite.

2.2.7 Preoperative area study

As we are planning to expand the SmartOR system to be able to track key features of the entire perioperative space including pre- and postoperative aspects that are relevant to patient and surgeon movement. We aim to integrate an OR personnel detection system within the SmartOR infrastructure using passive UHF (ultrahigh frequencies) and active/passive RFID technologies. The goal of this system is to

provide a nonintrusive detection system of the OR personnel (surgeons, anesthesiologists, etc.) as well as patient in a defined area of the hospital. These data can help improve the understanding the activity of OR suite, such as the time spent in certain rooms or areas, traffic volumes, and other statistical metrics [116]. The technology also allows us to discriminate the data to certain levels (all OR personnel, OR personnel categories, individuals, etc.) within the privacy limits allowed by the institution. Through initial testing, we have found that most OR staff members were not averse to location-based tracking. This may vary from institution to institution, as the culture of each hospital regarding technology acceptance can differ.

First case start time study

A need exists as well to follow physician movement in the preoperative space, as it is a requirement for the surgeon to meet with the patient before they are transported to the operating room. With cases scheduled each operating day to start at very specific times, a delay in the start of the first case results in downstream delays that can quickly compound. Implementing a system using the aforementioned RFID technology that notifies nursing staff that the patient has been seen by the surgeon in the preoperative area can increase efficiency and also serve to potentially identify or eliminate causes of delays in case start times [84].

Date	RFID time	Scheduled OR time (first case start)	Actual patient in-room time	Documented delay cause		Minutes between RFID and in-room time
03/19/15	7:23:17	7:30	7:30	N/A		0:06:43
03/23/15	7:27:34	7:30	7:40	Staff surgeon related		0:12:26
03/23/15	7:10:01	7:30	7:30	N/A		0:19:59
03/24/15	7:20:20	7:30	7:29	N/A		0:08:40
03/26/15	7:08:43	7:30	7:29	N/A		0:20:17
03/30/15	7:31:19	7:30	7:52	Staff surgeon related		0:20:41
04/01/15	8:57:08	9:00	9:02	Staff surgeon related		0:04:52
04/02/15	7:16:48	7:30	7:35	Staff surgeon related		0:18:12
04/06/15	7:31:37	7:30	7:38	N/A		0:06:23
04/07/15	7:32:15	7:30	7:42	Staff surgeon related		0:09:45
04/08/15	7:49:50	9:00	9:14	Staff nursing related		1:24:10
04/10/15	7:26:35	7:30	7:34	Staff surgeon related		0:07:25
04/16/15	7:24:07	7:30	7:30	N/A		0:05:53
04/20/15	7:38:03	7:30	7:41	Staff surgeon related		0:02:57
04/20/15	7:28:45	7:30	7:39	Staff surgeon related		0:10:15
04/27/15	6:47:41	7:30	7:36	Staff surgeon related		0:48:19
Mean (for 7:30 start times)	7:21:56		69 % late		Mean	0:17:56

FIGURE 2.10: Result of our detection with RFID tags of the time a surgeon goes to see his patient before the case in the morning. This gives a good reference to understand the source of possible late starts of the first case of the day.

To focus on potential events leading to delays of when the first surgical case starts (ultimately resulting in delays through the rest of the day), we installed a dedicated RFID system in the preoperative space where surgeons must see their patient before the patient can be taken to the OR (Fig. 2.11). Three staff surgeons were provided unique RFID tags to capture the time(s) that they entered the preoperative area. The goal was to first see how soon before the scheduled start time for the first case of the day they visited their patient and how often the first case starts on time. Finally, with the RFID component of our system, we were able to track when the three surgeons identified their first patient of the day, and then with our OR, sensors determine the actual time the patient entered the OR versus the scheduled time. We found that the average time the surgeons visited the patient was approximately 8 min prior to the time the case was schedule to start and that 69% of the first cases of the day started late, see Fig. 2.10. The implications here are large as a late start to the first case of the day in an OR can easily result in delays over the course of the day in that OR.

FIGURE 2.11: Installation of the RFID system at the entry of the preoperative are of the OR where the surgeon is suppose to go see his patient before a case. On the right, the RFID tag is placed on the pager of the surgeon.

Patient tracking

Finally, perioperative management and efficiency require the knowledge of patient locations in real time. With current systems on the market relying on manual entry by OR staff when a patient reaches each designated area, the incidence of inaccurate or altogether nonexistent patient statuses is frequent and results in this important feature being neglected by those reading the OR board. By applying our software to tiny, low-powered, lightweight, and inexpensive programmable radio-frequency modules, we build the ability to create a virtual network through attachment of these modules either to the patient's chart (that travels with them in the perioperative space) or easily to the patient in the form of a wristband (Fig. 2.12). This simple system establishes a multihop mesh network that is autoforming, instant-on, peer-to-peer and allows over-the-air programming and remote procedure calls. Moreover, the modules work interchangeably as antenna, receiver, sensors processor, wireless bridge, or gateway. We have started to pilot this concept by placing the small battery-powered modules in the patient data binders as they always travel with the patient whenever they leave their room and serve as a reliable proxy for patient location throughout the hospital.

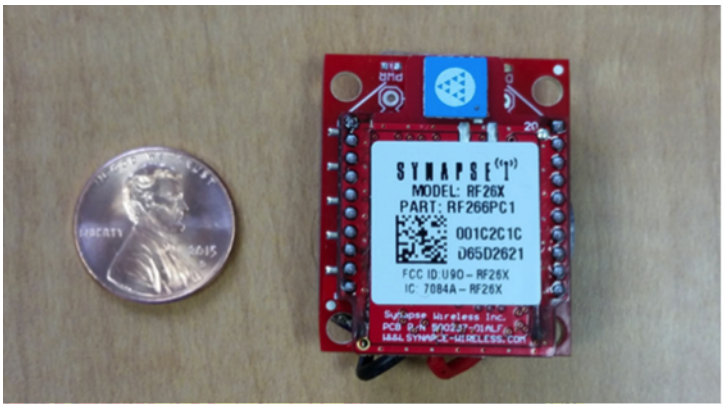


FIGURE 2.12: Picture of the RF module used to track the binder of the patient.

2.3 Results

2.3.1 Generalities

From November 2014 to December 2015, intraoperative data were collected on 1003 cases. Of these, 504 were laparoscopic, and the remainder a combination of general surgery, vascular, plastics, neurosurgery, and colorectal procedures. The database we built gives us access to a very broad range of types of procedures from a range of surgical specialties Results obtained confirm the capability of accurately identifying the steps of the operative procedure outlined in Fig 2.1 in a repeatable and reliable way. A representative generated timeline of sensor-derived data from a single OR on 1 day is depicted in Fig. 2.4. The doorway pressure sensor and later the magnetometer reliably detect entrance and exit of the patient bed and initiation as well as cessation of the ventilator function (indicating when the patient was intubated as well as extubated) was clearly captured by the motion sensor camera placed on the ventilator bellows. On the generated timeline, changes in ambient light within the OR are visually depicted as a decrease in peak intensity of the ventilator movement and signify " going green" in the room for the laparoscopic portion of the operation. When focus is turned to the non-procedural portions of the OR cycle such as the time between cases (turnover time), the system demonstrates how easily and precisely it can automatically detect, quantify, and generate meaningful data to be used by the team to improve efficiency.

2.3.2 Turnover time

Over 600 segments of time between cases were detected with the smartOR system, and out of these, 374 turnover times were identified. Turnover time was defined as the time between two cases that were scheduled to immediately follow one another, meaning the time between a patient leaves the OR and the time the next one enters. Any time between 2 surgical cases that exceeded 60 min was deemed not to be a true turnover time and excluded from the analyses, as there would have been many potential alternative reasons for the extended time between those cases (purposeful scheduling, cancelations, room changes, etc.). Our institutional goal is a 30-min turnover time, and we determine the mean to be 36 min with 72% of cases exceeding the 30-min threshold.(Fig. 2.13).

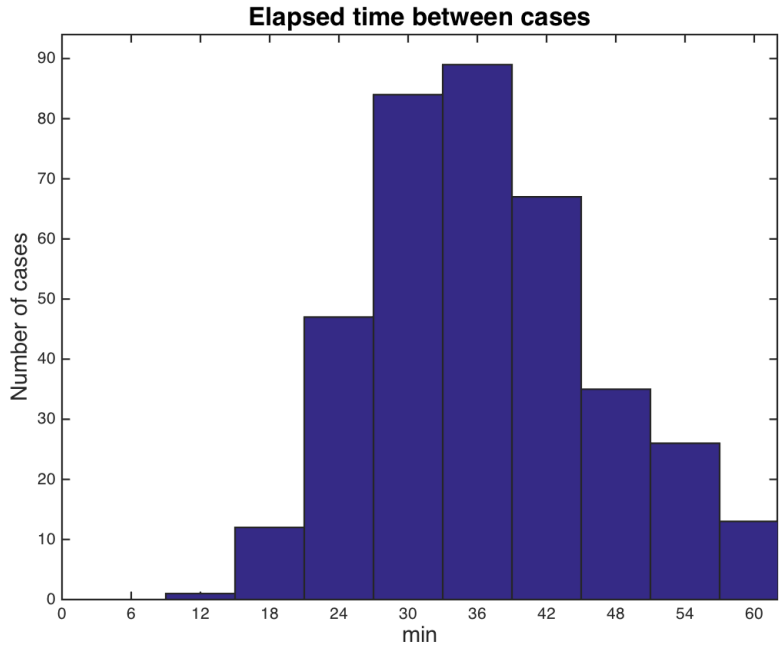


FIGURE 2.13: Distribution of turnover time shorter or equal than 60 minutes.

2.3.3 Elapsed time

While performing the data analyses and segmentation, we did statistical analyses on each part of the OR cycle. We also separated out the different types of procedures and did a more in depth analysis of common general surgery procedures. We first analyzed the different elapsed time given by the smartOR : time in the OR, from the bed entering to the bed exiting, time under anesthesia, from intubation to extubation and for MIS cases, total time of the laparoscopic portion, see Fig. 2.14. Due to the number of cases we analyzed it was possible to extract robust mean and standard deviation and confirm that the distribution of any elapsed time in the OR follow a lognormal distribution as Strum et. al already showed it in [121]. As the SmartOR system is capable of segmenting the OR cycle, all laparoscopic cases were identified by looking for operations where there was the characteristic decrease in ambient light intensity after the operation was under way. Using this method, 504 laparoscopic cases were then segmented into 4 parts of the OR cycle, and means along with standard deviations calculated. Once mean values were calculated and standard deviations were determined, the percentage of case segments that exceeded 1 standard deviation from the mean were identified (Fig. 2.15). In total, we found that 38% of the examined laparoscopic cases were potentially suboptimal with greater than or equal to one standard deviation above the mean. Looking at how cases progressed through an operative day, a downward trend in the total case length along with decreases in laparoscopic times was observed. This can have two reasons: teamwork during the day improve the efficiency of the whole process, but also it is common for OR managers to schedule shorter cases at the end of the day rather than in the morning.

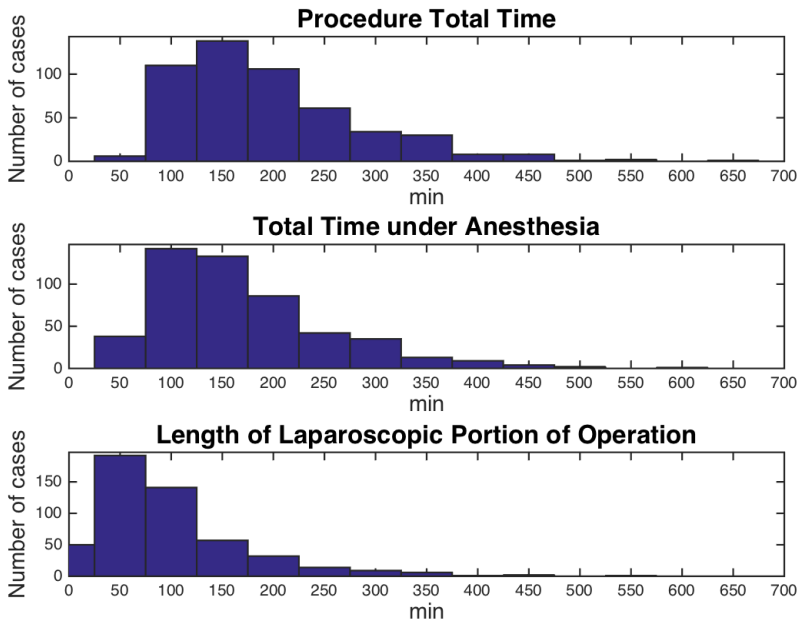


FIGURE 2.14: Distribution of different total time of MIS surgeries spend in the OR, spend under anesthesia and spend under laparoscopy.

2.3.4 Detection of outliers and reasons for delays

For clinical relevance, we focused on examining the outliers in each portion of the OR cycle and overall outliers in common general surgery procedures. A case is defined as an outlier as soon as its length in, at least, one part of the operation extends the mean plus 1 standard deviation from the other cases. With outliers identified, we can track back the reason(s) of the delay(s) during (or before/after) the operation on the EMR. This way, the feedback we can give to the OR staff is stronger because it has this post processing value that no other system could have before. For example, our system captured an operation in which the patient spent a significantly extended length of time in the OR see Fig. 2.14 in comparison to all the other cases (open or laparoscopic ones with intubation). This case exceeded the rest of the cases by the mean (174 min) plus 6 standard deviations (1 SD = 83 min). Going back to the EMR, we understood that this case was a very complex one with different surgeons involved. To focus on portions of the OR cycle that should have an approximate average time frame irrespective of the type of procedure performed (and which could be a realistic focal point for OR efficiency improvement), we focused then on the time between when the patient enter (bed detected) and the ventilation starts (the bellows starts to move) as well as the time between the end of the ventilation and the patient exiting the room. As before, we analyzed 504 cases, computed the mean and standard deviations, then identified outliers. We found that overall, 23% of the cases were suboptimal in one of this two parts. Here as well, some cases had longer durations in these portions of the operation than other. If we take the example of the case on the far right on Fig. 2.15 top left which exceeded 9 standard deviations (1 SD = 6.5 min), this indicated that there were significant and unusual circumstances

that prevented the procedure from progressing in an expected fashion. When we referred back to the anesthesiologist's record in the EMR, we were able to see segments of time between when the patient entered the room and when they were intubated where no activity was noted even though this time frame was nearly one hour in length. On the other end of the operation, between when the patient was extubated and exited the room, the system identified cases that again exceeded the mean by at least 6 SD (Fig. 2.15 bottom right). Upon reviewing the case details, there were multiple etiologists to these delays with the most common being that the recovery room was not yet ready to receive the patient. With or without reported causes in the EMR, the system has proven its ability and usefulness in better understanding and identifying problem points of OR workflow on a broad range and number of cases. The system can be leveraged to focus on very specific case types as well.

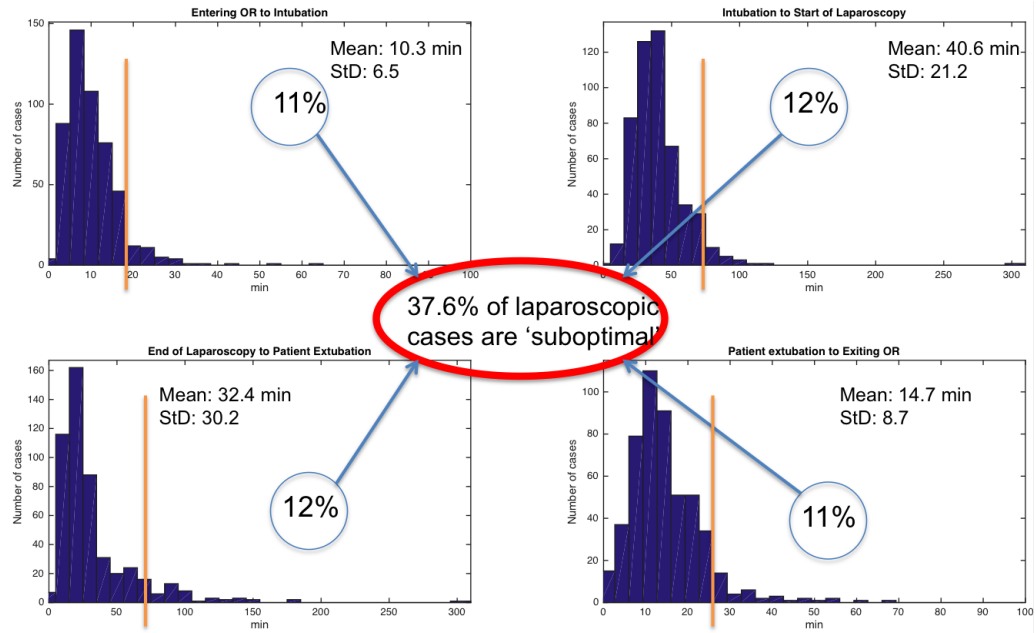


FIGURE 2.15: Segmentation of the operation and identification of cases exceeding 1 standard deviation beyond the mean

2.3.5 Analysis of specific type of surgeries

The system can be leveraged to focus on very specific case types as well. When filtering for laparoscopic cholecystectomies (one of the most common general surgery procedures), our system had captured and analyzed 21 of them and identified one large outlier in overall case length that was reported on the EMR as a delay due to the recovery room not being ready to accept the patient from the OR. OR time depends on multiple factors such as the patient's comorbidities, anesthetic considerations, efficiency of the surgeon etc. We conducted our study to assess if there are factors that can help predict time disruption in the OR. As the SmartOR is expanded to an increasing number of operating rooms, suites, and ultimately hospitals, we continue to add to the database of type of procedure(s), procedure length, turnover times, and first case start time as well as generalized patient details such as BMI and age. With this database of information, we will be able to generate statistical models [141] not only for expected case lengths based on procedure types, but even for case lengths

based on patient age and BMI with the ability to correlate with expected outcomes [69, 106]. The hope is that with this body of information, we can, not only increase OR efficiency from an operational standpoint, but serve to improve patient care as a whole and take part in developing best practices in regard to optimal times for each part of the surgical experience for the patient. We collected data on 70 bariatric surgeries performed by three surgeons over one year. Our data includes time in OR prior to laparoscopy, laparoscopy, closing and exiting the OR. We have analyzed factors such as surgeon/assistant, BMI, age, smoking, cardiopulmonary conditions, previous surgery, etc. We used multivariate statistical analysis to study our population sample and classify the impact of each factor or their combination with the use of principal component analysis. We used systematic clustering to identify subpopulation that have significant differences in statistical distribution to identify the combination of criteria that influence the process of selecting the subset of patients for the adequate prediction of surgical time. The main determinant of surgery duration was the surgeon and the level of his assistant. Prior surgeries, BMI and smoking had a statistically significant impact on the laparoscopy time, with BMI affecting total OR duration as well. Removing the impact of surgeons we detected four clusters of patients based on more than 15 patient characteristics. This study may have some practical implications on improving scheduling in at least 40% of the cases. Better predictability can lead to more efficient use of OR time and staff and can potentially lead to cost savings.

2.3.6 RFID study for first start case

When focusing on RFID acquired data, and correlating events in the preoperative area with OR start times, it was seen that an average of 22 min passed between patient identification in the preoperative area by the surgeon to the patient entering the OR. The data also showed that the sampled surgeons were visiting the patients on average at 7:19 a.m. for a scheduled 7:30 a.m. in-room time, which translated into consistently late case starts, beginning at approximately 7:40 a.m. Overall, the system and hardware design was robust, with the only component requiring rare changes being the pressure sensor mat as it was subjected to direct wheel contact on a daily basis. Otherwise, all systems performed reliably on our dedicated wireless network. As the statistical analyses were completed, cases that deviated far from the mean (in excess of 6 standard deviations) were examined, and in nearly all situations, extenuating circumstances that resulted in excessive case lengths and/or delays were identified. To have the ability to track this, and notify OR management in real time as these events were occurring would allow for reallocation of OR resources more efficiently. Building a statistical model of OR behavior, case type lengths, and even personnel/resource allocation based on data collected from the SmartOR system also allows for the creation of OR optimization techniques in the future.

2.3.7 Comparison with data from the EMR

As we did for the validation of the system, we use the data from the hospital record on one year and compare it with the one we got from the detection of our system. We were able for example to compare the time the first case of the day was scheduled and the real time the patient was actually entering the room. We can see on Fig. 2.16 the large difference between the 2 plot with a mean deviation of around 15 minutes late. We also conclude that number of cases first has no season effect and also has

no impact on turnover time length which means that is a no impact on effectiveness of the suite as turnover time is good scale to quantify inefficiencies in the OR, the longer it gets the less efficient and cost effective is the OR suite. We also found that our system is more "optimistic" than the time stamps entered by the staff, the system detecting the event usually a bit earlier, which can be explained by the fact that time stamps are entered a lot after the events happened. In the middle of the study our home institution changed its EMR system and passed to EPIC system. We got access to the data from December 2016 and January 2017. These data present more information than the one we access on the study in 2015, like the scheduled length of case and its actual length are now entered in the system. Here as well, we were able to compare scheduled lengths and real ones. An interesting fact to notice is that when plotting the scheduled length distribution of time, it is not totally following a log normal distribution as we found with our 1000 cases, which could mean that improvements could be done on the prediction of time of surgery and would profit to management and scheduling.

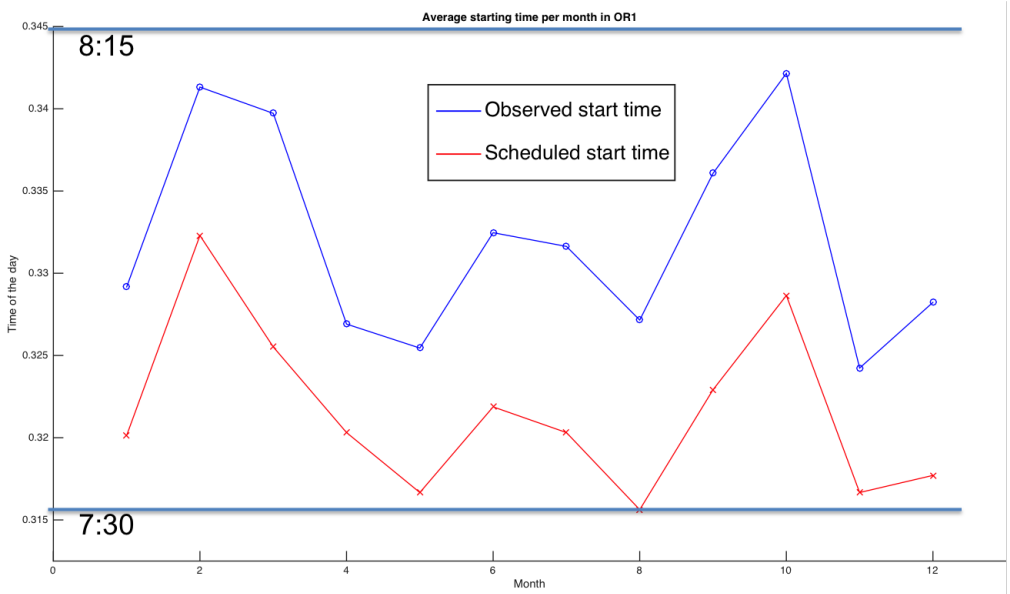


FIGURE 2.16: Comparison between scheduled and observed mean start times in one OR per month over one year

2.4 Conclusion

With this ongoing study, we have demonstrated that by using a refined set of simple, wireless sensors, we can accurately and effectively capture key events in the cycle of the operating room. Retrospective analyses of these collected data also allow us to quickly and easily generate clinically and operationally relevant statistical measurements that can be used as focal points for OR efficiency improvements. As the data collection continues to increase, ultimately, correlations between events and event lengths with patient outcomes may become possible. This would fully leverage the system's ability to automatically track and record OR activity and result in a refined system that can notify appropriate OR staff/ team members if certain events or event lengths are risking patient safety in real-time. Several intraoperative events such as length of time in the OR as well as time under anesthesia contribute to poor patient

outcomes, and our system can assist in preventing these. The final goal of the system is to build a new, efficient, dynamic, and real-time OR management platform. Along with hardware and software refinement, we also plan to add the capability of patient localization. To address this, we tested small programmable radio frequency modules that can be either worn by the patient or attached to the patient's chart as it travels with the patient in the perioperative space as well as when they are transported for procedures or imaging around the hospital. The user interface of the system will be of high importance as well. Building an intuitive graphic user interface that distils the information collected in real-time by the sensor network will bring the system together in a centralized, interactive screen. This will provide real-time updates, patient locations, as well as the status of each OR with the touch of a button. Our system will also be able to interface with EMRs via the now-standardized HL7 (health level 7) protocols for patient data transmission. Ultimately, this interface will be the product that the end user interacts with. All the data collection, patient and procedural tracking, as well as statistical analyses and implementation will all be done behind that interface. Surgical flow in a large multi-disciplinary OR suite is a very complex phenomena. In a typical large OR suite, the number of staff and patient involved during the daily activity is about several hundred. The environment is stressful and demanding: teamwork quality and coordination have a profound impact on the optimum management of resources. We envision and will present in chapter 4 that a system approach to model this complexity can get us a better understanding of the root cause of delays and poor efficiency.

Chapter 3

Monitoring of indoor air quality and link with OR activity

3.1 Introduction on HVAC

The principle of a HVAC system is to react to the need of its users, if they are cold they turn the thermostat higher and if they are hot, the system turns the A/C on as they lower the thermostat. How this can be possible is the science of the HVAC designer, architect, and maintenance personnel who have the understanding of how the system behaves following a request from the user to maintain the desired conditions. What characterized a good or a bad HVAC system are: the amount of fresh air required to control airborne contaminants, keep the environment comfortable for the occupants and the response time of the system to a change from the occupants. Of course, these requirements differ from one type of occupancy to another. In our case, for example, hospital surgical theater architects have to take into account smaller airborne contaminants, choose the good diffuser in the OR, the velocity of the inlets to keep the surgical space safe but also comfortable to work in, pressurization to prevent infiltration of contaminants from the outside etc. An office space, on the other hand, would not focus so much on minimizing the risk of airborne contamination but more on air temperature and the amount of fresh air. The HVAC system, including heating, ventilation and A/C, regulates the IAQ and thermal comfort of indoor spaces. IEQ is the quality of an indoor environment for the occupants of this space, it includes IAQ, thermal comfort, construction method and materials, acoustics, lighting etc... With the time patients and staff spend in the hospital, IEQ becomes an important consideration when it comes to build or renew hospitals. IEQ has a large impact on the health and wellbeing of occupants. Not only it can increase patient satisfaction, it can also enhance employee productivity and decreases sick time off, last but not least improving IEQ can decrease building operation and maintenance cost. We chose to focus here on IAQ only. Airborne pollutants such as carbon monoxide can accumulate and recirculate in indoor environments and can have very negative effects on human health. Common pollutants are dust, pollen, bacteria, viruses, formaldehyde..., see Fig. 3.1. These pollutants can trigger asthma and cause illnesses and odors. The quality of air brought by the ventilation system is measured by its ventilation effectiveness, which measures the ability of the system to remove the airborne contaminant from a space by inserting new fresh air in it. To ensure that buildings such as hospitals provide safe and still comfortable air quality, designers follow standards from ASHRAE Standard 55-2004 and ISO 7730 when building HVAC systems for healthcare.

There are a lot of possibilities to follow airflow and particles in the OR, commonly experimental trials in real or mock conditions, and numerical analysis are the

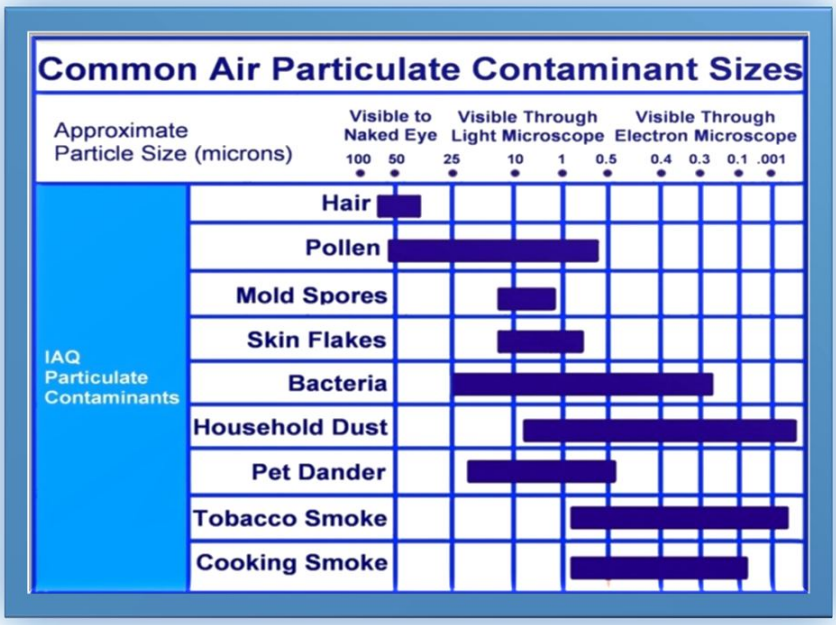


FIGURE 3.1: Representation of the size of the most common particles that you can find in an hospital, picture taken from ASHRAE website.

two most common choices. This chapter is going to present the experimental approach and we will see the numerical analysis in the last chapter. The advantage with experiments is that we study realistic airflows paths but they can be complicated to put in place, especially in a busy hospital and are usually time-consuming. Lots of parameters have to be taken into account when building a HVAC system in a hospital and especially in an OR. Infection control is more challenging there due to the obvious risks coming from the nature of the surgery itself. OR is a unique area and has to be treated like it, the sources of infection are multiple: the patient himself, the staff, the surgical instruments, the room, air supplied and infiltrated... That is why very strict guidelines exist: the American College of Architecture is requiring a positive pressure in normal ORs of at least 2.5 Pa. The idea is to push air out of the OR and be able to make at least 12 changes of air per hour (ASHRAE – infection control in the hospital). Due to the complexity of this room and its specific activities, not everything can be controlled. For example, you can see on Fig. 3.2 the air distribution system of a normal OR with positive pressure. The system blows a laminar flow directly on the surgical table to remove as fast as possible any contaminant close to the patient and then this air is controlled through side ceiling inlets and exhausted by low-level return air. This laminar flow plus the others ceiling inlets create a sterile field around the OR table. The problem is this does not take into account neither the dynamic of such a room nor the amount of particles produce by the surgery itself nor by the human activity at the door. In his paper, Andersson et. al [3] recorded the number of openings of the door during a case and the reason for the opening, they showed that more than 27% of the time this opening was unnecessary (social visits, no reasons...) and in 17% of this was for logistic reasons or for planning the rest of the day which could have been avoided with a better system of real-time tracking of the advancement of the procedure, see Chapter 2. This chapter is going to present the experiments designed and implemented in our lab and in a real OR suite with

the goal to understand better the source of contaminants, the link between IAQ and activity in the OR, the impact of the door being open or close and finally the possible contamination from one OR to another or to the rest of the surgical suite in general. The final goal being to gather enough information to build a close to reality numerical model, which will be presented in the last chapter.

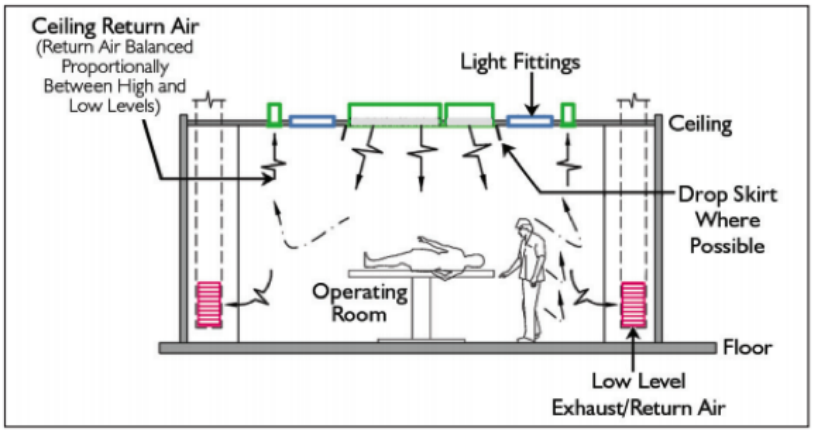


FIGURE 3.2: General representation of the airflow system in an OR. Most OR in the US follows these technics with laminar flow from the ceiling and outlet on the wall at the ground level.

3.2 Method

Air circulates in a room and between rooms as a consequence of the HVAC system, the dynamics of its occupants, equipment, doors..., the buoyancy-driven flow (also called natural ventilation) due to temperature gradients and human respiratory activities. The complexity of understanding the behavior of inside airflow is to first be able to gather real experimental data on air velocities and movements, and second, the interpretation of this data in a non-trivial environment that is a hospital. To address these specific questions, the existing automatic OR status system presented in the previous chapter is used and another dedicated sensor is added. The accelerometer and gyroscope placed on the entry door can track the movement of the OR door, the number of openings, the opening angle and its velocity. Even if the reasons of openings was not recorded, like Andersson et. al [3], the high frequency of openings during a case was also underlined on the data, with the maximum of activity observed at the beginning and end of the surgery. The questions then to be answered are: how much air is exchanged at the doorway while the door is closed or open, and what are the path lines of particles produced in the OR or in the hallway. To tackle this we added to our system another sensor which is an air quality monitor at different places of the OR and in the OR suite. The next paragraphs are going to explain how the air quality of the operating room was monitored, linked with activity in the OR and finally used particles as trackers to follow pathlines of the airflow in the OR suite that are going to be used as input of our CFD model presented in the next chapter.

The sensor: A good sensor needs to meet some specific requirements:

i. needs to be sensitive to the sensed parameter

ii. does not influence the sensed parameter

TABLE 3.1: Air quality chart for small particles count

Particles pCF x.01	Air quality
3000 +	Very poor
1050-3000	Poor
300-1050	Fair
150-300	Good
75-150	Very good
0-75	Excellent

iii. is not influenced by other properties

The point ii. is very important when following fluid dynamics parameters because placing a sensor in a room will change its design and will for sure have an impact on the airflow. That's why we chose the sensor DC1700 from the company Dylos. It is a small air quality monitor with a true laser particle counter with 2 size ranges of detection: small (>= 0.5 microns) and large (> 2.5 microns). It is constituted of a laser source, a detection chamber, and a detector. The laser points at the particles and the detector analyses the change in light characteristics. It allows monitoring of indoor air quality in real time, with the possibility to save one week worth of data on it. It is also equipped with a battery that can last for 6 hours. The DC1700 can detect levels of airborne particulates, the impact of these on the health of occupants can be very variable from one individual to another. The EPA defines Particulate Matter (PM) as a complex mixture of extremely small particles and liquid droplets that get into the air. Once inhaled, these particles can affect the heart and lungs and cause serious health effects. The sensor displays the concentration of particles in the air, the numbers represent particles in 0.01 cubic foot (CF) of air. The number will tell you how clean the air you are breathing is. As said even if this is hard to link with the impact on health, we know that particles smaller than 10 microns, called PM10 by the EPA can get to the alveoli of the lungs and the ones smaller than 2.5 microns (PM2.5) can go into the bloodstream. To read the data presented in the graphs of this chapter, here is a rating of the air relative to the count reading:

3.2.1 First test

To get used to the air quality sensor, we first installed it in the mock OR of our lab. As for the experiments on the smartOR, even if it is an old OR it has the specific design and airflow of a normal OR and is under positive pressure. By letting the sensors running during a couple of weeks and looking at the data we discovered a defect in the HVAC of our building. The inlet of the ventilation system was very close to the exhaust of one of the hospital kitchen and cooking smoke was blown directly into the lab. Once this issue was taking care by the safety and the FMS department we were able to make more tests without any noise from the system itself. We were able to show, by putting multiple sensors all over the room as well as outside in front of the door that:

i. the system was able to track particles we were emitting with a hair spray product

ii. the sensors were very accurate and reliable even compared to the professional system used by the hospital

iii. there is a close to a uniform spread of particles in the OR
iv. the positive pressure blows airborne particle out of the OR

After these validations, we were ready to put the system in a real OR and follow the air quality in it during a day of activity. Two sensors were placed in one of the OR of Dunn OR 3 suite at the Houston Methodist Hospital: one on a shelf at a height of about 1.8 m far from the OR table (3 m) close to the door and another one on the medical instrument tower that goes close to the surgical site during a case. The goal here was to find out if particles are emitted during a case, understand their diffusion in the room and finally see if we can link air quality with activity in the OR (door openings, cases going on, cleaning, room empty...).

After 2 weeks of recording, the results helped to understand that:

i. there is a strong correlation between the decrease in air quality and activity in the OR

ii. some kind of surgeries emit more particles than others and even very thin ones in high concentration

iii. the time between cases is also very active and the air gets polluted, we saw that during the cleaning of the room the nurse usually leaves the door opened for a long time. Also, the use of an alcoholic based product to clean the room produces a lot of small particles

iv. Lots of particles goes from the OR table to the door.

You can see a plot of the data coming from our sensors during one day on Fig. 3.3. There is a very strong correlation between the two sensor outputs, which validated the quasi-uniform distribution of the air around the OR. The difference in values comes from the placement of the sensors, not all the particles goes to this specific shelf due to the deposition rate and the difference in heights of the sensor. The one far is at 1.8 m when particles have the tendency to stay low because of gravity as well as the laminar flow from the ceiling. Finally, some patterns can be detected that happen during every case. There is always a decrease of quality of air in the OR at the beginning and end of a procedure (delimited by the green steps). There is usually a spike after the patient leaves the OR representing the moment the OR is being cleaned with the use of alcoholic solutions. The other large peaks during the procedure are going to be analyzed more in details in the next paragraphs. A first result on airflow can be seen on this plot as the sensor close to the OR table is usually triggered first, this cannot be very quantitative as the position of the sensor close to the table can change between two surgeries. More analysis will be done in the next experiments. Last but not least, some of the peaks reached a level of particles that are known to correspond to very poor air quality (see Tab. 3.1) and can have a very unhealthy impact on the staff spending the whole day in this environment.

This result brought two new questions: what is producing such an amount of particles during the case and can particles go out of the room or enter from the outside? To understand better and answer these questions two other tests were conducted to understand the source of the particles and find a way to track the complete airflow in and around the OR.

3.2.2 Surgical smoke plume monitoring

The correlation between air quality level in the OR and its activity is not a surprise, just the fact that there are more occupants present in this closed space would have an impact by itself. What we want to focus on are the larger peaks we detected during

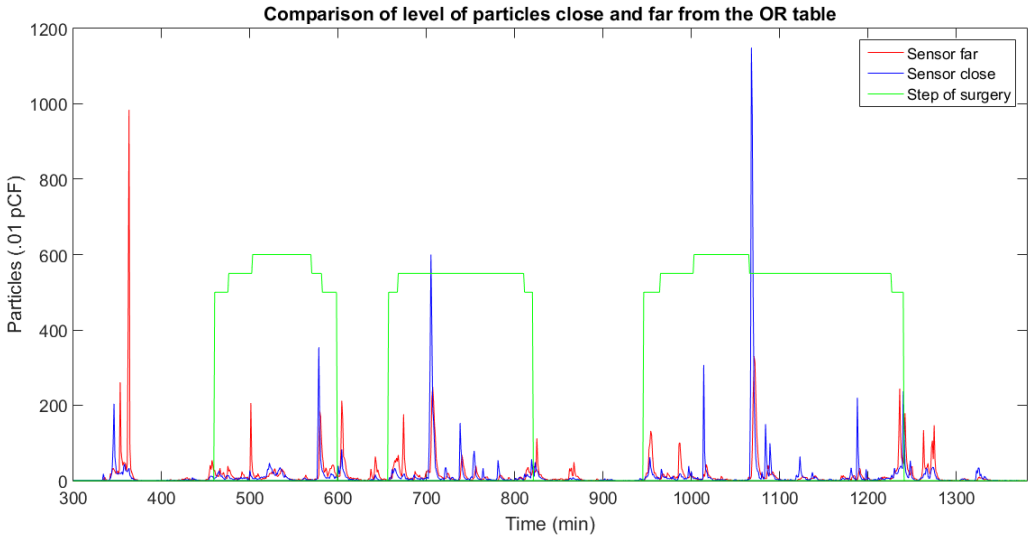


FIGURE 3.3: Representation of the air quality from tow sensors in the OR between 5 am and 11pm. The green steps function shows us the different stage of the surgeries (500 = surgery start or end, 550 = end or start of intubation , 600 = end or start of laparoscopic portion, if applicable). We analyze here three cases, two being laparoscopic. The red plot is the output of the sensor at about 3 m from the OR table and the blue one is closer, around 1 m.

the cases, see Fig. 3.3, where a lot of small particles are created inside the OR. Our first guess, on top of particles from people present in the OR and the patient, were the electrosurgical instruments and the particles present in the smoke they generate. As these instruments destroy tissue, fluid, and blood, they create a gas named surgical smoke plume. This smoke is known to be dangerous as it contains toxic components such as benzene, carbon monoxide... These very small particles (smaller than 5 microns) can irritate the lungs and can have the same effect on the body than cigarette smoke [12]. These components pose a health risk to exposed OR staff and patients. With our particles detection system, we can detect this specific smoke as the size of these particles fit our sensors detection range, see Fig. 3.1. First, it is very interesting for safety reason and the health of everyone in the OR to follow the concentration of these particles but also it can help us to follow the airflow of the OR by using them as a tracker. Understanding the diffusion of this smoke plume will help us understand airborne disease dissemination. We designed an experiment to be able to know how much smoke (particles) each electrosurgical instrument were producing and if it could be the source of the peaks. To analyze this, we used the most common electrosurgical instruments on pieces of meat and followed their plumes by placing three sensors at different places in the room. We compared four different instruments using different technics and with two different positions of the three sensors. One of the positions was aiming at following the dispersion between the OR table and the door 3.4. The figure represent the dispersion of the particles from the source to the door at a different distance, the coefficient of dispersion is clearly noticeable as the sensors are triggered with some delays depending on how far they are from the source and the maximum value is decreasing as well with the distance. This analysis will be pushed further in Chapter 5. The other placement was following the dispersion around the table to simulate the position of the surgeon, nurse,

TABLE 3.2: Level of particles for different electrosurgical instruments

Instrument	Concentration of particles
Bovie pen	++++
Ethicon Endo surgery Harmonic	++
Covidien Bipolar LigaSure	+
Erbe APC	+++

and anesthesiologist.

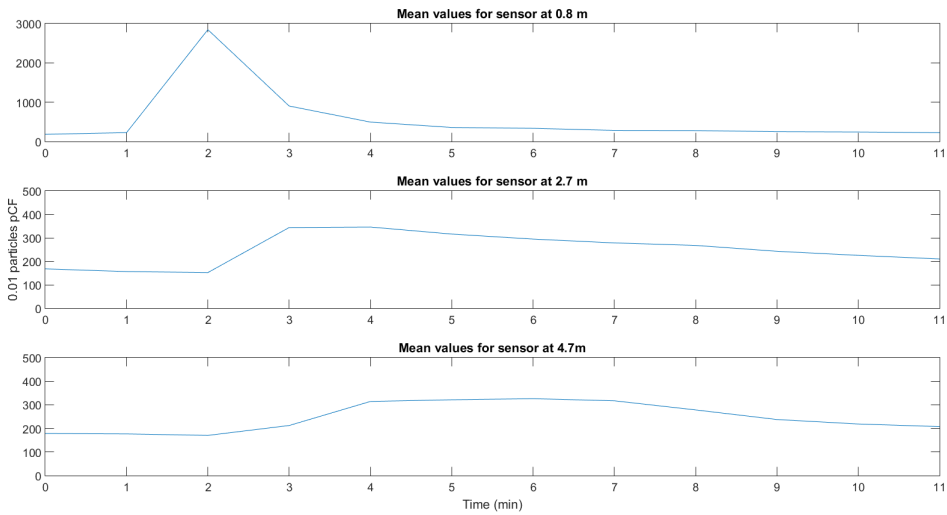


FIGURE 3.4: Representation of the mean of number of particles detected in regard to the distance to the source.

In their review of the literature on surgical smoke, Barrett and Garber explain [12] that the amount and content of the smoke can be very different depending on the kind of surgery and the kind of instrument used. They found that the three most common type of electrosurgical instruments were producing particles between 0.07 and 1.0 microns [138] which most of them falling into the detection range of our sensor or are close enough to its low detection limit. First, we found that the type of smoke was visually very different, with different colors and different opacities. This is another well-known problem, especially in MIS were the smoke can impact the visibility of the field depending on the instruments used [138]. Then, through the data from the sensors we also saw that the instruments were not producing the same amount of particles, see the results in Table 3.2. The instrument making the most particles, detected by the sensor, is also the most used in the OR and called is a monopolar electrosurgical instrument, commonly called bovie. It is used for electrosurgical dissection and hemostasis (stop of bleeding). As 95% of today surgeries, open or MIS, produce a smoke plume we assume that this is the source of the peak we see in the OR and following a case in the OR while looking at the real-time air quality level confirmed it too.

On Fig. 3.5 you can see a picture of the experiment. Pieces of pork bought at the supermarket with a thickness of 2 cm were used and all of the pieces had the same

amount of fatness. The test was done in one of the teaching OR of the Research Institute of the hospital. We were helped by one of the residents working in our lab to be able to use the instrument in real conditions with the most common parameters. We were using the instruments between 30 and 60 sec depending on the amount of smoke produced (see Chapter 5 for more results). This OR does not have positive pressure but has the same architecture than real ORs. As the goal here was to compare the smoke between the instruments, the training facility MITIE of the Methodist Hospital was an adequate space as they have every kind of instruments that can be used in close to reality environment.

FIGURE 3.5: Settings of the test done on pieces of meat to understand the different smoke produced by common electrosurgical instruments.

3.2.3 Air quality in an OR, a way to track airflow

Now that we found the source of particles emission in the OR, we also need to understand the diffusion of this plume in the OR and if some particles could reach the door and be expulsed by the positive pressure or the opening of the door. In this new set of experiments, we first let the sensor on the shelf in the OR where it was before and we added one in front of the door of the OR in the hallway. This sensor needed more maintenance because it could only run on battery, the hallway of an OR suite is very active and plugs are generally used to charge medical equipment. Data were recorded from these two sensors for a couple of days and in parallel, the information on surgery status from the smartOR was still recorded and the activity at the entry door too. You can see a snapshot of two laparoscopic cases followed on Fig. 3.6. When focusing on important parts of the surgery like the positioning of the trocars, using the smartOR, which we know usually comes with the use of the bovie instrument on the skin layers of the patient after the first incision made with a classic scalpel, lots of particles are detected in the OR. When zooming in, on Fig. 3.6 and looking at the black circles, we can see the correlation between the output of the two sensors, with peaks in the OR that are detected in the hallway as well. This justified our hypothesis on the fact that there is a lot of particles exchange at the door

of the OR with the door closed or open probably pushed out following the positive pressure in the room and the leakage at the door edges.

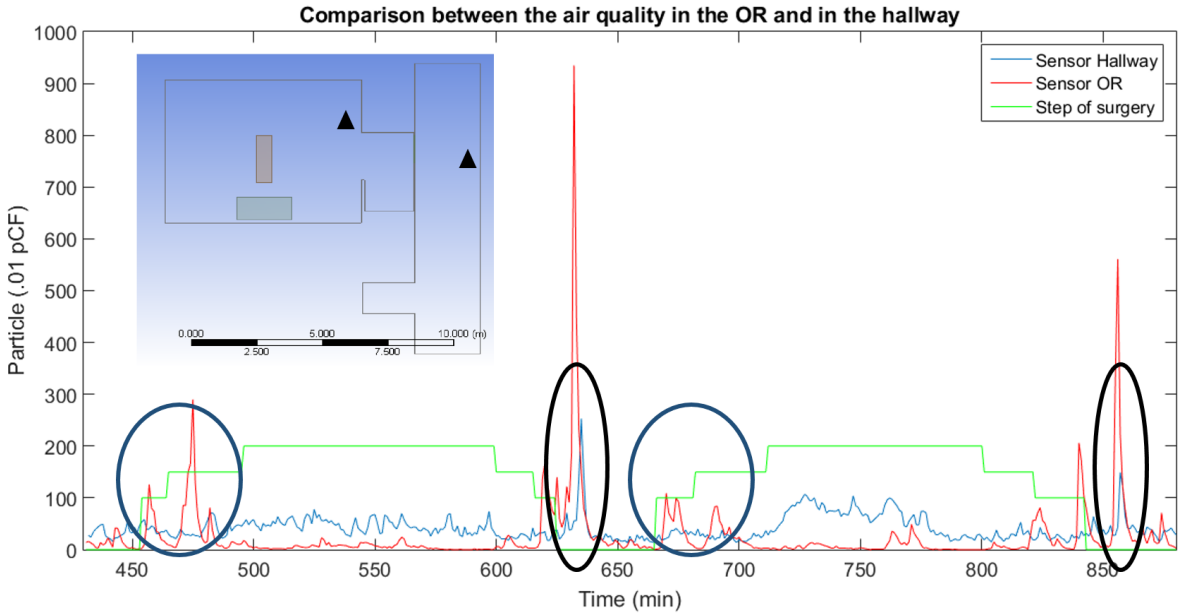


FIGURE 3.6: Number of particles during two laparoscopic cases between 7.15 am and 2.45 pm with the comparison between the level of particles in the OR (Red) and in front of its door in the hallway (light blue). In green, it is the representation of the steps of the surgery like on Fig. 3.3. In black circles, you can see particles detected first in the OR that is then detected in the hallway at the end of the surgery. In dark blue you can see the amount of particles emitted at the beginning of the case, probably corresponding to the use of the bovie to place the trocars for the second spike that happens during the preparation of the laparoscopic portion (green plot at 250).

3.2.4 Air contamination in the OR suite: can one OR contaminate another one?

Finally, after proving the emission from the OR table to the door and from the door to outside of the room during cases, the last question was to see if the contamination between ORs can be possible; can we track a particle produced by the surgery in OR 1 and follow it being diffused in this OR, then pushed out of the room, goes to the hallway, follows the airflow there and would be pushed in OR 2 due to its own door activity? We tried to answer this question based on the OR suite we have access to in our home institution. OR suites are probably one of the busiest space of a hospital after the ER, following particles around multiple ORs during a normal day is very complex because the whole system presents lots of noise and proving the source of a contaminant can get difficult. This is the reason why these experiments were made at night when no case is scheduled and traffic of people is at its lowest. This time five sensors were installed at different places in and around two adjacent ORs and particles were emitted due to a common hair spray product, the same used in our mock OR during the first tests. We divided the experiments into different phases that were answering the different questions.

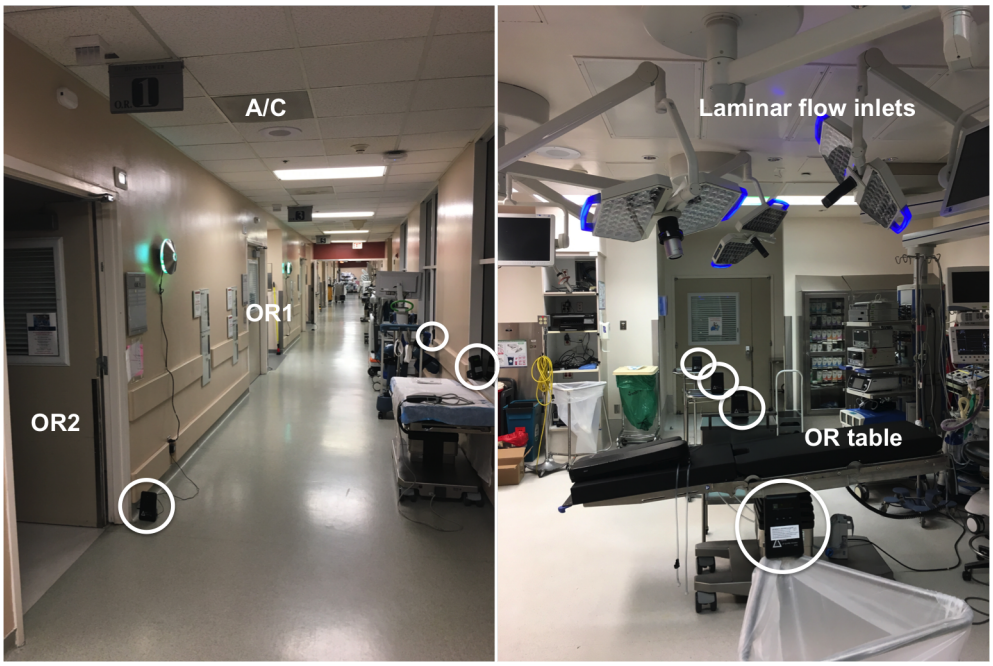


FIGURE 3.7: Picture of the settings of two of our experiments. The one on the left represents the positioning of the sensors in the OR to follow the distribution around the table as well as between the table and the door. The one on the right represents the tracking of the particles emitted in the OR or in the hallway and their propagation inside it as well as the possible detection of them in front of the adjacent OR 2 or even inside (not shown on the picture).

Door closed: What happens to particles emitted in the hallway?

In this first situation, we placed the sensors all around the hallway and one in the OR at 2 m from the door and used the hair spray as a source of particles in front of the door, see Fig 3.8. The goal here was to see how particles are dispersed in the hallway and is there a possibility that some get inside the OR even with the positive pressure and the door closed. You can see the emplacements of the sensors in the hallway on the left picture of Fig. 3.7. Every test is always done at least three times for robustness and to have the possibility to average the values as it was complicated to control exactly the amount of particles emitted between one trial and another. The important result of this experiment was the influence of the airflow produced by the AC in the hallway. No particles were detected on the right side of the door when looking at it in the hallway when a lot were detected on all the sensors on the left side (sensors 2, 4, 5, 3). At the beginning, the sensor 3 was placed on the right side of the OR but as nothing was detected on it, we placed it at the end of the hallway to take a deeper look at the distribution and the impact of this unidirectional airflow. This result was important for the next experiments as it was now totally useless to follow the particles level on that side of the hallway. Also, we did not detect any particular peak on the data coming from inside the OR which means that not or a very small amount of particles that cannot be segmented from the noise pass the doorway from the hallway while the door stays closed. This is not surprising as the OR is under positive pressure and there is no external activity that could reverse this steady system except the buoyancy effect driven by the difference in temperature between the cold OR and the warmer hallway [126].

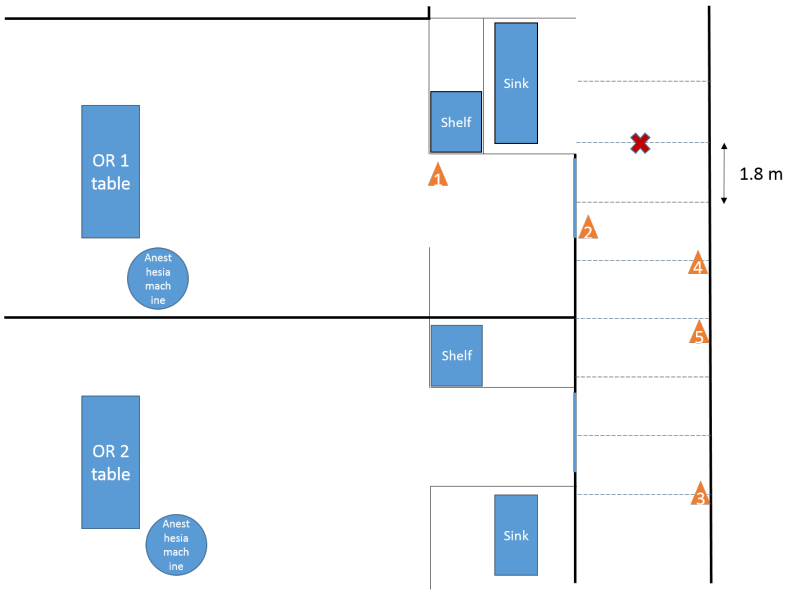


FIGURE 3.8: Hallway experiment: we placed the sensors in order to understand better the diffusion of particles in it.

Door closed: What happens to particles emitted on the table during the case?

Now that we understand the airflow in the hallway, we want to see how a particle emitted on the OR table can reach the door and go in the hallway before following its specific pathways. We placed the sensors as shown on Fig. 3.9 and you can see their installation in the OR on the right picture of Fig. 3.7. The goal here was to follow the dispersion of the particles between the OR table and the door, detect the one that passes through the gaps under or on the side of the door and finally see how far can they go in the hallway. The source of the particles was sprayed on top of the OR table with the spray pointing upwards. First, the results show us very well the dispersion of the particles in the room and how they are pushed away from the table (sensors 4 and 5), or the sterile area with multiple laminar flows from the inlets of the ceiling. Second and using the sensor 2 on the ground close to the door outside of the room we detected a non-negligible concentration of particles being pushed out from the OR through the edges of the door, see 3.9 . This is induced by the positive pressure maintained at any time in the OR, even when there is no activity to avoid any deposition of particles in places they usually do not reach. This positive pressure is created by introducing more air through the ceiling inlets than the outlets on the wall can handle, this create a positive pression in the room and air try to escape the room by any gaps, like the door edges for example or any other leakage due to construction. When the particles are out of the room they follow then the airflow in the hallway that has been analyzed in the previous test. They are going from the door to the end of the hallway pushed by the A/C of the corridor. This makes them pass in front of the door of the next OR and we can imagine that someone entering the room at that moment, reversing the positive pressure of this room and would push(or pull) particles with him that could contaminate this adjacent OR.

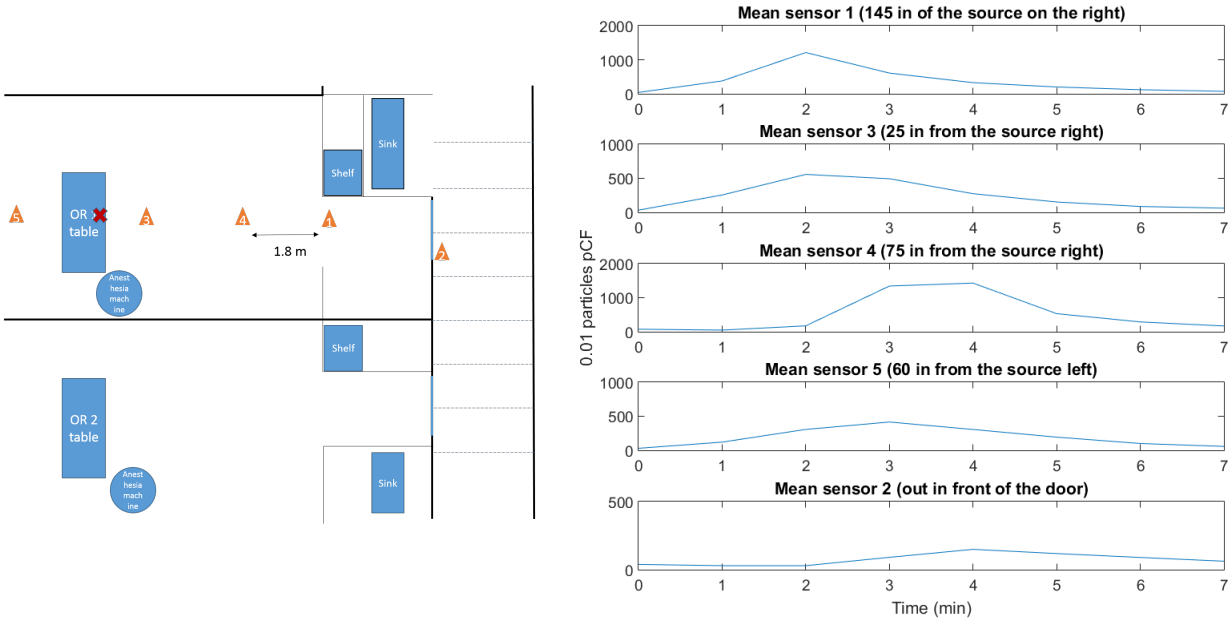
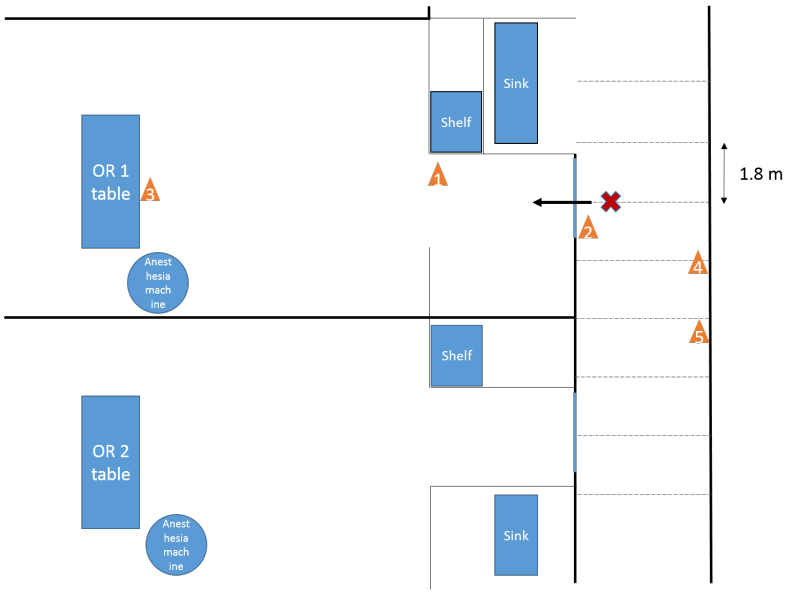


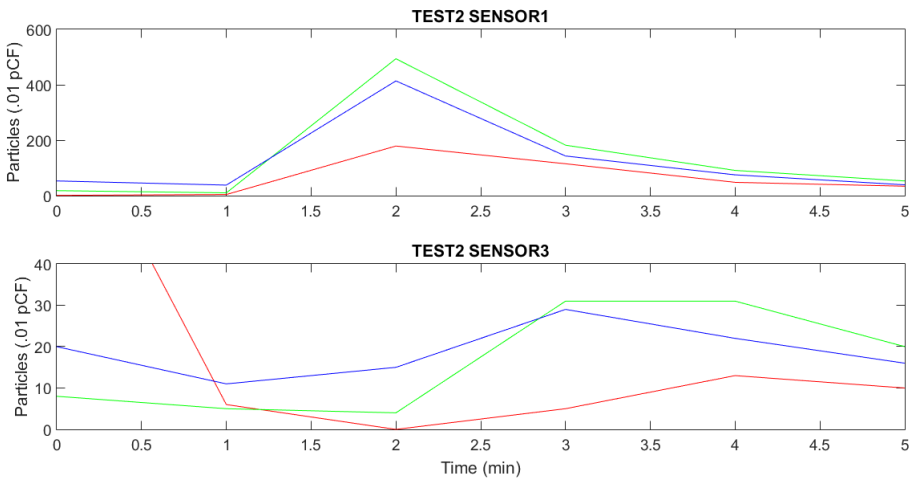
FIGURE 3.9: Tracking of the dispersion of the particles in the OR with the source on top of OR table. Depending on their distance from the source and positioning the OR, the sensors are triggered at different time. Distribution in the OR. The laminar flow from the inlets of the ceiling drive most of the flow in the surgical theater but the architecture of room, the different equipement, tables and the activity of the room take an important part in the airflow as well. We want to track here the distribution around the OR table (sensors 5 and 3) but also the one between the table and the door (sensors 4, 1) as well as the number of particles passing through the door (sensor2)

Opening the door

Last but not least, we focused this test on the exchange of air when someone enters the room. To do this we put the sensor in the configuration presented on Fig. 3.10a to be able to focus on the dispersion in the OR of particles coming from the outside. The source was a spray holds for around 1.5 sec of hair product in front of the door, then wait 1 sec and finally someone was entering the room from the hallway and going close to the OR table like it could happen during a real case, if for example, a nurse brings extra materials to the scrub nurse. You can see the detection of the particles in the OR on the plots of Fig. 3.10b. Of course, the concentrations are smaller than what we find in the hallway but we noticed a non-negligible amount of particles coming from the outside and reaching the sensor 1 (close to the door, on the ground) as well as sensor 3. This last sensor is a very relevant result as it is placed at the same heights of the OR table just next to it. We proved the possibility of contamination from the outside of the room due to the activity at the door and the pumping effect of the door as shown in [126].



(A) Impact of someone entering the room on air quality and movement of particles in and out of the room.



(B) Result from the two sensors in the OR placed between the door and the surgical table.

FIGURE 3.10: Experiment to track the impact of the door opening on the particles entering the room.

Using the plume as a tracker for other particles such as bacteria

A pathogen is a microorganism that causes disease. In the hospital, there are three general classifications of airborne pathogens: viruses, bacteria, and fungi. Generally, small particles are of chemical concerns while the larger one a more of biological concerns. To follow these larger particles, studies has been made where biological tests were made to follow the link between activity in the OR such as a number of occupants in the room and the level of bacteria contamination by using single stage slit-type impactor at different places of the OR and see the deposition of this pathogen [115]. Here on the other, we want to focus on smaller particles and we are using particles of a hair product sprayed into the OR to track the general flow that would follow particles of any surgical smoke plume. This gives us also the general pattern of the airflow in the OR suite for any kind of particles. The air of an OR can contain particles from the surgical smoke like skin particles and be dangerous if by any ways it could reach the adjacent OR but it can also contain nosocomial diseases that would follow the same pathways as bacteria and viruses have the same size than the particles we track, see Fig. 3.1 and this can be very dangerous for all the occupants of the hospital. Our OR suite is constituted of about 17 working ORs under positive pressure which multiple the chance of contamination by the same number. To prove our point and the possible contamination of one OR from another we placed the sensor in almost the same than before (Fig. 3.10a) but with sensor two positioned inside the adjacent OR. The door of the OR 2 stayed open the whole time, while the one of OR 1 was open only one time per run to simulate someone going out of the room during a case. Also, this same person was entering OR 2 after 2 minutes of the initial emissions. We made different tests with different position of the source. Of course, if the source is in the hallway close to the door of OR1 the particles are present in a large concentration in front of the OR 2 after around 35 seconds and someone entering the room at that moment will pull with him particles from outside as you can see on Fig. 3.11. If the source is in the OR, somewhere in the room like from the surgical table, the rate is lower but still nonnegligible. The level at the sensor inside the OR is harder to segment from the noise of the HVAC system but we can see an increase in particles number every time someone enters the room.

3.3 Conclusion

The primary purpose of indoor spaces is to provide safe and comfortable environments for occupants. Hospitals and especially OR suites have to follow very strict rules on IAQ quality to avoid as much as possible the risk of nosocomial disease spreading inside the hospital. We placed air quality sensors all over the OR suite and tracked particles that we emitted from a hair spray product. This were very important steps in order to understand better the airflow in and around the OR. First, it gave us the general airflow of inside the OR, then the one in the hallway. Finally, by putting these 2 results we were able to understand the whole airflow between 2 ORs next of each other and a possible contamination rate between the two. Indeed, we found that some particles produced in OR1 were detected in front of the door of OR2. This is due to the positive pressure of the room and the influence if the A/C in the hallway blowing from the top to the bottom on the figures. The implementation of air quality sensors in and around the OR monitor the security and safety of patient and staff. The sensors can detect the toxic surgical smoke plume, calculate its concentration and detect if occupants are exposed to a possible health-threatening level of toxic gasses coming from the use of electrosurgical instruments during open

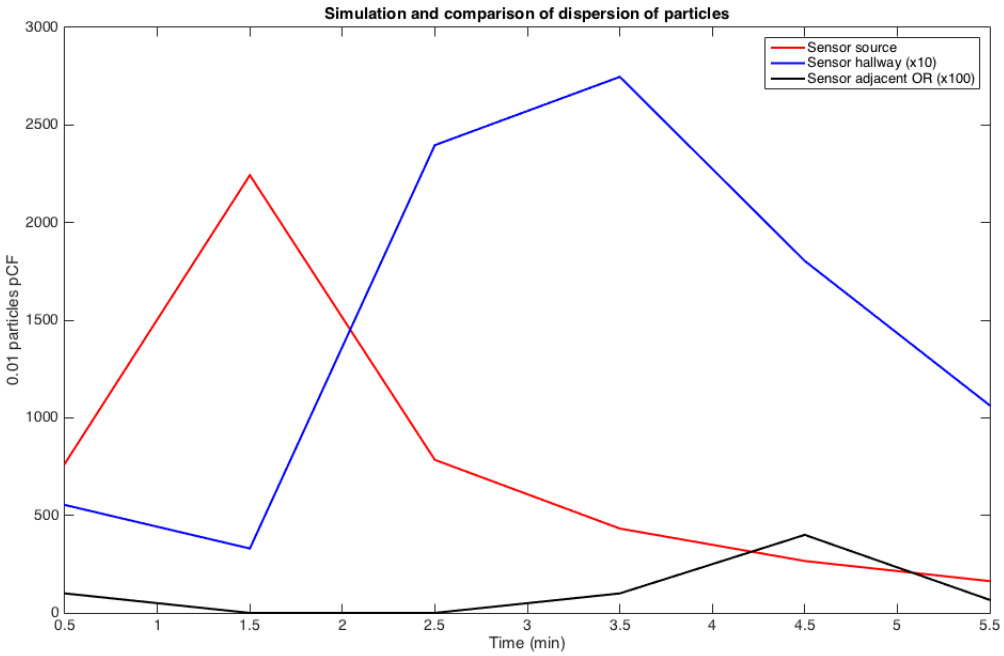


FIGURE 3.11: **Detection of particles from one OR to another.** The particles are emitted in the OR, it takes them around 2 minutes to be detected in large quantity in the hallway and after 4.5 minutes a non-negligible amount of particles can be detected inside the adjacent OR.

surgeries and MIS. To our knowledge, this is inexistent from OR suites today, even if the toxicity of this smoke has been proven on multiple aspects. Second, the sensors, when placed at different strategic places of the surgical suite, can track the spread of the smoke and underline the main path lines of airflows inside the OR suite. This allows a novel technic to follow possible contamination from the ventilation system of nosocomial diseases and contamination from one OR to another. We can imagine the implementation of one sensor in each room that would monitor the amount of smoke and pollutants emitted during a case and alert the occupants if a non-healthy level is reached. This implies that we can simulate the airflow in the OR and outside to place the system at key spaces that reflect accurately the level of smoke without having to be on the way of the staff. In Chapter 5 we are going to see the design of such simulation solutions helped by mathematical modeling.

Chapter 4

OR Workflow modelization : a multi-scale approach

4.1 Introduction

Surgery accounts for approximately 50% of revenue for a hospital [88, 89, 49] and flow through the OR contains a number of bottlenecks that lead to stakeholder frustration and have a negative impact on quality outcomes [35, 39, 80, 25, 129]. Common sources of frustration for OR management include:

- Turnover time between surgeries that is above desired
- Delays in the starting time of the first case of the day
- Surgeries that run longer than anticipated. These event may also lead to overtime compensations and cancelation of other cases

In most large hospital systems, large delays are the rule rather than the exception [129]. Today, most of the surgical flow management relies either on:
(i) prior determination of an optimized scheduling of procedures or
(ii) post-analysis to improve assumptions usually made in scheduling and correct cause(s) of delay.
No matter how sophisticated the scheduling method [13, 19, 21, 32] or a posteriori data analysis is, both approaches have inherent limitations due to:

• Lack of reliable and detailed information for planning: for example surgery time [6, 77, 73, 84] carries large uncertainties that is patient specific.
• Uncertainties of the processes coming from multiple sources at multiple levels of the system, such as add-on cases and cancellations [16, 15, 103, 100].

This chapter concentrates on the optimum *real-time management* of a large suite of operating rooms. We believe that most standard techniques, such as check lists [97, 27, 55] and team work protocols cannot maintain satisfactory performance in a stressful and uncertain environment. Staff needs to have access to a user-friendly cyber-physical infrastructure [82, 11] that constantly monitors events and uses a sophisticated model of surgical flow to help anticipate difficulties and efficiently assists rescheduling. We hypothesize that the following three key ingredients will provide the level of accuracy needed to improve OR management:
1. Construction of a multiple scale model that links all key elements of the complex surgical infrastructure and processes in the surgical flow
2. Real time updates of the model with ad hoc sensors of tasks/stages [52, 66, 67] see also [1, 39, 40]

3. Careful analysis of patient characteristics and staff behavior [71, 123]
As opposed to many other industrial sectors such as air civil aviation or nuclear energy that have mastered the topic of industries organization, and achieved remarkable reliability and consistency in their procedure flow, progress in surgical flow management has been very slow. We believe that human factors are at the center of the difficulty of OR suite management and should be incorporated in the model whenever possible. This chapter focuses on the construction of the theoretical model to support this plan. The model allows us to test various configuration of OR suite management in term of staff population, elapsed time statistic of surgical procedures and infrastructure resources and look at the impact on the overall performance of the system. We will show that the result are both in quantitative agreement with our smart OR data as well as in qualitative agreement with a number of observations previously communicated either in the literature or in our hospital system. The salient feature of this approach is however that a model should offer a tool to perform root cause analysis of difficulties encountered in trying to optimize daily OR management.

4.2 Methods

4.2.1 Acquisition of data

Constructing our model requires unbiased collection of time stamp for key events in the OR suite that can be acquired without perturbing the staff. To acquire this, we equipped several ORs with sensors that capture time stamps, see chapter 1. As said previously, the philosophy behind this smartOR system is that the sensors target tasks and are not tracking staff, in any way. In particular we do not videotape staff. The system is fully automatic and the end users do not have to change any of their activities. We were able to analyze 1003 cases from the system and build statistic on different elapsed time. Even though we are able to segment out and identify parts of an OR cycle that have inefficiencies using this system, determining their etiologies is complex and multi-factorial in many situations. In some cases, such as delays in preparedness of the recovery room, which leads to the patient not exiting the OR in a timely fashion, the source is clear. In other situations, such as delays in first case starts, the analysis might be more complex and involve either late patient identification by the surgeon, unforeseen anesthesia hold-ups, the need for specific OR set-ups or a combination of these, see RFID. It is clear to us that our current sensor system by itself is not enough to fully understand the complex activities and behaviors in and around the OR. We see a specific need to leverage a range of techniques, technologies, and expertise to not only track surgical flow but also be able to predict situational behavior. The OR and the perioperative space are such a complex system of teams, activities, timing and behaviors, it is clear that a model needs to be developed to address all of these factors. Finally we were able to look at some of the data that provide the elapsed time of the surgery itself. We observe that the cases were evenly distributed between open surgery and laparoscopic surgery. Fig. 4.1 shows the distribution of time for both type of surgeries. Most importantly for the construction of our model, we noticed that the lognormal distribution was the one fitting the best the elapsed times. The standard deviation of these distributions is quite large which explains why scheduling is particularly challenging. It was reported in [86] that one can obtain a better probability distribution of the surgical time, provided one take into account carefully patient conditions and co-morbidity. In our model,

we will assume a probability distribution of the surgical time: the better the statistical model can be fine tuned to patient classification, the more accurate should be our model. Our main emphasis here is to build a modular multi-scale model that helps analyze the overall organization and resources features that impact performance.

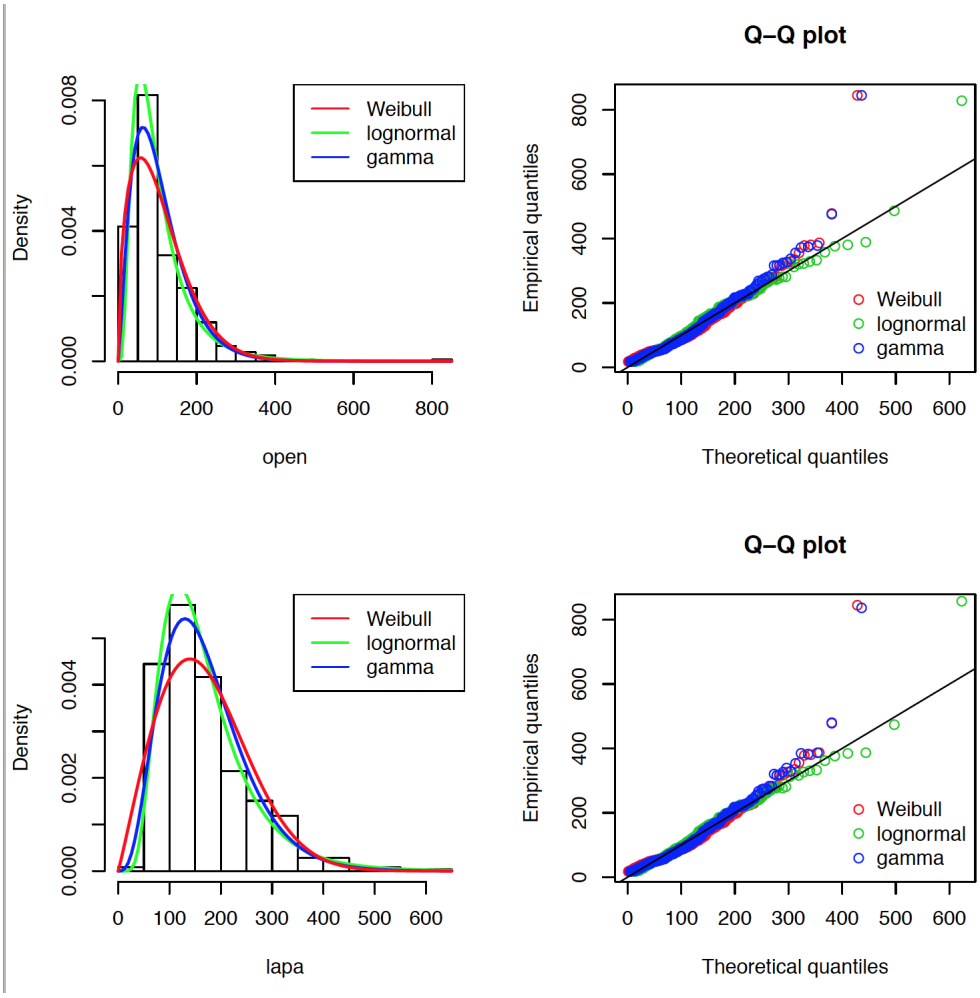


FIGURE 4.1: **Performance factors.** Distribution of elapsed time of open surgery and minimally invasive surgery (MIS) observed during an extensive period of time that captures 1000 procedures (one half is open the other is MIS). In principle, these measurements can be broken down into a number of subcategories of surgery in order to lower the dispersion of elapsed time of a procedure.

4.2.2 Construction of the ABM

Agent based modeling is a decentralized, individual-centric approach to model design. Compared to traditional modeling the agents (people, companies, projects...) here are active entities not passive and the modeler defines their behavior (reactions, leadership, states...) and finally put them in a certain environement, make them interact, establish connections and run simulations. The final result is the global behavior of the agents that depends on the inputs (assumptions) of the whole system and reflects the stories coming out of these assumptions. We started the construction of this model by concentrating on the description of the surgical flow in an OR suite.

Figure 4.2 serves as an illustration of the surgical flow at OR scale. This flow chart should be adapted to each OR suite context. It describes how each node of the flow chart advanced in time as a function of the human factor.

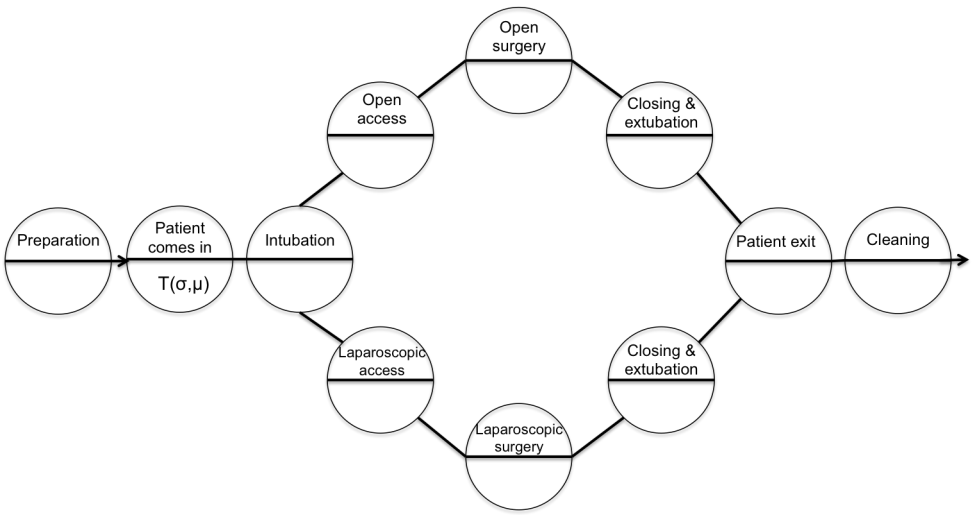


FIGURE 4.2: **Flow Chart of Surgical Procedures:** we consider that in each operating room, 50% of the cases are open surgery and 50% are minimally invasive surgeries. Example of surgical flow in each OR with the task progression going from left to right.

The salient feature of our approach is to take into account individual staff performance skills. The generally accepted concept which explains inefficiencies in the hospital system is lack of training and communication [48, 30, 92, 107, 93]. However, the complexity comes from the fact that it is impossible to decide, a priori and quantitatively, what the dominant parameters or emerging properties of the overall task/agent dynamical system are. We start here with probably one of the simplest ways of incorporating this human behavior factor into an agent-based model [109, 112, 114, 90, 91, 19]. A set of coupled time dependent systems of equations simultaneously describes the progression of the task(s), and state of the agents associated with the task(s).

We propose a staff-specific agent-based model intended to retain the key features we observed daily in clinical practice. The proposed model specifically takes into account the OR staff and their communicational and technical skill levels. The model framework is designed to be adaptively simplified or completed according to the detail of measures available in the clinical activity.

We use six main categories of agents: A for surgeons, B for surgeon's assistants, C for anesthesiologists, R for Certified Registered Nurse Anesthetists (CRNA), D for scrub nurses, E for cleaning crew. For simplicity, we assume that a surgical team, denoted S, in any given OR consists of one agent in each category. Most importantly each agent is associated with a level of technical skill and a level of communication skill. For example, a team of N surgeons noted $\{A(j,n)\}$ working in the ORs suite is represented by a $N \times 2$ matrix of performance level. The first index is the ID of the agent in the set $\{1 \ldots N\}$, the second is for the performance type. n=1 corresponds to the technical performance and is denoted by p_t^A; n=2 is for the communication performance index denoted p_c^A. Initially, we can set up individual technical skills as a function of the number of years of experience in the current position, and communication skills as a function of the time spent working with the current team,

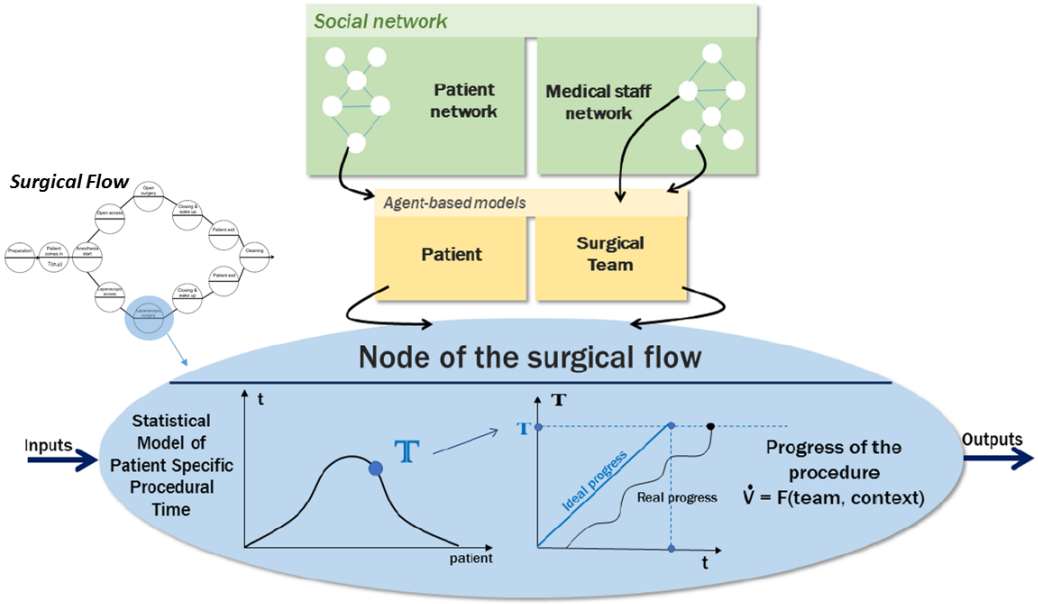


FIGURE 4.3: **Description of Task Advancement in the Flow Chart:** the estimated time T to achieve that task in the ideal case is obtain from a statistical distribution of surgical time with respect to patient conditions. The realistic time $t < T$ to achieve that task depends on the efficiency of the surgical team integrated by equation 4.2.

since frequency in team composition change is negatively correlated to information sharing [10, 109, 56].

The duration for each macro step, such as patient intubation, access time, surgical procedure itself, patient extubation, or time to move the patients out of the OR - see figure 4.2 is unknown. It should depend theoretically on the patient's medical conditions and reflects the ideal time that a perfect surgical team should achieve. As we will see later on, our model is stochastic and accounts for delays due to team members' lack of timely availability, poor coordination between tasks, or suboptimal performance of the surgical team.

For any given OR, only one task can be in process at any given time, as reflected on the flowchart - see figure 4.3. The progression of that task T_k^i from 0 to 1 is described by an ordinary differential equation with the right hand side depending on the team skills. $\tilde{T}$ is set to 0 if the task is not completed, i.e. $0 \leq T_k^i < 1$, and 1 otherwise. M is a sparse matrix that corresponds to the directed graph of Fig 4.2 . The master equation that provides the time evolution of the state of the graph of tasks $\{T_k^i\}$ handled by the team S_i that advances the task T_q at time step q is:

$$\tilde{T}(t_{q+1}) = [M \times (\tilde{T}(t_q))] \circ [(G(t_q - t_0))S_i.E_k]. \tag{4.1}$$

Here $\times$ denotes the sparse matrix vector product, and $\circ$ the vector product component-wise, and . the product of a vector by a scalar.

This model has three components:

• $M \times (\tilde{T}(t_q))$ where M is a sparse matrix that expresses the dependency on previous tasks.

• $G(t_q - t_0)S_i$ reflects the time-dependent progression of the individual task.

• $0 \leq E_k \leq 1$ is a positive factor representing a penalty for the environment conditions. It may represent the limitation resulting from shared equipment or specific overload of the hospital system due to epidemic or crisis.

Conceptually we can represent the ABM computing kernel for each node of the flow graph as in Figure 4.3.

The advancement of task provided by $G(t)$ is not linear in time, i.e. $\dot{G} \neq constant$, but instead depends on team performance and coordination. We conveniently use an ordinary set of differential equations to integrate that progression in time:

$$\dot{G} \;=\; \beta F_k(S) \;+\; H_o \tag{4.2}$$

The initial condition is zero, and β is a normalizing constant such that G reaches 1 at completion of the task in the optimal configuration. Time integration starts only when all staff required for that specific task are present in the OR. More precisely, we define the optimum performance of a team as one that (i) has full awareness on the case, (ii) does not show any sign of fatigue or stress, and (iii) has best technical and communication skills. We represent each of these elements (i) to (iii) in our model's equation below.

In equation (4.2), the factor $f(t)$ represents the combination of the effect of awareness and fatigue acting on the all team as time goes.

It is assumed that the team performs globally better for the second case than the first one. After the second case, the performance should go back to some base line for any further case. The step function in Fig. 4.4 (middle graph) represents that notion. Similarly, it is assumed that the fatigue starts to manifest after a given period of time spent in the OR and linearly decays until some sustainable minimum value.

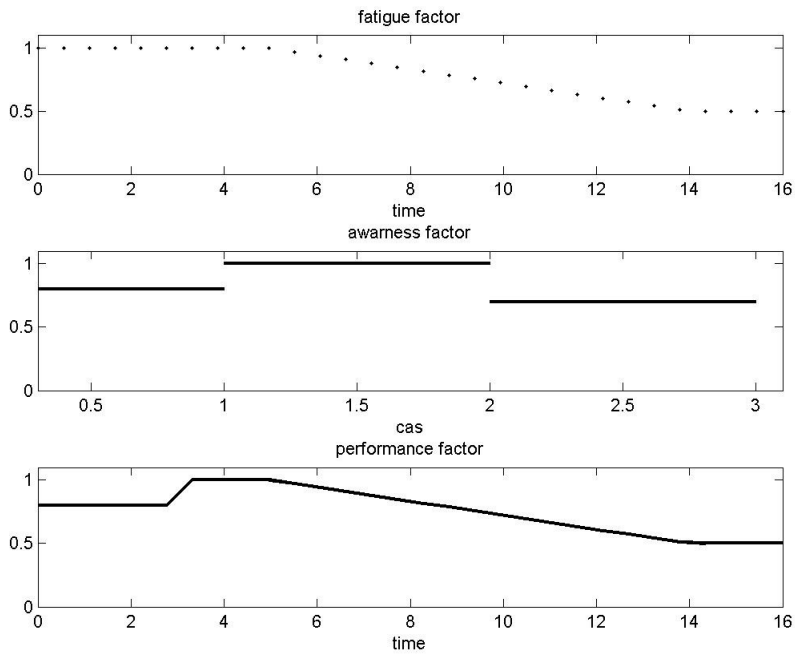


FIGURE 4.4: **Performance factors** depending on the case number of the day and the elapse time spent by the surgical team in the OR during the day.

Overall performance cannot go below a given threshold H_o corresponding to a minimum processing rate, since the team has been granted surgical privileges.

In equation (4.2), $1 \geq F_k(S) \geq 0$ stands for the team efficiency at task T_k.

The team performance component of the surgeon and his assistant for a specific task of the graph of nodes described at the high level is additive on technical skills and can be impacted by the worst skill in communication on the team. This is a known heuristic in teaching hospitals but not rigorously modeled [81]. As observed many times in the OR, a scrub nurse who does not know enough about the surgical "algorithm" and lack of communication skills might be a bottleneck bringing delays in the OR and affecting patient safety.

We have applied these basic principles to the team performance description of each task in figure 4.2 and used the following example in our simulations:

- task T_1 placing the patient under anesthesia ($\alpha_3^1 + \alpha_4^1 = 1,\ 0 \leq \beta_1 \leq 1$):

$$F_1(t) \ = \ \frac{1}{9}\beta_1 \ [\alpha_3^1 p_t^C + \alpha_4^1 p_t^R] \ min(p_c^C.p_c^R)] \ + \ (1-\beta_1). \tag{4.3}$$

- task T_2 preparation for laparoscopy procedure to provide access ($\alpha_2^2 + \alpha_5^2 = 1,\ 0 \leq \beta_2 \leq 1$):

$$F_2(t) \ = \ \frac{1}{9}\beta_2 \ [\alpha_2^2 p_t^B + \alpha_5^2 p_t^D] \ min(p_c^B.p_c^D)] \ + \ (1-\beta_2). \tag{4.4}$$

- task T_3 preparation for open surgical procedure to provide access ($\alpha_1^3 + \alpha_2^3 + \alpha_5^3 = 1,\ 0 \leq \beta_3 \leq 1$):

$$F_3(t) \ = \ \frac{1}{9}\beta_3 \ [\alpha_1^3 p_t^A + \alpha_2^3 p_t^B + \alpha_5^3 p_t^D] \ min(p_c^A, p_c^B.p_c^D)] \ + \ (1-\beta_3). \tag{4.5}$$

- task T_4 laparoscopic procedure ($\alpha_1^4 + \alpha_2^4 = 1,\ 0 \leq \alpha_3^4 \leq 1,\ 0 \leq \alpha_5^4 \leq 1,\ 0 \leq \beta_4 \leq 1$):

$$F_4(t) \ = \ \frac{1}{9}\beta_4 \ [\alpha_3^4[\alpha_5^4[\alpha_1^4 p_t^A + \alpha_2^4 p_t^B] + (1-\alpha_5^4)p_t^D] + (1-\alpha_3^4)p_t^R] \ min(p_c^A, p_c^B, p_c^R, p_c^D)] \\ + \ (1-\beta_4). \tag{4.6}$$

- task T_5 open surgery procedure ($\alpha_1^5 + \alpha_2^5 = 1,\ 0 \leq \alpha_3^5 \leq 1,\ 0 \leq \alpha_5^5 \leq 1,\ 0 \leq \beta_5 \leq 1$):

$$F_5(t) \ = \ \frac{1}{9}\beta_5 \ [\alpha_3^5[\alpha_5^5[\alpha_1^5 p_t^A + \alpha_2^5 p_t^B] + (1-\alpha_5^5)p_t^D] + (1-\alpha_3^5)p_t^R] \ min(p_c^A, p_c^B, p_c^R, p_c^D)] \\ + \ (1-\beta_5). \tag{4.7}$$

- task T_6 closing laparoscopic procedure: similar to T_2.
- task T_7 closing open surgery procedure: similar to the above.
- task T_8 waking up procedure ($\alpha_3^8 + \alpha_4^8 = 1,\ 0 \leq \beta_8 \leq 1$):

$$F_8(t) \ = \ \frac{1}{9}\beta_8 \ [\alpha_3^8 p_t^C + \alpha_4^8 p_t^R] \ min(p_c^A, p_c^C, p_c^R)] \ + \ (1-\beta_8). \tag{4.8}$$

- task T_9 cleaning the OR ($0 \leq \beta_9 \leq 1$):

$$F_9(t) \;=\; \beta_9 p_t^E \; p_c^E + (1 - \beta_9). \tag{4.9}$$

Overall the team performance impact on task advancement are provided by the matrix α and vector β:

$$\begin{pmatrix} 0 & 0 & 0.6 & 0.4 & 0 \\ 0 & 0.5 & 0 & 0 & 0.5 \\ 0.5 & 0.3 & 0 & 0 & 0.2 \\ 0.6 & 0.4 & 0 & 0.8 & 0.8 \\ 0.8 & 0.2 & 0 & 0.8 & 0.8 \\ 0 & 0.6 & 0 & 0 & 0.4 \\ 0.3 & 0.5 & 0 & 0 & 0.2 \\ 0 & 0 & 0.6 & 0.4 & 0 \end{pmatrix}$$

and

$$\beta \;=\; [0.7\; 0.6\; 0.3\; 0.5\; 0.5\; 0.3\; 0.3\; 0.7]^t$$

This matrix is largely the result of a heuristic effort based on a priori knowledge. However our plan is to eventually retrieve these values from clinical data provided for example by the black box system [124] that has the ability to report most of these parameters.

Let us summarize below some of the basic principles of the construction of our agent-based model:

(i) We use a fixed number of ORs (the block of ORs).

(ii) The pool of staff allocated to the block of ORs is given.

(iii) The schedule of surgeries for the day is given and has 2 to 3 surgeries per day with an average of 2.5.

(iv) We have 6 categories of personnel in our model: surgeon, surgical assistant, anesthesiologist, assistant of anesthesiologist, scrub nurse, cleaning crew.

(v) The flow charts of the procedures are divided as follows: at the highest level, anesthesia induction is followed by surgery and then followed by waking the patient up. At the lowest level, each surgery is decomposed into preparation or access, the surgical procedure itself, and then closing.

(vi) For now we limit our model to two different types of operations and provide the proportion of each that is scheduled. One may think about two categories of operations such as open surgery and laparoscopic surgery.

(vii) Overall performance of the OR team is given by a formula that combines individual technical competence skill and communication skills [46, 109, 112, 114, 90, 91, 19, 48, 30, 92, 107, 93]. We clearly separate these two sets of skills, based on the data suggesting communication is one of the main issues in team performance. The weight of individual skills performance on the overall team performance depends on the type of procedure. It is a parameter of the model that we fixed a priori based on our experiences and observations.

(viii) We assume we have a smaller number of cleaning teams than the number of ORs in the block.

(ix) We assume we have a smaller number of anesthesiologists than the number of ORs, but enough anesthesiology staff.

(x) Allocation of anesthesiologists and cleaning teams, is based on a first asked, first served allocation, provided staff is available. At this stage, we have not assumed

here any constraints on which a specific anesthesiologist would be preferred for a specific operation, although such specialization exists in the clinical world.

(xi) The number of bed in the post-surgery recovery area is fixed, and a patient can leave the OR only if a bed is available. Time to recover is a probability distribution specific to patient and surgery types.

The unknown parameters of the model are the time to perform each task of the flow chart of Figure 4.2 that would take with a perfect team in ideal conditions, and the elapsed time for staff such as anesthesiologist and cleaning teams to be aware that they are needed and show up to their OR of interest. We will recover these unknowns by fitting the simulation results to our smartOR data set as described in next section.

4.3 Method to retrofit the model to the data and validate input parameters

From our smartOR data set we extracted 5 important normalized density distributions of duration of events and more precisely how long:

• (1) and (2) the patient is under anesthesia for open surgery, respectively laparoscopic surgery.

• (3) it takes for the patient to be under anesthesia once in the OR.

• (4) the patient stays in the OR after extubation.

• (5) the turnover time.

We will denote $\delta_j^E, j = 1...5 : \quad (0, \infty) \longrightarrow \ (0, 1)$ the functions that corresponds to a data set acquired over a period of a year. We will denote in a similar way the distribution function δ_j^S computed by the multi-scale model.

The objective function to fit our model was the distance in L2 norm between the normal distribution of the clinical time listed above and time predicted by our model,

$$F_{objective} \ = \sum_{j=1...5} [\int_0^\infty \sqrt{(\delta^E - \delta^S)}]^2. \tag{4.10}$$

We used the ratio $R_1 = 1/4$ of one anesthesiologist per 4 ORs. We take into account that hospitals have enough CRNAs to meet the requirements of the American College of Graduate Medical Education and have at least one staff all the time in the room, the anesthesiologist being needed only during crucial phases of the operation [43]. We assume a ratio $R_2 = 1/5$ of one janitorial team for 5 ORs that was reported by the staff. We assume also that start time is a random number within 15 minutes of the target that is 7:30 am. We hypothesized that the population of staff has normal distribution of skills in the range (1,3) with $\mu = 0, \sigma = 1$. In order to avoid overfitting, we keep our model relatively simple, using 12 unknowns parameters listed as below to fit all 5 curves at once:

- γ_1 is the ideal time to put the patient under anesthesia.
- γ_2 is the shortest time achievable for minimally invasive surgery of less than 60 min.
- γ_3 is the shortest time achievable for open surgery of less than 60 min.
- γ_4 is the shortest time achievable for all other minimally invasive surgery.
- γ_5 is the shortest time achievable for all other open surgery.

- γ_6 is a factor that augment γ_2 and γ_3 time of minimally invasive surgery depending on patient condition denoted $p(x)$) as follows:

$$\gamma_{2/3}\ (1 + \gamma_6 p(x)).$$

  we set $p(x)$ to be a uniform probability distribution in (0,1).

- γ_7 is a factor that augments γ_4 and γ_5 time of open surgery depending on patient condition denoted $p(x)$ in a similar way.

- γ_8 is the ideal wake up time for the patient.

- γ_9 is the ideal time to clean and disinfect the OR according to best practices.

- γ_{10} is the awareness delay for anesthesiologist to come to the OR expressed in minute per OR in the surgical suite.

- γ_{11} is the awareness and communication delay for a janitorial team to come to the OR expressed in minutes per OR in the surgical suite.

- γ_{12} is the average recovery time in post operative area after surgery.

We used a standard genetic algorithm to minimize the stochastic objective function (4.10) in order to retrieve the 12 unknowns $\gamma_j,\ j = 1...12$ of our multi-scale model.

Numerous run were used to verify the robustness of the result. We will also check that all the elapsed times from surgery time down to awareness time are absolutely necessary to reproduce observed clinical data.

4.4 Verification

The multi-scale ABM (Agent-Based Model) code has been implemented in Matlab. This interpreted language allows at run time numerous ways to debug the code due to the ease way of displaying the state of each variable at any specific step of the algorithm.

ABMs are however known to be rather difficult to verify because of the stochastic nature of the algorithm and the complexity of the decision tree corresponding to each ABM rules. To insure reproducibility in the debug phase, we stored in a large enough file some sequences of random numbers generated. This file was used when it was necessary to compare runs in a deterministic way.

We implemented checkpoints to verify the balance on shared resources that are in conservative quantities. We used also linear stability to check that each parameter of the model, taken separately, had the expected effect on the gradient of the output.

Finally we fixed the interval of variation for each parameters and checked the output with extreme value. The code was also commented to be shared and verified by several members of the team.

To run a simulation of 10 ORs over a year period takes about 10 minutes. We were able to repeat such simulation many times to verify the robustness of the result.

Macro step/parameters	γ_1	γ_2	γ_4	γ_6	γ_8	γ_9	R_1	R_2	γ_{10}	γ_{11}	γ_{12}
Time to intubate	2				3		1				
Time to leave the OR			2				3				1
Turnover time						2	4	3		1	5

TABLE 4.1: Ranking the influence of the parameters on key factors of OR efficiency, such as anesthesia time, wake up time and turnover

γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	γ_9	γ_{10}	γ_{11}	γ_{12}
0.05	0.74	0.4	1.36	1.14	0.74	1.1	0.05	0.13	0.004	0.0073	1.86

TABLE 4.2: Solution of the unknown parameters values

4.5 Results

4.5.1 Comparing the model to data

Sensitivity Analysis: We ran a Monte-Carlo simulation to rank the impact of each input parameters on the segment of the surgery procedure that are most sensitive to resources sharing and coordination, and are key indicators of OR efficiency. Table 4.1 provides the ranking in each row starting from one for the most influential parameters and up to 5. We have included only the parameters that have a significant impact.

We expect that time to put the patient under anesthesia δ_3 depends first on the availability of an anesthesiologist characterized by ratio R_1 and second on the optimum time to put the patient under anesthesia γ_1.

Time δ_4 to wake up and leave the OR is most sensitive to the availability of beds in the recovery area, see γ_{12} parameter. This reflects the feedback we have received during staff interviews. δ_4 relation, to some extent, with open surgery time is far less obvious. It should be noticed that open surgeries in our clinical data seem in average much shorter than minimally invasive surgeries, which may explains why γ_2 influence does not compare to γ_4. We found that δ_4 depends at the same level on γ_3 that is the expected time to get out of anesthesia in ideal condition and number of anesthesiologist on call, i.e. ratio R_1.

TOT is perhaps the most "nonlinear" event of all three listed in Table 4.1, characterized by a sharp pick distribution with a long tail of large delayed time. TOT depends heavily on awareness delay of janitorial teams. Once again, this was confirmed by our interviews with staff in the surgical suite. Dependency of TOT on ideal time to clean up the OR space or number of janitorial team on call is rather clear.

It seems counterintuitive that turnover may depend on anesthesiologists awareness or on the number of bed in the recovery area. Our interpretation of such distance correlation relies on cascading effect between delay in each phase of the surgical flow in any OR may induces additional one in later phases in other OR.

Fitting Statistical Distribution Curves of Surgical Events:

The results of our nonlinear fitting algorithm with a Genetic Algorithm (GA) are given in Figure 4.5 and figure 4.6. The optimal value of the parameters obtained by our GA is given in table 4.2. Despite the level of noise and uncertainty in the system, we achieved relatively good fitting.

For example, we have treated the description of surgery in a very coarse way in our model. Our data set includes very short surgeries such as cholecystectomy or appendectomy as well as much longer one such as organ transplantation. Obviously,

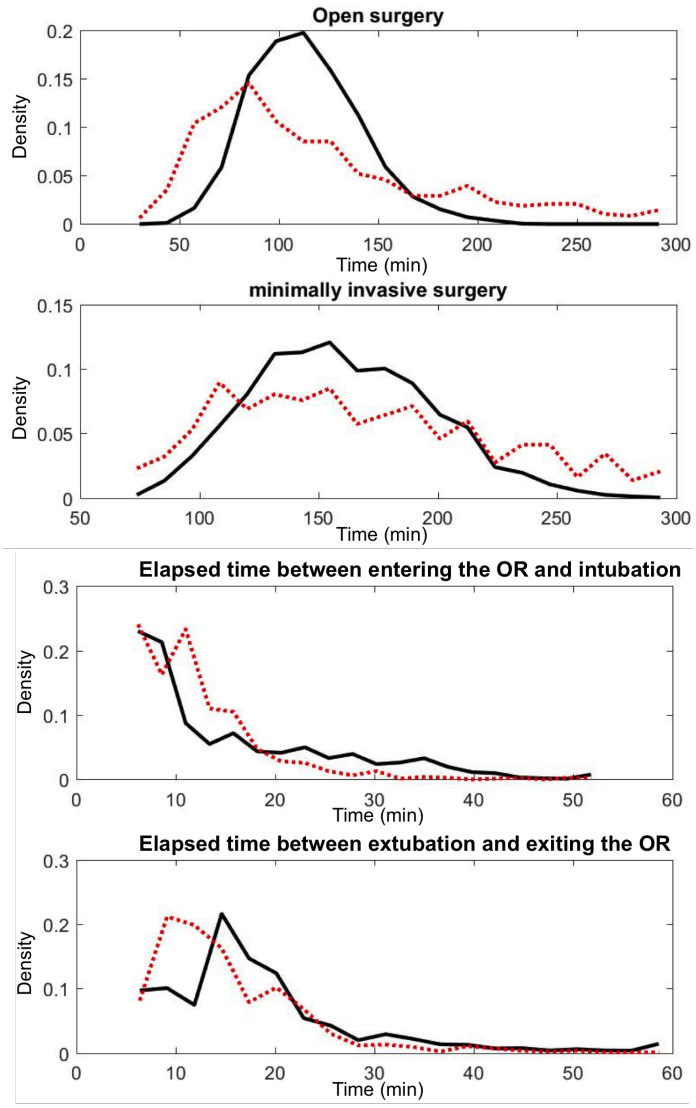


FIGURE 4.5: **Comparison of normalized distribution of cases length** with respect to elapsed time for open surgery, minimally invasive surgery, anesthesia and waking up time between observed (red dots) and simuated (black line) data.

we need to refine our surgical flow chart by including more specific description of surgery types and acquire estimates of parameter values similar to γ_3 to γ_6 for each class of surgery. We do not expect to get a better fitting of δ_1 and δ_2 distribution than the one we got from the data of the smartOR.

The prediction of anesthesia time and wake up time seem accurate enough to be of practical value, see figure 4.5. The prediction of TOT on Figure 4.6, one of the key targets for improvement in OR suite management is interesting, especially considering the fact that this is the most non-linear factor.

The validation of the multi-scale model comes also in part from the optimal value of the parameters we retrieved through in the fitting process. Of course parameters γ_1 to γ_9 are hard to exploit, since these are best possible performances of various portion of the surgical procedure. They seems to have however a reasonable order of magnitude. More interestingly, we found that the delay of OR awareness for the cleaning team (γ_{10}), is between 5 and 10 min while for anesthesiologist (γ_{11}) it is

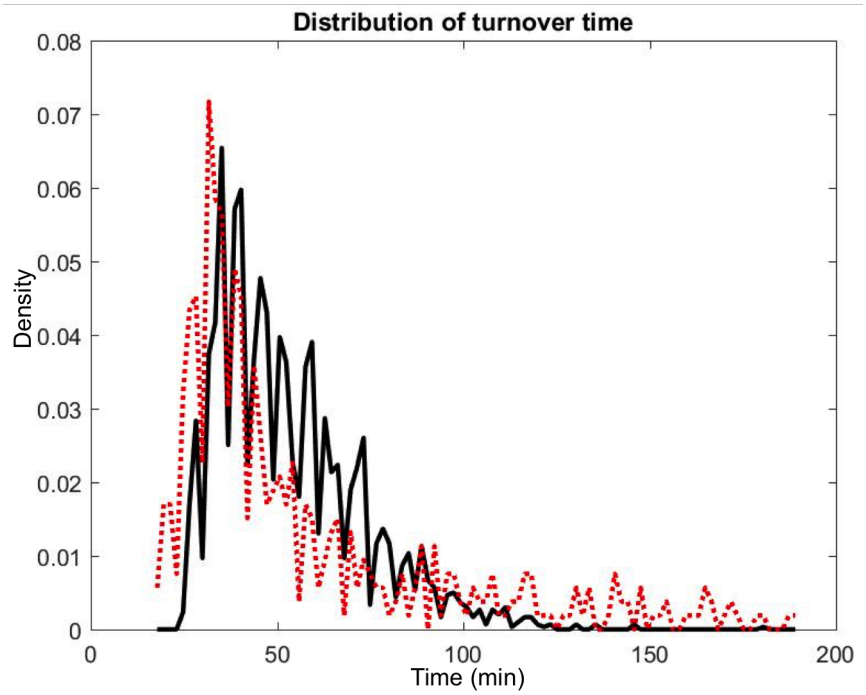


FIGURE 4.6: **Comparison of normalized distribution of cases** with respect to turnover time between observed (red dots) and simuated (black line) data.

between 2.5 and 5 min. This is in agreement with our observation during monitoring of the white board activity [70]. The main reason for the delay is that OR state changes are entered manually and communication is often depending on individual cell phone conversation (call or text message).

The model also predicts that the average time spent by the patient on the bed in the recovery room is about 1.8 hours, which is in agreement with our observation.

We should notice that if we skip the awareness delay and limitation on recovery room space in our model, or skip the dependency on share personal with ratio of personal R_1 and R_2 that should be far less than 1, the model cannot fit the clinical.

For example, instead of a lognormal distribution of surgical time as it can be demonstrated by analyzing our data, we get only normal distribution of time δ_1 to δ_4, and instead of a turnover time distribution δ_5 that has a slow decay toward the worst performance we would achieve a normal distribution with a very narrow standard deviation. This is a key feature that a good model must account for because those rare long delays are what makes the OR surgical flow most chaotic.

4.5.2 Ask the model "what if?"

We have established the credibility of the model in the previous section. Let us then question the model about potential improvement in surgical management. According to our numerous interviews of staff members in various hospitals, the following measures are among the most significant:

- *First Case Start Time Delay:* this time stamp is crucial for a smooth continuity of the day in the surgical suite. Indeed, a delay at this stage of the day will be affected on all the cases left. Surgeons, usually get the blame for this delay because they do not visit their patient -a legal requirement- in the preoperative

area early enough before the scheduled beginning of the case. As mentioned before, by putting a RFID antenna at the entry of this area and passive RFID tags on 3 surgeons we were able to track the moment their were visiting their patient in the morning. While the results proved that surgeons are not always on time, we also observed late start cases when the surgeon was visiting the patient early enough. This implies a cause of delays at another point of the surgical workflow.

- *Idle time:* management of surgical staff time is also a very important point for an hospital. Having a surgeon to wait for a case to start is a huge lost of money for the hospital and brings frustration to the OR which can impact safety of the surgery. Waiting on the janitorial crew to come clean a room, looking for a critical tool or waiting for a shared piece of equipment (like CT scan or robots) are only some examples of what can increase idle time.

- *Total OR time and Overtime:* we define total OR time as the time all ORs of a surgical suite are being used. With a cost of the order of $100 per minute per OR, this time can rapidly increase the cost for the hospital. In general, total OR time is around 8 hours per OR per day with an active time form 7am to 3pm. Everything before or after this time is counted as overtime with surgical staff staying longer than their scheduled shift or even the need to ask the help of staff on-call.

- *Maximum OR time:* maximum of hours an OR can be used for surgery taking into account necessary cleaning time and maintenance. Knowing this information can give us an idea of the worst case scenario during 24 hours and can be compared to real situations.

We are now going to ask our model to provide us statistics on all these indicators. We are able to change the parameters of the system and simulate perfect or bad situation and see their impact(s) on management and organization:

• *How does shortage of shared personnel in the OR suite affect overall performances?*

Let us assume that the OR suite has 10 ORs. Fig.4.7 shows the most efficient number of anesthesiologists in order to minimize OR idle time or overtime. The ratio of 1:2 seems quasi optimal, like it has been found in the paper of Epstein and Dexter, but a floating anesthesiologist helps for critical part of the day like first case start when a lot of cases need intubation in parallel [43]. Also this would decrease the number of first start cases delayed as understaffing of anesthesiologist team was showed by our numerical experiment to be its first cause. We do a similar study concerning the number of cleaning crews. Increasing the number of cleaning teams not only decrease the idle time, but could have a significant impact on cost of surgery by decreasing the non-used time of ORs. This would quickly compensate for the cost brought by the additional employees needed.

• *How distribution of staff's skills impacts performances?*

This study showed us that partial team performance improvement has almost no correlation with overall performance. The most striking result is reported in Fig.4.8. For example, here we focus on surgeons' skills and its impact on daily performance, assuming the rest of the staff has an uniform skill distribution. We define three possible distributions of skill level: 1 corresponds to the worst skill level, 2 to medium and 3 to best skill level. We formed four corresponding teams, which we use for our analysis. In team 1 (in red) the distribution of skills amongst the members of the team is uniform, which means everyone in the team has the same skill level

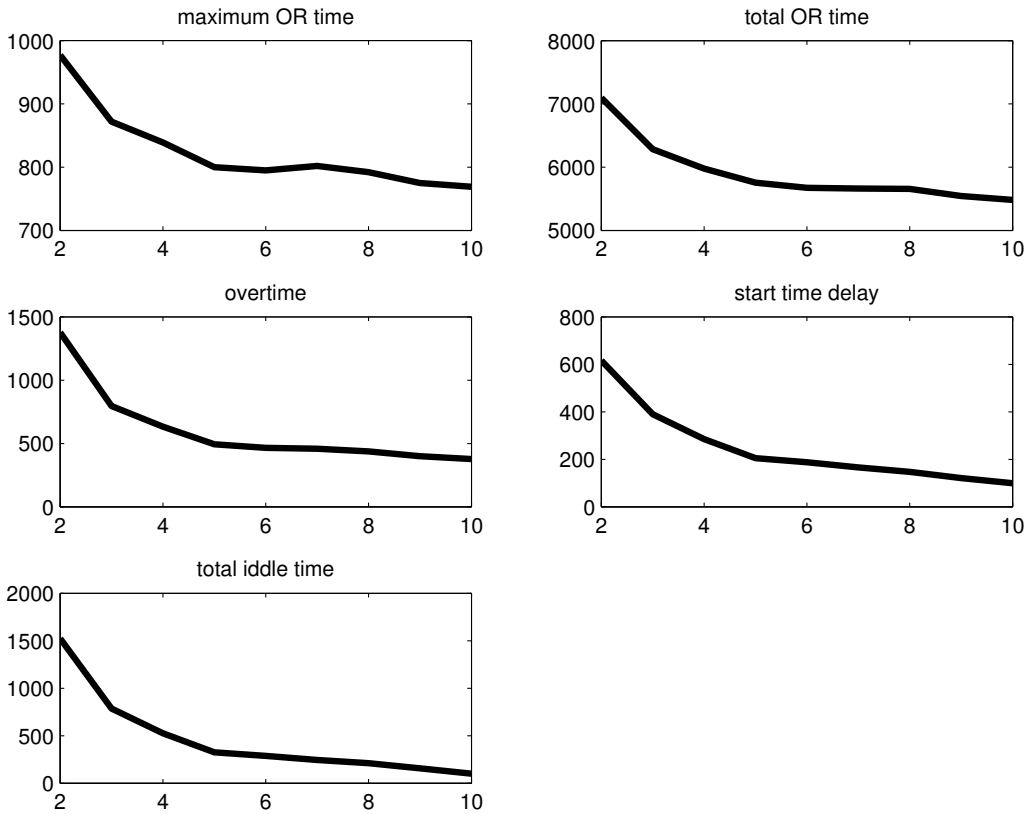


FIGURE 4.7: **Impact of the number of anesthesiologists on outcome.** Dependence of the overall performance of the block of ORs as a function of the proportion of the number of anesthesiologist per number of ORs. We have run the simulation with 10 ORs and considered a variation from 2 to 10 anesthesiologists. Total time on vertical axis is expressed in minute. Interpretation of such curves indicates that a 1:2 ratio of anesthesiologists to ORs is close to optimal.

((1,1,1)*1/3). In team 2, (in blue) there are three times as many 2's and 3's as there are 1's ((1,3,3)*1/7). Team 3 (in green) is built with an equal number of 1's and 2's and an additional 3 ((2,2,3)*1/7). Team 4 (in black) is constituted of only 3's (0,0,1) and presents the team with the best skills. Applying these distribution as input of our simulation model and focusing on only one group of staff, like for example surgeons on Fig. 4.8, the effects on performance are very limited. On the other hand, as Fig.4.9 demonstrates, applying these distributions of skills on the whole team has strong impact if and only if the whole team has highly skilled. This proves the importance of team training in order to make surgery more efficient and safer for the patient as well as for the surgical team. This result is not surprising to well known practitioners in the field [9].

• *Does the size of the OR suite matters?*

As noticed earlier OR suites efficiency is very sensitive to delay in awareness. Because we assume that awareness delay is proportional to the number of ORs in our model, we found an exponential decrease of performance as the number of ORs in the suite grows.

While large OR suites' performance decrease because of coordination issues, they also allow for better sharing of resources and provide more flexibility in scheduling. We observed that large OR suites accrue less surgical overtime compared to smaller OR suites in response to add-on cases which typically account for 10-20 % of

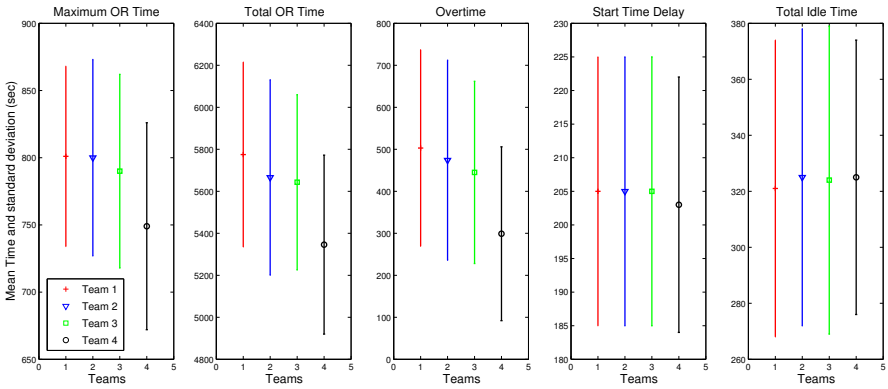


FIGURE 4.8: **Impact of surgeon skills on team performance.** Taking the same distribution of surgeon skills as explained above and assuming that all other personnel has uniform skills distribution, we analyzed the effect of these on the five measured items and found that the impact is minimal.

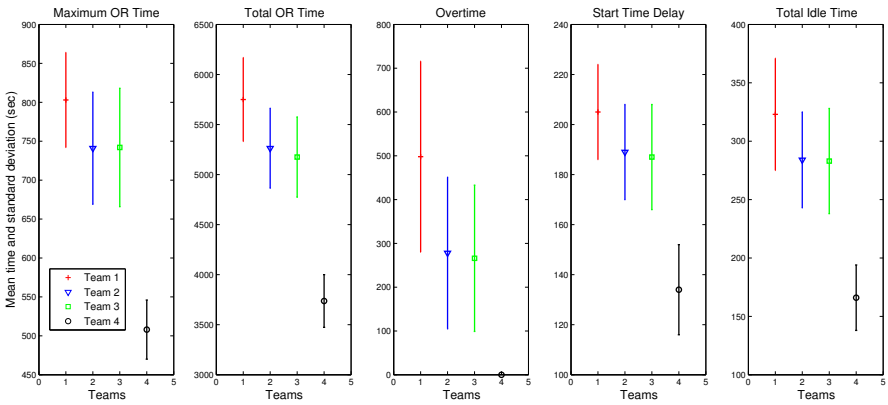


FIGURE 4.9: **Impact of global team skills on outcomes.** Taking the same distribution of team skills as described above, we analyzed the effect of these on the five measured items and found that the optimal results is achieved only by Team 4 (only the best skill level for everyone).

the daily OR suite capacity [120]. To prove our point, we computed in our simulation how often a segment of one hour with an empty OR would be available before surgery time go over the official end of the day. Each occurrence would be a potential slot for add-on. Table 3 summarizes the result of our simulation for increasing OR suite sizes.

Nº OR	5	10	20
Nº add-on: mean	1.45	2.32	3.56
Nº add-on: SD	0.94	1.2	1.5

Table 3: number of potential add-ons as a function of the number of OR in the suite.

Clearly the number of potential add-on cases increases with the number of OR, but most importantly the ratio of the mean versus the standard deviation increases non-linearly and favor large OR suite. In other words, the reliability to be able to add-on cases in large OR suites is higher than in small OR suites.

Similarly, we found in our simulation that large OR suites perform better than small ones when there is a limited capacity in the recovery area. This result holds under the ratio of bed in the post-operative area per OR, which is also proportionally linked to the number of ORs in the suite. This is a major problem since the patient is often kept in the OR because there is no other space available in the post-operative area, delaying the next case.

4.6 Conclusion

We envision the smartOR as part of an operating room management system where the OR events are captured by the sensor arrays and transmitted as real-time status updates on a digital screen and paired with the patient and surgical data. At the same time, case-related data are continuously collected in a database for a statistical model generation that may ultimately guide operative scheduling and planning to increase OR efficiency. The main objective of this chapter was to build a multi-scale agent based model of the surgical flow in an OR suite in such a way that it can be used to separately study each combination of factors that impact performances, and determine the best combinations options. As a matter of fact the overall dynamic of the system is complex, in particular its human behavior components, that it is difficult to assume that a single recipe such as enforcing check list or tagging staff with RFID can work and be adopted in the long run. We used also the database of unbiased time stamp on surgical flow build with the smartOR presented in Chapter 2. However, it was not enough to run a root cause analysis, except in simple situations such as the patient being hold in the OR because no bed in the recovery area was available, or a staff was missing to complete the surgical team.

This model was used to test various hypotheses on the effect of the demography of competence skills, consequences of under staffing, scaling effect due to the size of the OR suite etc.... We reported some qualitative agreements with results published in the literature and some of our observations in the clinic. Our main new finding was that, according to the model, team training is a key to increase the overall efficiency and inertia effect due to delay in OR awareness has the most negative impact on large OR suite.

Chapter 5

Air quality and safety inside the OR suite, a numerical and system approach

5.1 Introduction

The largest source of airborne contamination in today ORs is the surgical team and patients themselves. Scrubbing and gowning usage are here to help minimize the quantities of airborne contaminants but they do not totally prevent them. With the positive pressure present between the OR and the corridor, there will be inevitable air recirculating inside the room at every time. On top of this, the workflow of the OR suite adds another source of contamination that is very complex to monitor. The goal is to be able to find a way to track and isolate these contaminants in order that they never reach the surgical zone and then, link their concentrations with activity in the OR. The use of CFD software can give detailed information about thermal comfort variables such as pressure, airflow velocities, temperature, humidity... Moreover, it gives the possibility to track the mass ratio of contaminants introduce inside the model. Very accurate estimation of their concentrations can be achieved with the help of information from the clinical world such as velocities at inlets and outlets or steps of procedures. This will allow us to follow particles in and around one OR and even between ORs. To then focus further on the propagation of particles inside a complete OR suite with 11 ORs, we propose a multi-domain mathematical model of particle flow in it to simulate transport phenomenon of airborne particles. Our findings of particles detection will monitor exposure of surgical staff to unhealthy concentrations. In addition, our general and simplified system approach may provide new insight on some aspects of the propagation of disease and infection. At the end, the idea is to put all these parts together in order to reach a higher level of efficiency and safety inside the surgical suite, see Fig. 5.1.

By modeling a part of one of the surgical suite of Houston Methodist Hospital, we can simulate the whole airflow inside it and follow how particles interact with its architecture, how they can pass the doorstep one way or the other and affect people health. We want to answer different questions with this model and see how it fits what we found with our experiments in reality:

- How particles leave the OR?
- Is there a backflow and potential reverse pollution?
- How much particles do surgeons, nurses, anesthesiologists get during a case?
- What is the concentration of pollutant in the hall and can particles reach an adjacent OR?

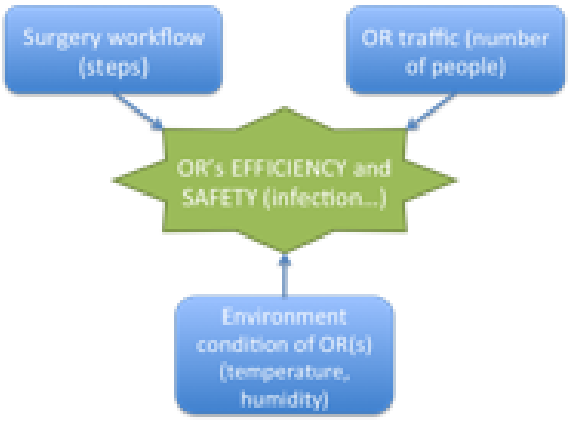


FIGURE 5.1: Multi-scale model to reach higher efficiency and safety in the OR suite.

• Where to put the particles sensors?

99% of ORs are under positive pressure, the other 1% is under negative pressure for contagious patients but this special case will not be discuss in this thesis. The positive pressure is achieved by supplying more air to the room than the volume that extracted from the room. This gradient of pressure between the OR and the hallway of the surgical suite plus the normal airflow of the OR brings a very specific shape to the airflow in the room. We are going to present the construction of two models based on real OR architecture and real HVAC solution to model this airflow and understand if yes or no air from the OR table can escape the room, spread itself to the hallway, reach adjacent ORs and compare with our experimental data.

5.2 Numerical analysis of airflow in a surgical suite

5.2.1 Background

HVAC systems rely on fluid movements in order to serve their function of providing comfort and safety. Fluid mechanics define many of the rules used in HVAC industry. This field of engineering is complex and has a lot of different applications. In the previous chapter we saw how to follow airflow with experience in the real world using trackers. In this chapter we are using the second possibility, which is the numerical approach. It exists other ways to observe and quantify airflows in a building and some of them are explained in the work of Tang *et al.* [127]. The case of a physical analogue model is not discussed in this thesis but it could be an extension, also the breathing is not taking into account in the model either. CFD is a numerical method of calculating the movement of fluid (air here) within a delimited space (open or closed) based on the physical laws of mass, momentum and energy conservation. This technique is generally split into three phases.

The first step is to describe and build a 2D or 3D model of the geometry you want to consider. The level of simplification used will define if your model is close to reality or not. This depends on what is the research interest, is it in the detail of one very small part or is it general flow that you want to observe. Once this is done, this geometrical space is divided into discrete elements (2D or 3D). This is called a mesh and, here again, the accuracy of the result of your model depends a lot on

the size of this elements. If the rule "the more, the merrier" applies on the number of elements composing the mesh, the computation power needed and the time it will take to complete the calculation can quickly become an issue. Indeed, the third and final step is to compute the general law of fluid dynamics in all these elements in order to compute the flow and properties in all your model. Flow is described by the Navier-Stokes equation, which is a mathematical description of the conservation of momentum. Since the airflow inside the room presents turbulences with scales smaller than the size of the elements, a degree of approximation is necessary to model the path lines of airflow.

The governing equations to compute the fluid flow are the conservation of momentum, commonly referred as the Navier-Stokes equation, the conservation of mass and energy, which are both used to calculate the velocity and temperature fields in the model. The conservation of mass equation, sometimes called the continuity equation is:

$$\frac{\partial \rho}{\partial t} + \vec{\nabla} \cdot (\rho \vec{v}) = 0 \tag{5.1}$$

where ρ is the density, t is time and $\vec{u}$ is the velocity vector.

Conservation of momentum is given by:

$$\frac{\partial}{\partial t}(\rho \vec{v}) + \nabla \cdot (\rho \vec{v} \vec{v}) = -\nabla p + \nabla(\bar{\bar{\tau}}) + \rho \vec{g} \tag{5.2}$$

where p is the pressure, $\bar{\bar{\tau}}$ is the fluid stress tensor, and $\vec{g}$ is the gravitational vector. The fluid tensor for a Newtonian fluid takes into account the dynamic viscosity of the fluid. The last term of Equation 5.2 represents the buoyancy force. This is explained by the Boussinesq approximation, which assumes that the density can stay constant except in the buoyancy force term. The approximation is true only for small gradient of temperature so that the gradient of density is small too. On this term now the density has a linear dependence with the temperature:

$$\rho = \rho_0 - \alpha \rho_0 \Delta T, \tag{5.3}$$

where α is the coefficient of thermal expansion and subscript 0 represents the reference value. The resulting conservation equation is:

$$\frac{\partial}{\partial t}(\rho \vec{v}) + \nabla \cdot (\rho \vec{v} \vec{v}) = -\nabla p + \nabla(\bar{\bar{\tau}}) - \vec{g} \alpha \Delta T. \tag{5.4}$$

The conservation of energy is given by:

$$\frac{\partial}{\partial t}(\rho E) + \nabla \cdot [\vec{v}(\rho E + p)] = \nabla \cdot k_{eff} \nabla T + \nabla \cdot (\bar{\bar{\tau}}_{eff} \cdot \vec{v}) + S_h, \tag{5.5}$$

where E is total energy and k_{eff} represents the effective conductivity.

The k-ϵ turbulence model assumes that the flow is fully turbulent and the effects of molecular viscosity are negligible. k and ϵ are calculated using two additional transport equations.

The next part of the thesis is going to present the three part of building a CFD model: first the geometry of the space analyzed, then the mesh used and finally the boundary conditions used to solve the Navier-Stokes equations.

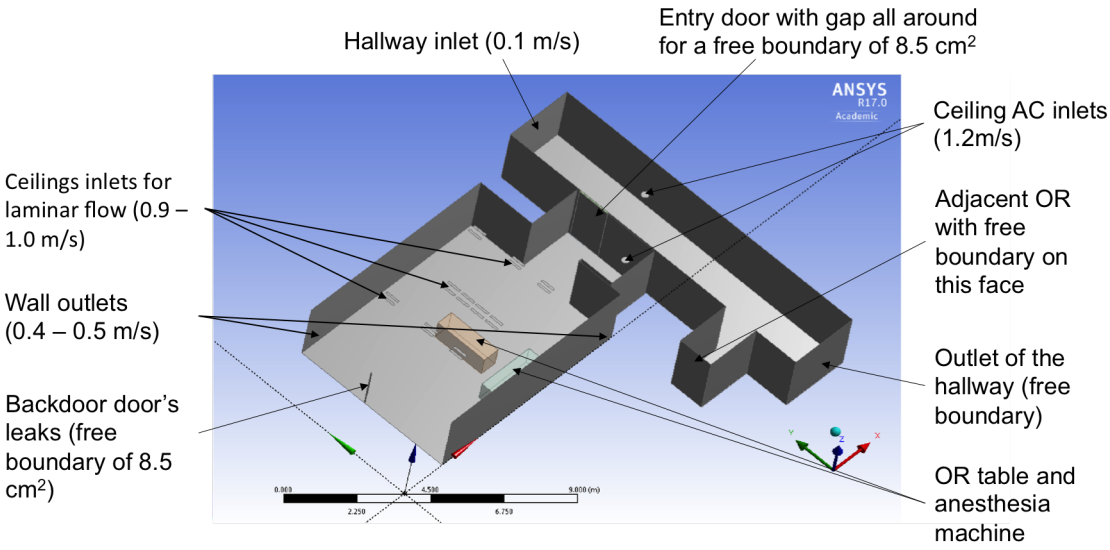


FIGURE 5.2: 3D representation of the domain studied.

5.2.2 Method

A 3D Cartesian coordinate system was used with length along the x-direction, width along the y-direction, and height along the z-direction. The OR is 7.5 m long, 6 m width and has a height of 2.7 m, see Fig. 5.2. To fit with the real OR we added the space on the right side of the OR door, when looking at it from the OR, with an inlet vent in the middle of it. Finally the corridor was modeled as a rectangle of 12 m long, 2.5m width and a height of 2.7m. Computation of the flow was done using ANSYS Fluent solver in steady states first and transient mode later, and using a pressure based solver. The model geometry was meshed using unstructured tetrahedral grid with around 1 243 370 elements (depending if the door is open or close) following a proximity size function which made the mesh more refined at the interfaces. The airflow is assumed to be turbulent and was modeled using the realizable $k - \epsilon$ turbulence model taking into account the gravity to introduce the boussinesq approximation in the equation. It is the most common model in which the turbulent kinetic energy k and turbulent dissipation rate ϵ are modeled. Also it has been proved to have good prediction of airflow in buildings [8].

Putting real measurements in our model was a very important part of our development. Lots of, mostly theoretical, researches have been done on this problem but by observing the life of an OR suite at Houston Methodist Hospital for almost three years the importance of modular solutions was striking. It is important to have a global model that can fit all situation and organization but in healthcare you always need to adapt a minimum to the situation, that has to do with the geography, the demography, the ethic... medicine is not an exact science as well as the place it is practiced in, the hospital and its architecture. This is what we implemented here, we started with a 2D square representing the OR linked to a rectangle representing the hallway which can be applied to any situation, we added some inlets and outlet, door and obstacles which can modeled any rooms and give an idea for example where to put the sensors seen in the previous chapter that helped to understand better the airflow. We then used devices to measure the velocity of the airflow, its temperature, its evolution during a day and more specifically its relation with the

activity of the OR. Finally, we finished with a 3D model taking into account the architecture of the room, the OR table and the airflow in it as well as in the hallway. Even if this can seems very specific to an isolated case, it actually underlines all the parameters to take into account when building an OR suite or updating it and its HVAC system. A lot of research has been done at the scale of the OR [4, 18] or of the ward [102] but nothing at the scale of the OR suite and what could be the rate of flow exchange between an OR and the OR adjacent to it. This is what we are going to analyze in the coming paragraphs.

5.2.3 Boundary conditions

Free boundary condition was applied at the doors and the end of the hallway, which allowed fluid to circulate between the OR and the corridor freely following the airflow and to leave the computational domain freely as well. Pressure and temperature in the model was taken as the same as the ambient one.

Our model is constituted of one OR containing different inlet vents at the ceiling, they simulate the laminar grid inlets of a real OR. There are three rows of inlets, the one in the middle is on top of the OR table and blows at velocities between 0.9 m/s and 1.1 m/s. The differences of airflow between the different rectangle inlets are here to simulate obstruction of surgical lights for example. The two rows on the left and right of the middle one are here to avoid any flow returning to the surgical table, the left ones blows at 1.1 m/s and the right ones at 0.9 m/s, this difference represents the difference of velocities observed by measuring with an anemometer (Fig. 5.12) in the real OR, see Tab. 5.1. All these inlets blow air at a temperature of 286.16 K (13 ° C). Then, the OR presents two outlet vents that suck the air in the OR with a velocity such that they pump less volume than the one injected by the ceiling inlets to create a positive pressure of about 8 Pa. Pressurization is a key factor in controlling room air flow patterns in a healthcare facility. Positive pressurization is used to maintain a flow from clean to less clean spaces. The appropriate airflow offset to reach a desired pressure differential depends mostly on the quality of construction of the room. It is difficult, if not impossible, to know what the room leakage area is before finishing the construction and doing measurement of airflow. We received from the FMS of the hospital the values of volume per minute that the inlets are blowing (2430 CFM, 1.15 m^3/s) and the ones going through the outlets (1165 CFM, 0.55 m^3/s). As the surface of the outlets is known, the velocity of the outlet vents were 0.5 m/s for the left one and 0.4 m/s for the right one, on Fig. 5.2. The volume of extra air present in the room is calculated using:

$$1.15 - 0.55 = 0.6m^3/s. \tag{5.6}$$

This volume, source of the sur-pression in the OR, has to leave the OR in such a way. By searching in the literature we found the velocity of the air at the leaks under a pressure of 8 Pa: around 700 FPM (3.55 m/s). The surface of free opening in the OR is then given by:

$$0.6/3.55 = 0.17m^2. \tag{5.7}$$

It is known in the literature that with a leakage area of 0.14 m^2 or more, it becomes very difficult to maintain a differential pressure of more than 2.5 Pa which explains the higher velocities present in our domain. For the same reason, it is very complicated to maintain positive pressure if a door is open.

This information was used to build the surface of free boundaries at the doors, one is represented by gaps at the edges of the door and the other one is modeled

by a single crack in the left wall of the OR on Fig. 5.2, each of the doors as a free boundaries surface of 8.5 cm^2.

For the hallway, the airflow was simulated as it is observed and measured with an anemometer (Peak Meter MS6252B) (refer to chapter 3), with the top wall being a ceiling inlet vent with a velocity of 0.1 m/s and one AC inlet vent close to the entry door of OR 1 with a velocity of 1.2 m/s. The entry of the next OR was modeled too, with a hypothetical door open and a free boundary in it, representing the reverse of surpression when someone is entering in the room. The other side of the corridor is a free boundary, see Fig. 5.2. The OR table is described by a box in the middle of the scheme and the anesthesia equipment is also simulated by a box close to the wall. The door is represented by a rectangle with a gap between the door and the wall/floor on each side. The door can also be characterized by its angle of opening. The goal is to be able to compare the effect of the opening of the door on the rate of droplets leaving or entering the OR. We analyzed two different cases: door close (0 degree) and totally open (90 degrees). To complete the model, measurements of temperatures at different point of the OR suite were made, see Tab. 5.1.

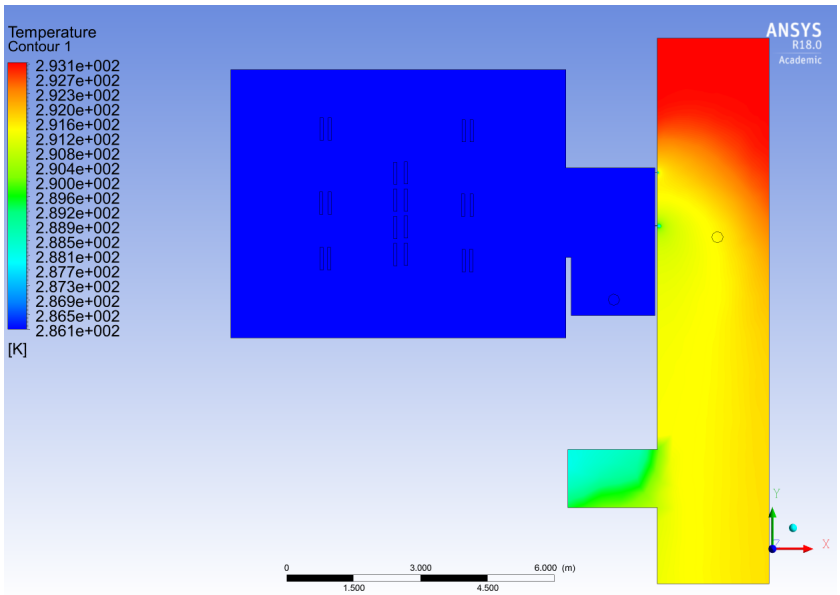


FIGURE 5.3: Representation of the temperature inside the OR and the hallway in steady mode with the door closed. There is a clear impact of the OR temperature and airflow on the temperature of the hallway.

5.2.4 Results

Steady mode with door closed

We first analyzed and compared the profiles in the steady mode. This mode represents the most common situation in the OR during a case for example, the door is supposed to stay closed as much as possible to avoid any unnecessary contamination. First, even with the door closed, the airflow in the OR has an impact on the airflow in the corridor, as seen on Fig. 5.4 which represents the 3D path lines coming from different inlets in the model. The change of direction of the path lines near the door in the hallway is due to the interaction between the air being expulsed through

TABLE 5.1: Boundaries conditions of our system with velocities and temperatures.

Boundary	Type	Velocity	Temperature
AC inside OR	Velocity inlet	1.2	286.15
A/C hallway	Velocity inlet	1.2	292.15
Top hallway	Velocity inlet	0.1	293.15
Inlet middle OR	Velocity inlet	4 x 1.0	286.15
Inlet right OR	Velocity inlet	3 x 1.1	286.15
Inlet left OR	Velocity inlet	3 x 0.9	286.15
Outlet right OR	Velocity outlet	0.4	290.15
Outlet left OR	Velocity outlet	0.5	290.15
Backdoor	Free	N/A	290.15
Bottom hallway	Free	N/A	295.15
OR 2	Free	N/A	288.15

positive pressure from the OR and the one coming from the top of the hallway. Because of the architecture of the room, the airflow does not stay laminar for a long time and turbulences happen already around the OR table. These turbulences, plus the stratification of the air create recirculation of the air inside the room that will have to be taken into account when following droplets in the model.

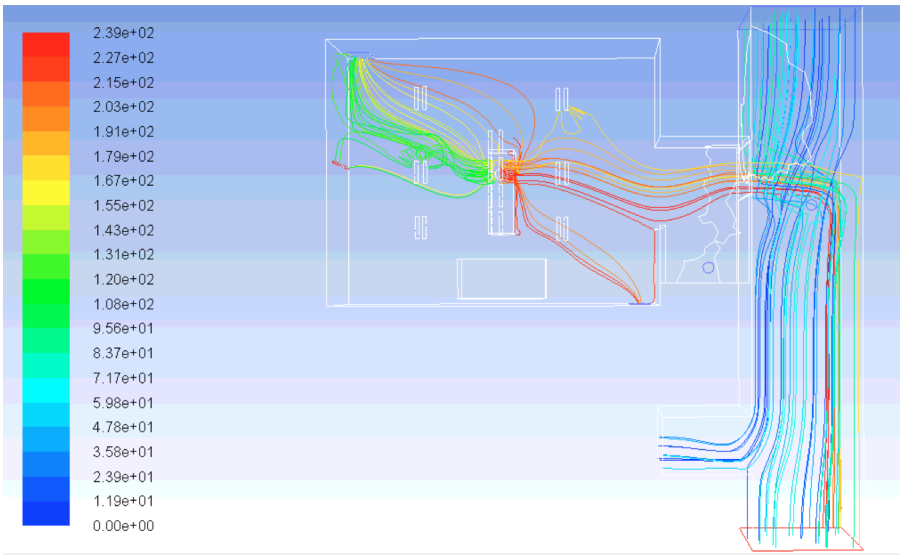
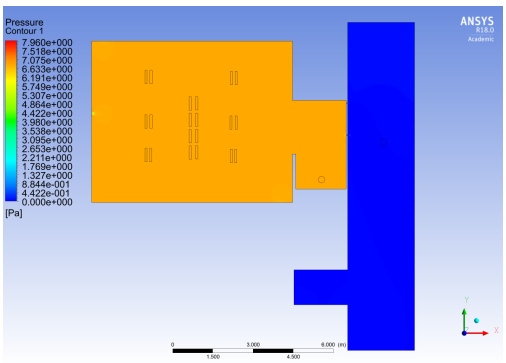


FIGURE 5.4: Representation of the path lines coming from one ceiling inlet inside the OR and from the top of the hallway

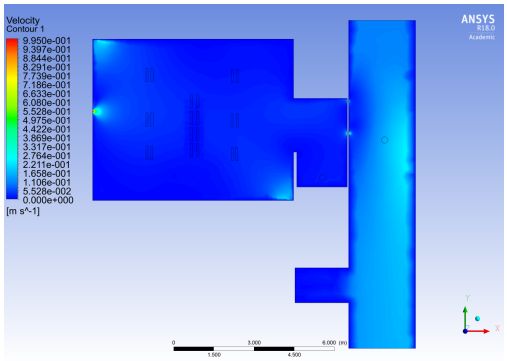
Temperature in the model is impacted by the airflow pattern too, as you can see on Fig. 5.3 the air that exits from the leaks of the OR is much cooler than the one in the hallway. Even if Boussinesq approximation is taken into account to solve the equations, see *Background*, when the door is closed, the velocities induced by the positive pressure are higher than the buoyancy-driven flow that could happen between two flows of different temperatures, that is to say there is no air entering from the corridor to the OR in steady mode with the door being closed.

The static pressure in steady state is around 7.5 Pa with a small gradient of pressure at the edges of the two doors. Without any activity at the door, the positive

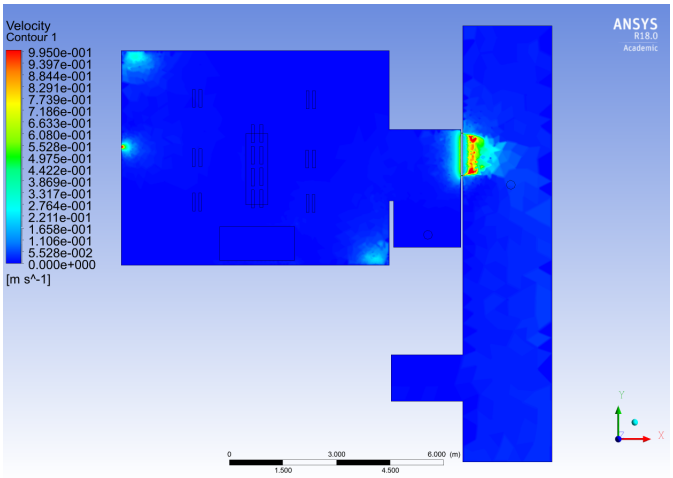
pressure is well-maintained in all the room which is important to avoid undesirable deposition of particles at specific spaces of the OR which could create a source of airborne contaminants. The positive pressure comes form the difference of airflow injected in the model and the one passing through the outlets, taking into account leakage. One more time this is in concordance with what the FMS staff told us as they want a pressure of 0.035 inch of water (in. wg) gauge which correspond to almost 8 Pa, ASHRAE recommends a pressure of at least 0.01 in. wg (2.5 Pa). The higher pressure is due to the larger than normal volume of the room studied as well as its surface of leakage.



(A) Representation of the static pressure inside the OR and the hallway in steady mode and with the door closed. The gradient of pressure is more than 7 Pa.



(B) Representation of the velocity at 1 meter from the floor. The only higher velocities are close to the exits and outlets.



(C) Representation of the velocities at 5 cm from the floor in front of the door. This presents the highest velocity of the domain.

FIGURE 5.5: Steady mode results on environment parameters of the model with the door closed

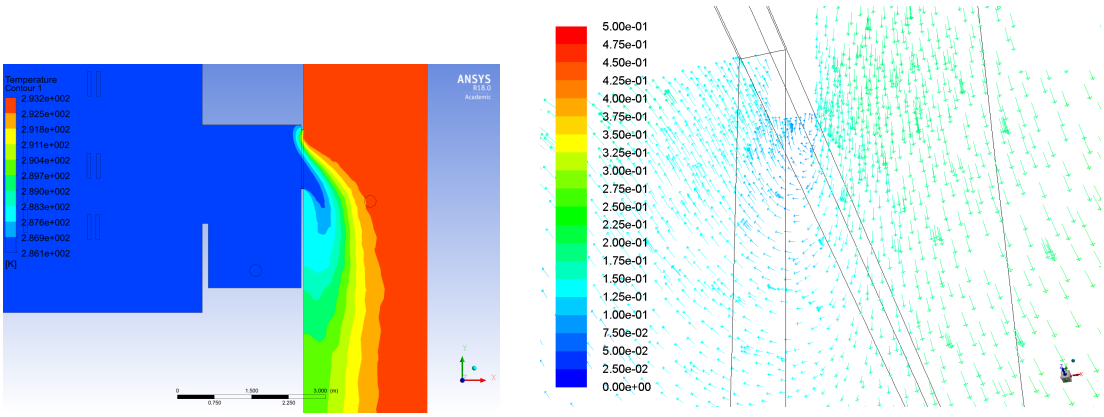
When looking at velocities, first, there are no velocities superior to 0.2 m/s inside the OR, at human heights, to maintain a level of comfort and try to avoid as much as possible turbulences and recirculating air. This is in concordance with the requirements from the regulations about airflow in the OR and with the measurements done with an anemometer, see Fig. 5.12. In the hallway the velocities are a bit higher because of the addition of the "jets" coming from the edges of the door and

the natural higher flow due to the specific A/C airflow and the architecture of the OR suite hallways at our institution.

At the door, the velocity inside the different gaps, with the floor, ceiling and walls is reaching around 3 m/s and exit the gap at less than 1 m/s just in front of the door, see Fig. 5.5c, which was also what was found in the literature to maintain a positive pressure of 8 Pa and what was found during measurements at the door, see Fig. 5.12 (Door and Under the door).

Steady mode with door open

There are multiple time that the door can stay fully open for more than couple of seconds; the moment the patient bed enters or exits, the door stays open at least 15 seconds according to our smartOR system, entering or exiting of large machines can take more than 10 seconds and can happen during a case if their use was not anticipated, during cleaning when nurses or janitorial crews leave the door open for more than 15 minutes sometimes to evaporate the cleaning product faster. This is the case simulated here, the door stays open long enough that a steady states is reached between the inside and the outside of the room. As it has been said earlier, the positive pressure cannot be maintained with such a large leakage of air, the pressure is now close to homogeny in the whole domain. In this situation, the AC system close to the door as well as the buoyancy driven effects are taking over and lead the airflow. Indeed, there is a continuous exchange of air from the inside like before but also from the outside. Following a gradient of temperature, warmer air as the tendency to go towards colder air. This is what is observed in the model when plotting the temperature profile at the doorway, there is warmer air inside the OR on the right side of the doorway when looking at it from the hallway, see Fig. 5.6a. Following the gradient of temperature and, as such, the one of density, there is also a flow created from warm air to colder air following the buoyancy effect. We observed this flow when plotting the velocities vector pattern at the door way and see that the velocity direction take a turn when reaching the edge of the door on the right side of the door, see Fig. 5.6b.



(A) Temperature profiles at the doorway

(B) Reverse of the velocity direction when reaching the door at the mixing of cold air from the OR and warm air from the hallway.

FIGURE 5.6: Observation of the buoyancy effect under the Boussinesq approximation on the direction of airflow when solving Navier-Stokes equations with the density not constant.

There is no more high velocities in the domain, the range of velocities is now restrained by the boundary conditions as there is less narrow edges behaving as accelerator of airflow.

Transient mode and CO_2 phase tracking

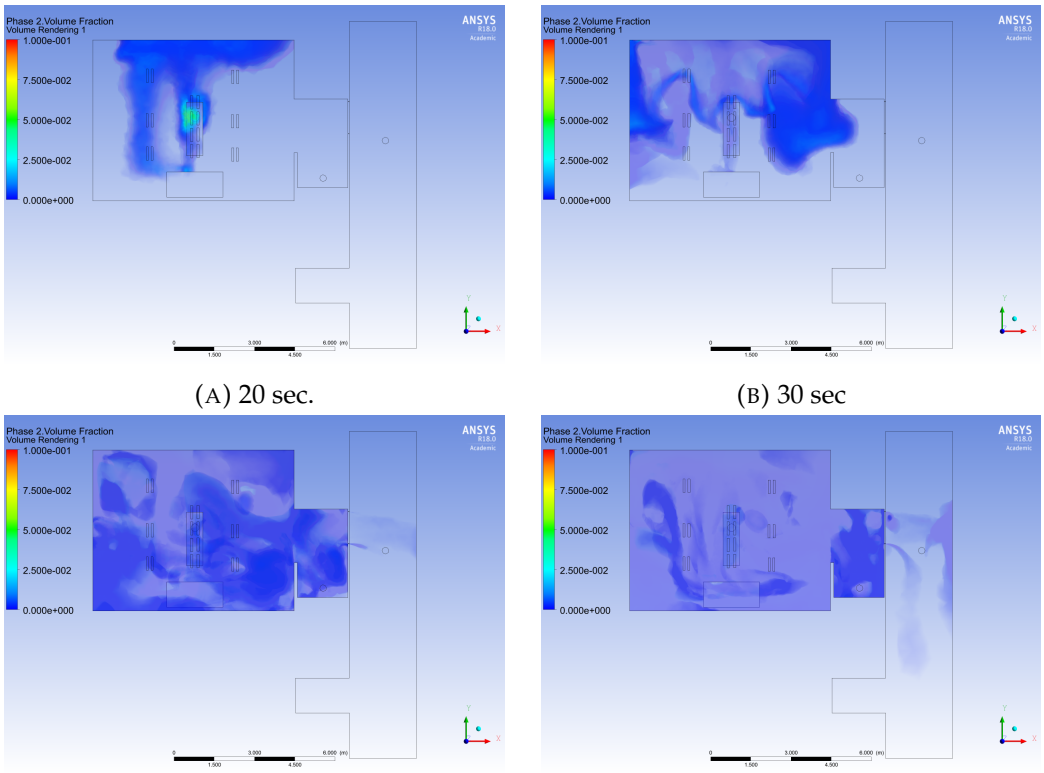
The steady mode was an important step to validate the model and see its behavior in regards to different boundary conditions. After adjusting the closest parameters to the reality using to measurement and airflow computations, we were ready to study the evolution of the system in time and follow volume fraction of contaminants. To go further in this model and compare with the results of clinical experiments presented in the previous chapter we added a second phase in the model. This phase simulate the smoke produced by electrosurgical instruments during a case. The plume is produced from the OR table and is constituted of CO2 with a density of $1.7878kg/m^3$ while the one of the air which is the second phase in the model is $1.225kg/m^3$. In order to compare the situation with the experiments in the OR, the gas was injected for 10 sec to have a high enough concentration and followed the volume fraction in the OR through time until most of it exits the domain. Same as in steady mode, two different situations were analyzed: door closed with injection inside the OR and door open with injection in the hallway to simulate contaminants coming from outside of the room.

Injection inside the OR with the door closed

The gas is injected from a source on the OR table and follows the airflow of the OR. As seen during the experiments and in the steady flow, the gas recirculate in the room and typically after about 60 seconds is dispersed in the whole room following recirculating air flows. The dispersion is not uniform around its source, it starts by following the axis of the OR table and go towards the wall on top of Fig. 5.7a after 20 sec. Then the plume follows the wall and split itself into two plumes. The most interesting plume is the one going towards the door. It takes the droplets around 30 sec. to be close to the door (Fig. 5.7b) and 60 sec. to start leaving the OR through the gaps of the door, see Fig. 5.7c . Indeed, as expected, even a narrow gap at the door is enough for the plume to go out of the room in large quantity after around 80 sec, which correlates with our experiments too. With our 3D model and a gap of only 1.5 cm between the door and its frame on the right side (looking from the OR) and 2 cm above and under the door (to reach the good leakage surface as seen before) the model shows smoke leaving the OR and reaching the end of the hallway after 2 minutes of simulation, see Fig. 5.7d. This is due to the differential pressure and the velocity of the airflow in the OR but also to the unidirectional airflow in the hallway. It has a strong influence on the flow of the hair product particles (see previous chapter) as well as on the CO_2 molecules used in the model. Finally, it takes about 700 seconds for the smoke to totally disappear from the domain without any activity at the doors, which fits the experiments too as the time between two injections was around 8 to 10 minutes, the time needed to reach a level of particles detected low enough. The backroom (on the right side of the door when looking at it from the OR) is also to take into account as it acts, like a reservoir of droplets.

Injection outside with the door open

In transient mode and the door open, the part that is of interest is the air exchange from the outside to the inside due to the buoyancy driven flow. Indeed, in the steady



(A) 20 sec. (B) 30 sec

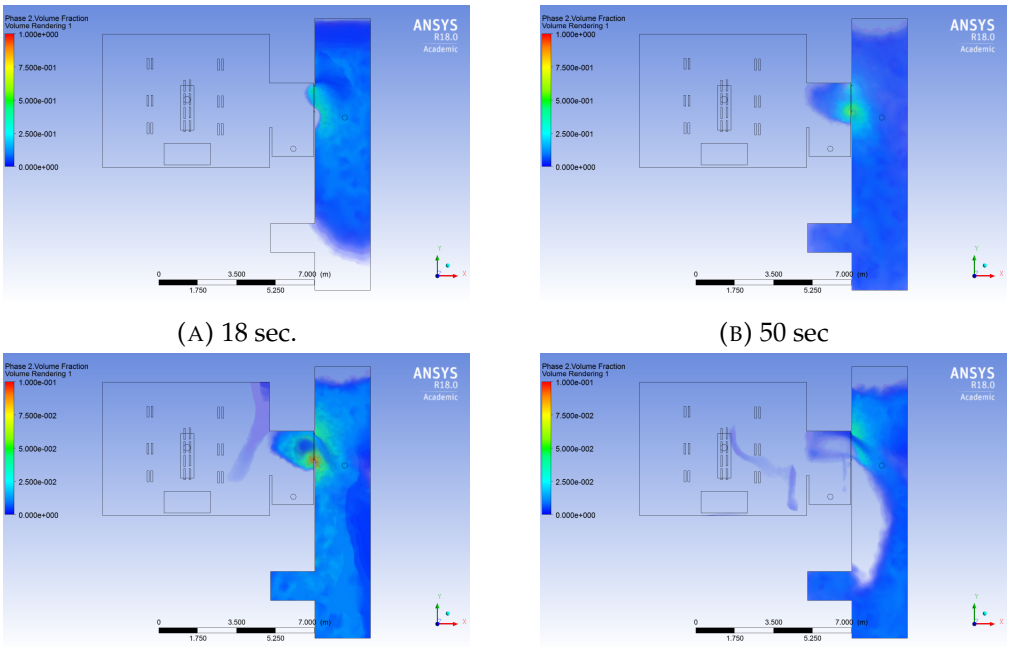
(C) 60 sec (D) 120 sec

FIGURE 5.7: Dispersion of a plume of smoke inside and outside the OR when the door is closed at different step time.

mode, the temperature profile at the doorway was not linear and the air in the OR can get warmer under this effect. The difference of density between warm air and cold air as the effect of creating a flow from warm air to cold air. As the gravity is taken into account in the model, the computation simulates this effect when solving the Navier-Stokes equation with ANSYS. The contamination is constituted of CO_2 coming out of the inlet at the top part of the hallway with a mixed flow of 50% air and 50% CO_2. The evolution of fraction of CO_2 is followed during 450 seconds. You can see the result of different time stamps on Fig. 5.8. After around 18 seconds of simulation, the smoke starts to enter the room following the same path lines found in steady mode, see Fig. 5.6 and 5.8a. Then it enters the room in higher concentration until the beginning of the OR where recirculating air and the row of first laminar flow slow down the progression. After 82 seconds, a little part of the plume, which was following the wall on the right side, is then taken into the flow of the OR and reach the OR table. This proves the importance of keeping the door closed to maintain the positive pressure as well as the gradient of temperature low between the hallway and the OR in order to control the contamination rate and nosocomial propagation in the OR suite.

5.2.5 Contamination from one OR to another

After showing that the airflow was going out of an OR, the goal is also to see if droplets, that have the size of possible airborne diseases, could leave the OR, follow the unidirectional flow in the hallway and reach the door of an adjacent OR. This can be a delicate problem for hospitals, positive pressure is for sure the solution to



(A) 18 sec. (B) 50 sec

(C) 82 sec (D) 130 sec

FIGURE 5.8: Dispertion of a plume of smoke inside the hallway at different step time and buoyancy effect with smoke coming inside the OR.

avoid any kind of contamination OR A – OR A. But it can also be source of contaminants in the hallway that can lead to a possible contamination OR A – OR B. While we already proved that droplets are leaving the OR following gradient of pressure and velocity at the door through clinical experiment and simulation, we also found a unidirectional pattern in the airflow coming out of the AC in the hallway that is pushing these existing particles towards the entry door of the adjacent OR. We pushed further the modeling and added to our model the door of the neighbor OR in our OR suite. This door is at 5 meters of OR 1. Now, the simulation ran for more than 15 minutes to follow the distribution of the plume in the hallway and its dissipation rate inside the OR. It takes 130 seconds for the plume to reach the adjacent OR and to start entering it, see Fig. 5.9. This means that without any specific activities at the door of OR 1, the surgical plume (or any other contaminant present in the room) can reach the door of the adjacent OR in just a little bit more than 2 minutes. In our model, the boundary conditions inside OR 2 are left free, just the temperature at the end edge is cooler than the hallway to simulate the cooler air inside the OR. This is to simulate the door of this OR left open or the moment someone enters and reverses the positive pressure for a short amount of time. The probability that this situation happens is low but one droplet of contaminant is enough to alter the air quality inside the room and augment the risk of wound infection. The model built in the next part will focus more on that rare situation taking into consideration the opening and closing of the doors in a large OR suite.

5.2.6 Verification

The verification process determine if a model implementation accurately represents the conceptual description of the model and the solution to the model. this process can be separated into 3 phases. First, you examine the iterative convergence, then

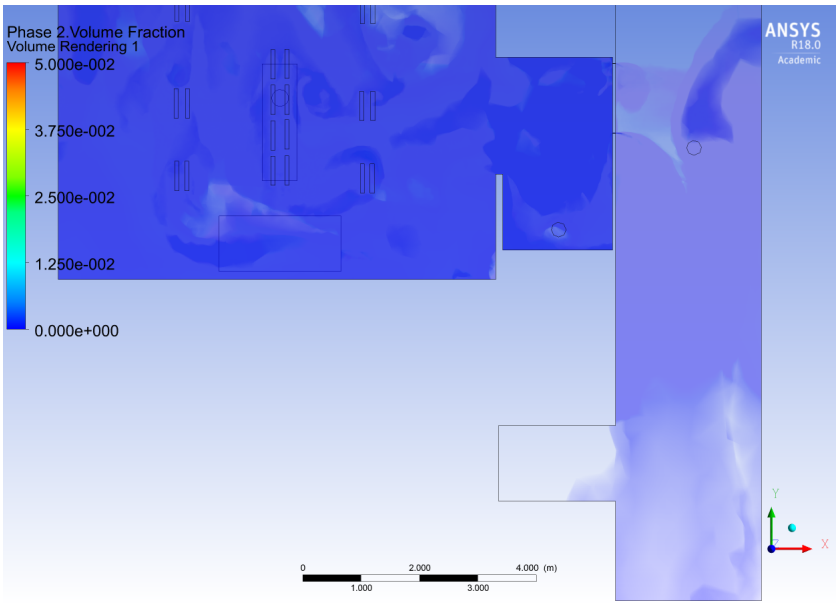


FIGURE 5.9: Presence of smoke inside the adjacent OR of the one with the source. It takes 130 seconds for the plume to reach and enter the other OR.

verification assessment requires that the grid used demonstrate spatial convergence and finally, the CFD simulation should demonstrate temporal convergence too, we are going to make sure these three points are verified with our model. For the last two points, we are going to base the verification on specific level set of fraction of volume of toxic gasses as this is what we want to monitor in our model to be able to know the spaces with good or bad air quality.

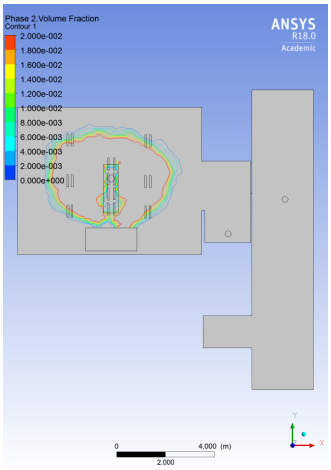
Convergence with respect to number of iteration of the solver and residual

CFD methods involve an iterative scheme to arrive at the simulation results. In a steady state simulation, the model starts with a uniform flow field and iterates until the steady-state flow field is obtained. This requires some criteria for determining convergence. The evolution of residuals of the equations was taken as criteria. We observed that the residual of every equation in our domain was reduced by 4 order of magnitude after 500 iterations and were staying constant after.

Convergence with respect to the grid

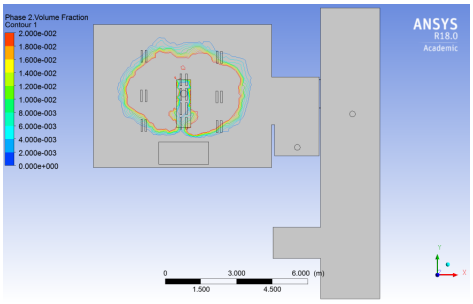
Then validation of the spatial grid convergence was also needed in order to verify the non-dependency of the results with the refinement of the mesh. All the results presented in this thesis were done with a mesh of around 1 200 000 elements. As this model was already pretty refined we wanted to test the results of the computation on a smaller number of elements and reduced it to 700 000 elements. The comparison of isolines of the volume fraction of CO_2 is plotted on Fig. 5.10 at different time steps (15 and 62 sec). We can see that the lines above a certain critic volume (in red) is the same in both models which means that with these two numbers of elements we could build an accurate model of zones where the concentration is unhealthy. It is important to note that a mesh of 500 000 elements was first tried but the results

were not accurate enough and we chose that 700 000 was the lowest limits of number of elements in our 3D model.

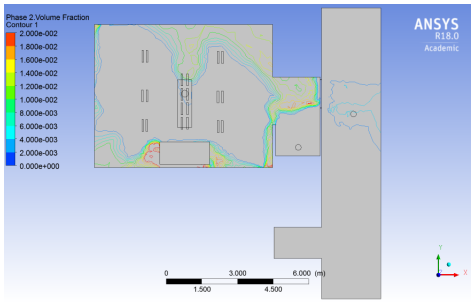


(A) 15 sec, fine mesh.

(B) 62 sec, fine mesh.



(C) 15 sec, coarse mesh



(D) 62 sec, coarse mesh

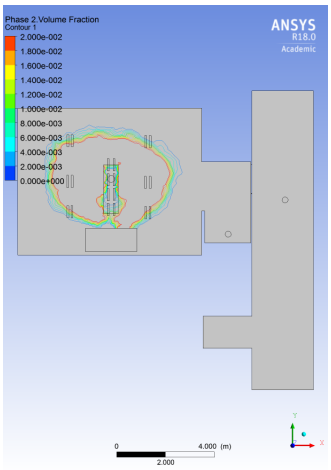
FIGURE 5.10: Examination of spatial grid convergence by comparing the isolines of fraction of volume of gas in the model with different refinement of the mesh: 1 200 000 elements on 5.10a - 5.10b and 700 000 elements on 5.10c - 5.10d.

Convergence with respect to the time step

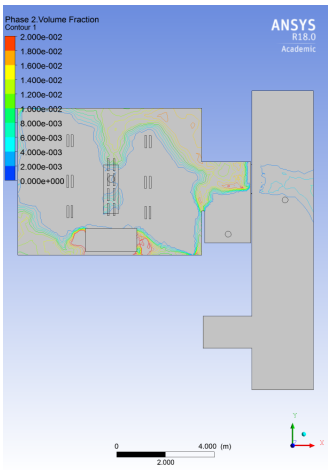
Finally, the examination of the temporal convergence was also done on the model. The time step used for the results presented in this thesis was of 1 sec. To examine the non-dependency of the result on the time step we did the simulation of propagation of a smoke plume inside the model with a time step of half a second. As seen on Fig. 5.11, the isoline of volume fraction of CO_2 gases are the same in both configurations. It is also interesting to note that we performed an analysis with a time step of 0.1 sec, which gave results that was a bit more accurate but the analysis took more than a 24 hours to simulate 300 seconds on a computer equipped with a dual processor.

5.2.7 Validation

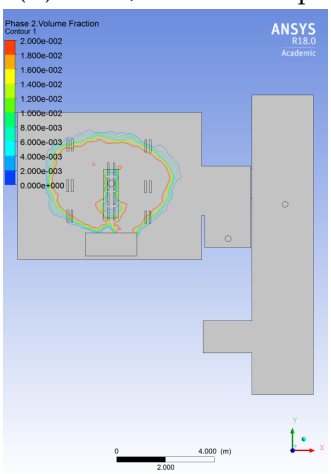
The validation process determines the degree to which a model is an accurate representation of the real world for the intended uses of the model. The idea is to identify and quantify uncertainties through comparison of results from the simulation with experimental data, thus everything is depending on the accuracy of these data. To



(A) 15 sec, 1 sec time step



(B) 62 sec, 1 sec time step.



(C) 15 sec, 0.5 sec time step

(D) 62 sec, 0.5 time step

FIGURE 5.11: Examination of temporal convergence by comparing the isolines of fraction of volume of gas in the model using different time step: 1 sec on 5.11a - 5.11b and 0.5 sec on 5.11c - 5.11d.

do this, we measured the velocities at different places of the OR and compared them with the profile we found with our model. An anemometer has been used to check the velocities of the inlets and outlets in the room that were used as boundaries conditions of our model but we also measured the velocities at the free boundaries. Due to the sensibility of the anemometer we used ($0.5 - 30m/s \pm 2.0\%$), we focus on the highest velocities present in the room, which were at the outlets and at the door gaps, see Fig. 5.12. The values of 1.5 m/s at the edges and 0.8 m/s in front of the door in the hallway have been found in the model, see Fig. 5.5c. Also, the maximum velocity inside the model is 3.6 m/s and was present inside the gap at the leaks, which corresponds to the velocity (3.55 m/s) needed for a positive pressure of around 8 Pa inside the room according to Flaniken [47]. As seen before, when the door is closed, the pressure of 7 to 8 Pa imposed by the building engineers of the hospital was also found in the steady mode of the model. Finally, when it comes to the distribution of toxic gasses in the model, we see that the smoke follows the same path and triggers the sensors in the same order than what we were seeing during our experimental tests. Also, the ratio, R, of the number of particles detected between the surgeon position (sensor 3) and the position of the sensor 1 is of the same order, 0.55, between

the experimental data (Fig. 5.17) and the simulation one (see Fig. 5.13). The delay to reach a sensor can be also compared, it was taking an average of 10.3 seconds to reach the sensor 3 when it takes 10 seconds in the model to reach a detectable fraction at this exact same position. These results are reported onTab. 5.2.

TABLE 5.2: Comparison of different values found by the model and the one found during experimental tests.

Parameter	Measurement	Simulation
Velocities (inside leaks)	3.55 [47]	3.6
Velocities (in front of the leaks)	1.5	1.2
Velocities (in front of the door)	0.8	0.8
Pressure (Pa)	7.5	7.3
R	0.56	0.6
Delay sensor 3 (sec)	10.33	10
Delay sensor 1 (sec)	31	29

FIGURE 5.12: Measurements of velocities inside the studied OR with an anemometer.

5.2.8 Conclusion

OR environment should be comfortable for occupants without putting on the side safety and possible wound infection due to airborne particles. Achieving this goal with the HVAC system involves to be able to simulate and control a number of factors. We built here a system that tries to mimic the reality of a part of a real OR suite. Lots of difficulties had to be overpassed in order to build a system as close as possible from the reality. First, it was impossible to restrain our self to a 2D model, mostly because of the stratification of the air inside the room due to the specific architecture of the ceiling inlets and low level wall outlets. Then, we needed measurements from the real site of different velocities, temperatures, pressures and design to build and then validate our model. At the end, we built a model where it is possible to simulate any kind of contamination from inside or outside of the OR. The monitoring of the propagation of a second phase has a lot of advantages, first it is simulating the emission of surgical smoke produced by the electrosurgical instruments and give

the opportunity to compare the model with clinical experiments as well as with a mathematical system model that is going to be explained in the next part of this chapter. As we did with the experimental tests we were able to answer crucial questions of air quality security concern. The main result being that smoke produced in one OR takes around 60 seconds to be spread in the whole room, then a part of it is pushed inside the hallway and lead by its unidirectional flow to finally reach the entry door of the adjacent OR with a probability different than zero to get inside it under certain condition such as someone entering the room. The model showed also the most strategic places to install the sensors and follow with higher accuracy the link between OR activity and increase of concentration of particles. On top of this, the system can be used to monitor the concentration of particles inhaled by the patient and the staff. This can be part of a awareness system that not only knows the activity inside the room as seen in Chapter 2 but also knows the status of the quality of the environment at any time depending on the status of the case. The system can compute the concentrations of toxic gases present where the staff are usually placed, see Fig. 5.13 and alert them if they reach a non-healthy level or even warn them to change position at certain steps of the surgery without compromising the security of the patient.

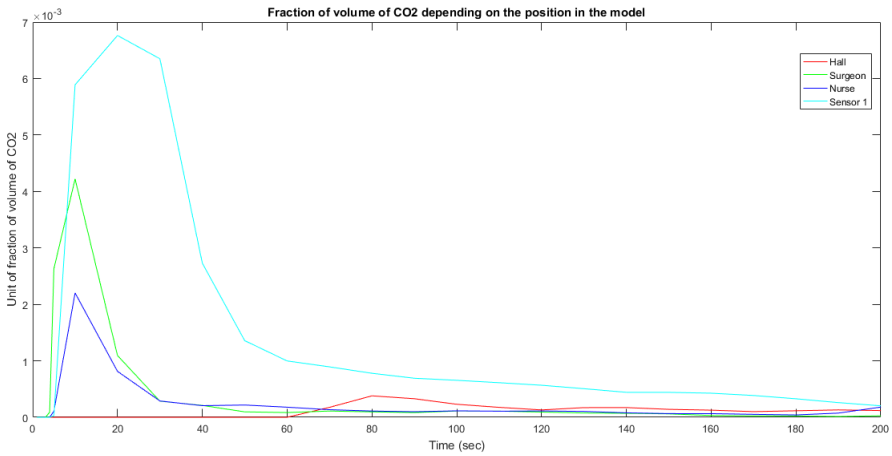


FIGURE 5.13: Simulated volume fraction of CO_2 inhaled by the surgeon and the nurse compared to the one of sensor 1 and what is in the hallway. It is intersting to observe the delays and different of amplitude of these plots that match the experimental results. The values are normalized and the amplitude depends on the initial concentration.

5.3 A system approach to assess transport and diffusion of airborne hazard in a large OR suite

5.3.1 Methods

In this part of the thesis, the concentration of a so called "marker" is monitored. It can be a specific gas or set of airborne particles in the air of the OR suite. The model was built step by step and all these steps are going to be presented in this chapter. As an example, let us consider a system of eleven identical ORs aligned on one side of a hall. Each OR has a one door access to the hall. The system is representing a standard OR suite, see Fig. 5.14. This set up is based on the infrastructure we have been using during the experimental set up seen in Chapter 3

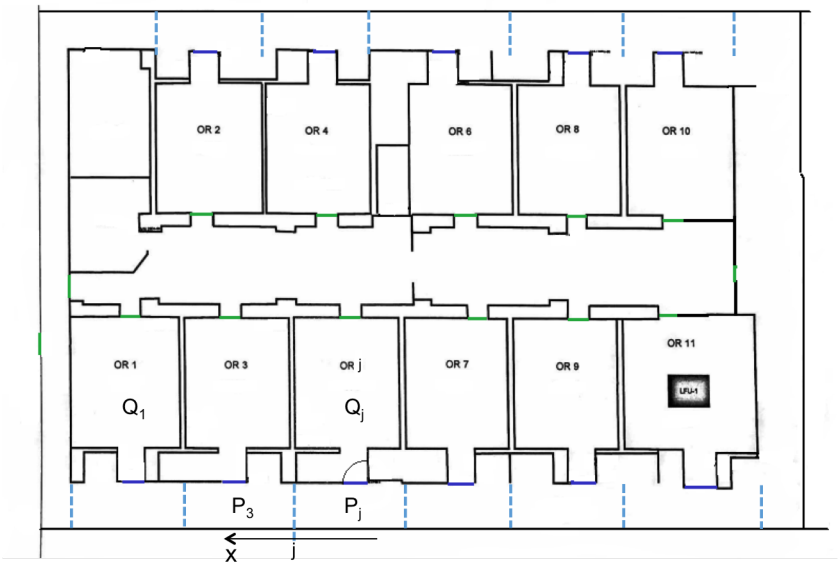


FIGURE 5.14: The architecture of the floor plan of the OR suite used during OR test. The blue dot lines represent the splitting for the customized compartement system approach.

The marker is generated at the OR table location to simulate the use of an electrosurgical instruments that produce thermal destruction of a tissue. It can be also the product of the evaporation of any alcohol-based chemical used either to prep the patient, or clean the OR. The model has two parts: first a compartment like model that can monitor the indoor pollution [26], second a multi-scale agent-based model that mimic the surgical flow activity related to indoor air quality [54]. We will see in particular that staff traffic in the OR suite with door opening and closing will be manifestly a key mechanism for propagation of markers. Tracking particles is represented by a linear set of differential equations that will be slightly more complex than a standard compartment model since the coefficients will be stochastic, some source/sink terms will have time delay build in, and the hallway will require a transport equation. The rational to build that specific model will come out of our set of experiments described thereafter and in Chapter 3.

Let us describe first the acquisition process to identify the production of airborne contaminant.

5.3.2 Experimental set up to asses the source of particles

We delivered energy to 2 cm thick pieces of pork meat on an OR table, by applying the tip of the energy device to its upper surface, see Fig. 5.15. We compared four types of energy delivery system, respectively electrosurgery (conduction) with the Covidien ForceTriad monopolar electrosurgery, ultrasonic (mechanic) with the Ethicon Harmonic Scalpel P06674, bipolar electrosurgery (conduction) with the Covidien Bipolar Ligasure and laser tissue ablation with Erbe APC (Argon Plasma Coagulation) 2. To keep the tissue burn superficial, we follow with the device a pattern of parallel lines and always used unburn pieces of meat. The energy was delivered for a period of 30 s up to 60 s in order to produce large quantity of smoke and thus particles. The measurement was done by several laser particle counters from Dylos Corp placed at various distance from the source like seen in Chapter 3 (`http://www.dylosproducts.com/dc1700.html`). They give an average particle count every minute in a unit system with units u_d that corresponds to 100 particles per cubic foot. A traditional problem with the validation of particle count in laboratory conditions is that particles should not be all the same uniform size. According to the company smartAir (`http://smartairfilters.com/cn/en/`) which is selling indoor air purifiers in China, the Dylos system output is highly correlated (r=0.8) to a "ground true" measurement provided by a professional system such as the Sibata LD 6S that is claimed to be accurate within 10 % in laboratory controlled conditions. According to smartAir, the Dylos system seems particularly accurate at the lower concentration ends that is of interest for our purpose. Semple *et al.* [117] also compared the Dylos system with a more expensive system: the Sidepak AM510 Personal Aerosol Monitors (TSI, Minnesota, USA). Even if this system is supposed to be more accurate, it was also 10 times more expensive, extremely noisy, and difficult to use, according to them. They concluded that the Dylos output agrees closely with the one produced by the Sidepak instrument with a mean difference of 0.09 $\mu g/m^3$.

FIGURE 5.15: Smoke generated by the use of electrosurgical instrument during our controlled tests on porc meat.

We set up the Dylos sensors to track particle of small size in the range from 0.5 to 2.5 microns, which are the size of particles that can load biological material. We checked systematically the results by comparing the measure of several sensors at the same location to show consistency, as well as checked that the particle count goes back to nearly zero in a clean air room with AC equipped with High Efficiency

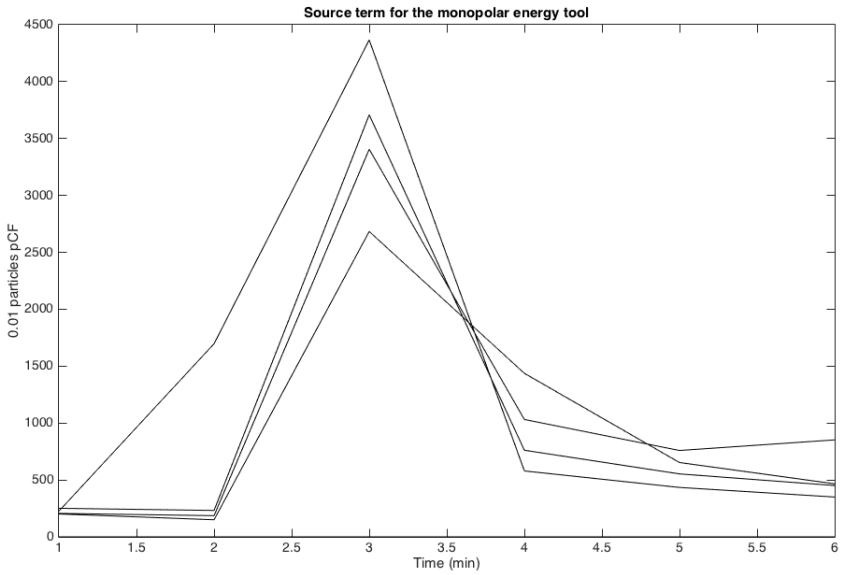


FIGURE 5.16: **Analysis of the source of particles** produced with the monopolar energy system in order to find the source term A of our system

Particulate Air (HEPA) filters. We started each experience from a clean air initial condition with a particle counter unit less than 50 units.

For each experiment, following the time of energy delivered, we observed that the concentration increases to a maximum within a minute, depending on the distance to the source, and relaxes to zero exponentially - see Fig 5.16. We used least square fitting to interpolate the data with an exponential function as follows $A\ \exp(-\rho\ (t-s))$ for the relaxation part of the process. We identify both the amplitude of the source A (see Fig. 5.16), the delay s on particle diffusion and transport to reach the sensor, and the rate of diffusion decay $\rho > 0$. s measures the time interval between the source delivery and the pick of the signal with an accuracy within one minute due to the accurarcy of the sensor. For each experiment, the concentration over a period of 6 minutes is monitored. Beyond 6 minutes the concentration becomes negligible compare to the peak value and the particles present naturally in the room. Each experiment were done 4 to 5 times. Therefore, about 24 to 30 data points were available to identify the parameters A, s and ρ. A and ρ were assumed constant while s may depend on the distance between the source and the sensor.

Let us now describe in complement of Chapter 3 our protocol of the experiments to asses transport and diffusion of particle in different area of a large OR suite.

5.3.3 Assimilation of experimental data

This set of experiments as opposed to the previous one was done in a large OR suite, late at night or during weekend when the ORs were empty and its activity was at its lowest. The source used was a hair spray product (Lamaur Vitae, unscented) for a duration of 1 to 2 seconds and keep the same setting of the Dylos system to track very small particles in the range of 0.5 microns. We first tested the propagation in the OR with closed door with the source above the OR table. The spray jet was done

in a direction close to the vertical pointing to the ceiling. The sensors were installed as shown in Fig. 5.17.

As seen in Chapter 3, all sensors distributed in the OR (sensors 5, 3 , 4 and 1 on Fig 5.17) space were getting a particle count of the same order of magnitude after a minute. We observed that the mixing was quite extensive within a minute due to the design of the AC input/output in the OR, and that the concentration on all sensors were quickly relaxing to zero as in our previous experiment set up.

To confirm that observation we implemented a 3D model of the flow circulation and particle dynamic in the OR that took explicitly in account all boundary conditions, in particular relalted to the air conditioning system, with the CFD Finite Element software Ansys. The 3D simulation with Ansys provided the same conclusion and was presented in the precedent part of this chapter. We used then a method identical to the previous one to identify the key parameters A and ρ. The model for OR diffusion of particle is then:

$$\frac{d}{dt}Q(t) \;=\; -\rho_{OR}Q(t) \;+S(t=0),\; t>=0 \tag{5.8}$$

where $S(t=0)$ denotes the source delivery at time zero. This simple model provides some average of particles concentration in the OR at the minute time scale.

A first order implicit Euler scheme with a time step dt that is one minute was used:

$$\frac{Q(t_{n+1}-Q(t_n))}{dt} \;=\; -\rho_{OR}Q(t_{n+1}),\; Q(t_0) \;=\; S(t=0). \tag{5.9}$$

A similar technique described the dynamic of particle diffusion and transport in the hallway, except that the hallway is discretized as a one dimension structure of consecutive hall block located at the same level than the OR block, see Fig. 5.14. In this experiment the source is set in the hallway, see Fig. 5.17 red cross 4.

One interesting finding is a true transport phenomenon along the hallway adjacent to the OR. As a matter of fact, the most frequently used access door to the hallway that is at one end of the corridor at the main entrance induces a very low flow speed denoted v_0 that run down the hallway toward the main entrance of the OR suite. Naturally the higher pressure of the OR is designed to drive the airflow out. The model of diffusion in the hallway of particle is then:

$$\frac{D}{Dt}P(t) \;=\; -\rho_{OR}Q(t) \;+S(t=0),\; t>=0, \tag{5.10}$$

where $\frac{D}{Dt}$ denotes the total derivative $\frac{\partial}{\partial t} \;-\; v_0\frac{\partial}{\partial x}$ using the x coordinate system in the one space dimension of the hallway block model, see Fig. 5.14.

To asses the transmission of particles to the adjacent hallway, the same experiments was conducted with the sensors placed in the hallway either facing the closed door, or at different distance from the door in the hallway, see Figure 5.17, sensor 6, 7, 8 and 12. As a matter of fact the door of the OR is not perfectly sealed, and due to the difference between the pressure inside the OR and the pressure in the hallway that is lower, a significant airflow with velocity of the order of 1 m/s exists at the gap location between the door side and the door frame. A similar technique is used to represent the diffusion coefficient as well as the delay s that is interpreted now as the time it takes for the particles to transport from the OR to the hallway at the outside door location. This transmission condition will be entered in the model that couple Eq. 5.9 and 5.10.

Finally, an entirely similar approach is implemented when the door of a specific OR is open. In that case the gradient of pressure between the OR and the hallway

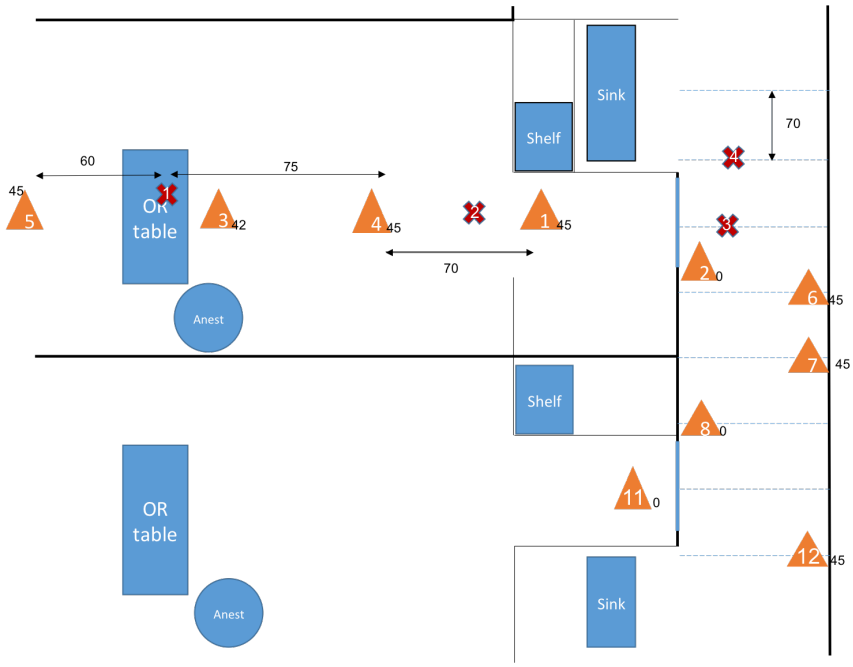


FIGURE 5.17: **Position of the sensors and sources.** We placed air quality sensors (orange triangles) at different places of the OR suite and during different experiments with multiple possible source of contaminants (red crosses)

almost immediately vanishes. A pure diffusion process in that section of the hall is expected, that is somehow the extension of what is the diffusion process in the OR. Indeed, the numerical model showed that there is no more gradient of pressure between the OR and the hallway when the door stays open.

We are going now to assemble our simple compartment-like model to monitor in time and in space the diffusion and transport of particles with intermittent source term in each OR that corresponds either to the use of some cleaning and sterilization products or the use of electrosurgical instruments during surgery. Our target is to get average exposure of staff working in the OR suite to particle concentration during the day. We are also interested to look at potential propagation of particles carrying potential biological material from one OR to another.

5.3.4 System model

As discussed earlier, particles concentration is monitored in time and in space with a coarse time step that is a minute. This time step scale is coherent with our measurement system of particle count and the limit imposed by the sensors. One minute is also roughly the time that the particles emitted from a point source next to the OR table needs to transport and diffuse in the OR block once released. The compartment model computes the global concentration of the particles in each OR as well as in each section of the hall adjacent to the OR. Let us denote those concentration respectively $Q_j(t_k)$ for OR of number j at time t_k and $P_j(t_k)$ for the corresponding section of the hall - see Fig. 5.14.

We denote $S_j(t_k)$ the source of particles. In principle $S_j(t_k)$ should be non-zero for limited period of time and follows a statistical model based on the different phases of the surgery and our knowledge of usage of electrosurgical instruments

during surgical procedure. Last but not least, we define the coefficients of decay inside the different parts of the model (ρ_{OR} and ρ_{Hall}) as well as the coefficients of transmission between these spaces (α_{OR} for from the OR to the hall and γ_{Hall} for the opposite). β_{OR} represents the flow from the OR to the hall when the door is open, this coefficient is set at 0.5 to represent a symmetric exchange of air when the door is open which fits the results of the CFD model and the impossibility to maintain positive pressure with such a large opening. After all, like the generation of the smoke, the frequency of opening of the door is following a statistical model based on the phase of the surgery we are at and is represented in the model by δ_j^{door} for the status (open or closed) of the door of OR j.

A scheduled day of surgery is simulated using our experience from the smartOR project [66, 67] and the results seen in Chapter 2. For instance, there is no use of electrosurgical instrument before intubation and the number of opening decrease during the surgical part of the procedure, without reaching zero.

The system model of marker transport-diffusion in the OR suite is written, for the OR j at time step t :

$$\frac{d}{dt}Q_j(t) \;=\; -\rho_{OR}Q_j(t) \;+S_j(t) \;+\; \delta_j^{door}(t)\gamma_{Hall}P_j(t)(t-s). \tag{5.11}$$

And for the hallway in front of OR j:

$$\frac{D}{Dt}P_j(t) \;=\; -\rho_{Hall}P_j(t) \;+\; \delta_j^{door}(t)\beta_{OR}Q_j(t) \;+\; (1-\delta_j^{door}(t))\alpha_{OR}Q_j(t-s). \tag{5.12}$$

We introduce an additional unknown to track back flow of marker in the OR coming from the hall:

$$\frac{d}{dt}B_j(t) \;=\; -\rho_{OR}B_j(t) \;+\; \delta_j^{door}(t)\gamma_{Hall}P_j(t)(t-s). \tag{5.13}$$

The benefit of this equation is that we can separately count how many particles may go from one OR to another and from what physic phenomenon do they come from. We expect this number to be very small, but we will see in the result section that it can be monitored and might be far from zero.

It is important to underline that the model (Equations 5.11, 5.12, 5.13) is not a standard box model. First, the source term has a delay s built-in to simulate the transmission conditions. The concentration of particles in our boxes is not uniform to fit the dispersion delay that we observed in our experiments and in our 3D model. Mixing type of air distribution is not suitable for an OR, the temperature is not uniform and stratification of air can be seen, moreover a uniform distribution of contaminants in the air would increase the risk of infection during surgical procedures. Second, the equation treating the diffusion in the hallway (Eq. 5.12) is a PDE, more precisely a linear transport equation, which brings an additional dimension compared to a classic box model. Third, most of the coefficients are stochastic, for example the opening or closing of the door at the OR j is controlled by a probabilistic function $\delta_j^{door}(t)$. Because the whole system of equations is linear, we used implicitly the superposition principle to retrieve each unknown coefficients from the results and observation made during the experimental protocols.

Let us describe now more precisely our surgical flow model to provide an accurate description on how the source term $S_j(t)$ is reconstructed in our model. For each of the standard OR stage of the surgery was attributed a given *State* value as follows:

- Phase 1: anesthesia preparation label as *State=1*.
- Phase 2: surgical preparation to access as *State=2*.
- Phase 3: surgery procedure as *State=3*.
- Phase 4: surgery closing as *State=2*.
- Phase 5: ending anesthesia as *State=1*.
- Phase 6: room in the process of cleaning or empty as *State=0*.

The type of airborne marker expected to be released depends on those *State* values. For example in *State 0*, cleaning crew uses a lot of chemical products that evaporate quickly in the OR. Similarly a different set of sterilization product is used to prep the patient in *State 1*. In *State 2*, cauterization is often used for a short period of time. In *State 3*, various phase of the surgery will require energy delivery instruments to cut tissue and access specific anatomy or tumors.

A stochastic model of energy delivery is used that consist to deliver short time fraction of energy in several consecutive minute. The parameters of that model are: the frequency of energy delivery denoted f, the duration of the impulse denoted ξ and the number of repetition r. The parameters of the model of energy delivery are derived from our observations at one of the large OR suite of our institution as well as with the smartOR data set. Each energy application is of the order of 3 seconds but it can be applied up to 6 times with an average of 3 applications: we call it the energy phase of the surgery and is representing as a probabilistic function in our equations. Each OR state has realistic duration and number of energy phase delivery session.

To provide the timeline of events, themodel has three surgical procedures in each OR which is very common for ORs in large hospital. The time line of each surgery will be such that: Phase 1 and Phase 5 last 12.5 min $\pm$ 5 min, Phase 2 and Phase 4 last 15 min $\pm$ 5 min, Phase 3 that is the surgery itself last 65 min $\pm$ 25 min and Phase 6 that corresponds to turnover time if it is in between surgery last 30 min $\pm$ 10 min. This simplified model of surgery scheduling has the correct order of time length for each phase and will be used to run sensitivity analysis with respect to the key parameters of the indoor air quality model.

Amplitude Source	Monopolar	APC	Harmonic
Mean (number of particles)	4800	1600	1050
Standard Deviation	5100	1100	870
Diffusion coefficient	Monopolar	APC	Harmonic
Mean	0.65	0.56	0.36
Standard Deviation	0.13	0.19	0.3
Number of experiments	5	5	4

TABLE 5.3: Comparison of amplitudes and diffusion coefficients for commonly used electrosurgical instruments.

The timeline and results of the model are coupled to a realistic multi-scale model of surgical flow that provides the same set of information but with a validated clinical data set (see Chapter 2) that corresponds to a true clinical activity over a one year period [54].

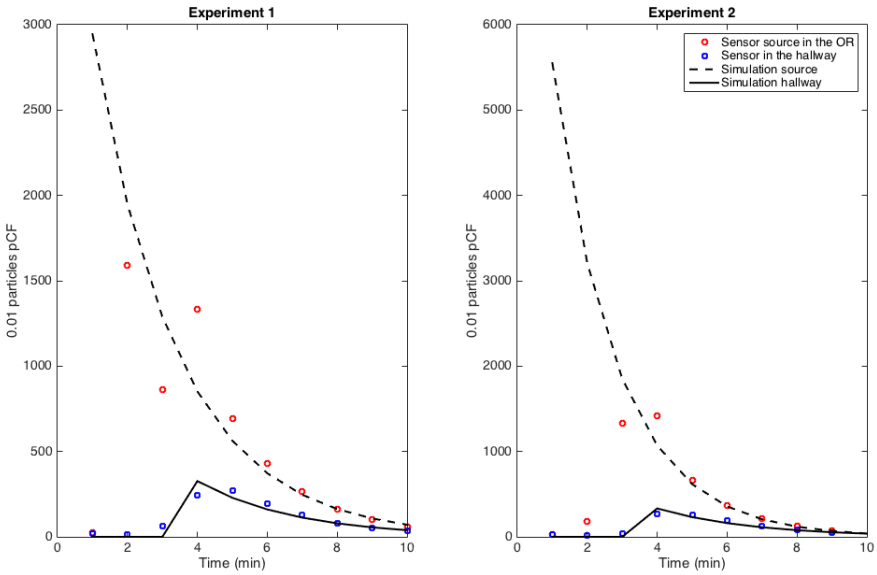


FIGURE 5.18: **Source inside the OR with closed door and impact on hallway air concentration.** We observe a 2 minutes delay in transmission from OR to hall, and an exponential decay for each signal.

Parameters	ρ_{OR}	ρ_{Hall}	α_{OR}
Mean	0.49	0.25	0.053
Standard Deviation	0.098	0.12	0.026
Number of Measures	9	9	9

TABLE 5.4: Parameters of the model extracted from the experimental tests and used in the PDEs.

5.3.5 Results

The rate of particles generated by various energy sources such as the monopolar electrosurgical instrument, APC and harmonic tool was measured in a space allocated to surgical training, i.e. not a clinical OR as opposed to previous experiments but it is still close to a real environment. Table 5.3 reports on the identification of the mean and standard deviation of the amplitude of the source as well as the diffusion coefficient for each instruments. These parameters are used inside the set of equations and quantify the concentration of particles transmitted from the OR to the hallway, see results in Fig. 5.18 with comparison with our experimental data.

There was no statistical significant difference between the rate of diffusion of the particles emitted by the monopolar and APC. The coefficient of diffusion corresponding to the harmonic instrument is lower but has strong variation. This is probably due to the fact that some of the particle emitted with this instrument are too small, 0.06 microns [138], to be detected by our sensors.

Let us report now on the identification from our experimental data set corresponding to the set up of Figure 5.17 sources 1 and 4.

The diffusion coefficients in the OR and the hallway are depending on the ventilation system that is by design more effective and more controlled in the OR than in the hall. The rate of decay in the OR is twice as much as the rate of the decay in

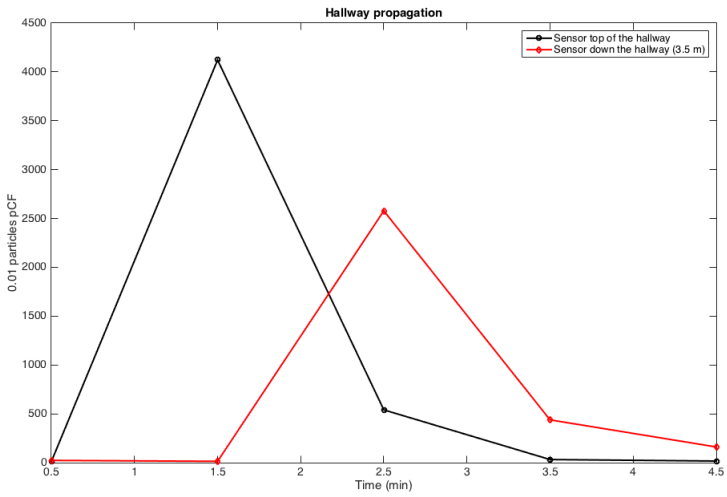


FIGURE 5.19: **Source in closed hall and propagation down the hall of marker.** We observe convection of the signal down the hall and an exponential damping of the signal.

the hall. As reported before the diffusion coefficient for our particle tracking setting is about the same for our spray than for the monopolar instrument or the APC.

We reconstruct from Fig. 5.19 the traveling wave velocity that is about one OR width in a minute. Measurements estimated that v_0 is about 0.1 m/s. It was not possible to measure directly that low velocity in the hallway with a standard anemometer, but this velocity is also in agreement with the results of the CFD model presented above. All the parameters of the system were now known and the simulation in the whole system was possible. We simulated the dispersion of gas emitted in the same conditions than during our experimental tests to be able to compare the results. Fig. 5.20 represents this comparison. The model uses a stochastic emission of smoke as well as a stochastic number of door openings. The system is able to track back the source term and follow the concentration in the OR and in the hallway. The same exponential decay is observed, with a higher rate in the OR than in the hallway like expected because of the more effective ventilation system inside the OR. This is a very complementary result with the CFD simulation that was not taking into account the activity of the area such as door opening movements. This new dimension gives the model the possibility to run on longer period and simulate the full activity of the environment. It is now possible to analyze and simulate the correlation between OR activity and level of air quality that was detected with our array of sensors, see Fig. 5.21. The model simulates three MIS and uses the different phases seen previously, to characterize the frequency of use of electrosurgical instruments and door openings. Results are represented in Fig. 5.22, the higher concentration of particles at the beginning and end of the procedure is present. More experimental data will have to be gathered in order to simulate the level during the case as it is delicate to place a sensor close to the OR table and have the full characteristics of the source in the OR especially during MIS because the smoke goes out of the body as small jets due to the pressure inside the abdominal cavity.

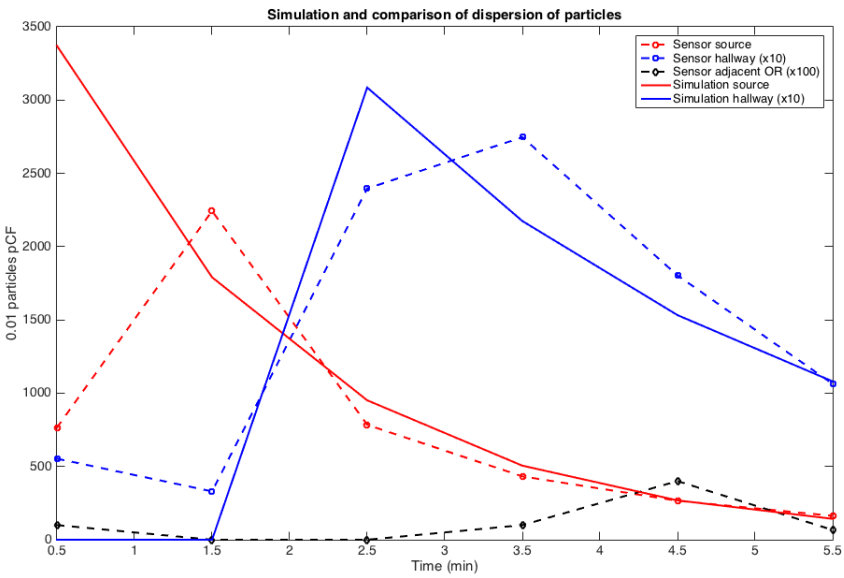


FIGURE 5.20: **Effect of door opening and closing** on propagation of marker from one OR, to the hallway, to the next OR down the hall. The dashed lines represent the data from the experiments, the solid lines are the one from the simulation.

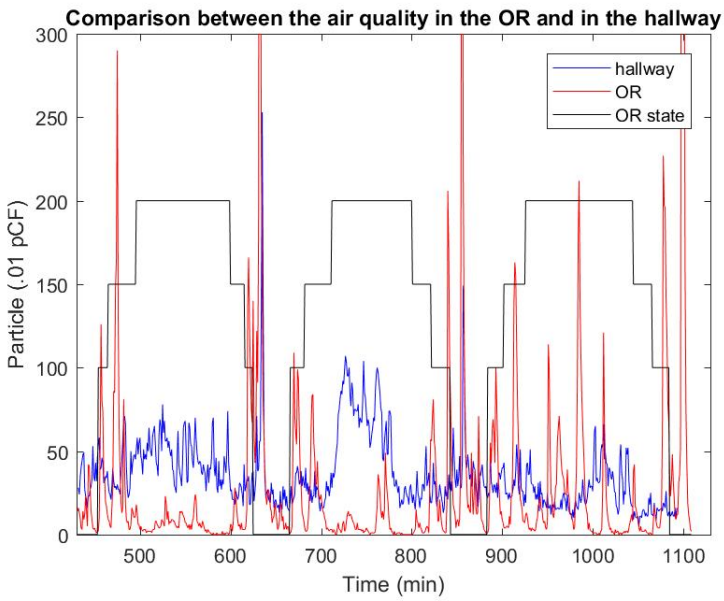


FIGURE 5.21: **IAQ measurement for laparoscopy surgeries in clinical condition**. We removed the product detergent peak during cleaning.

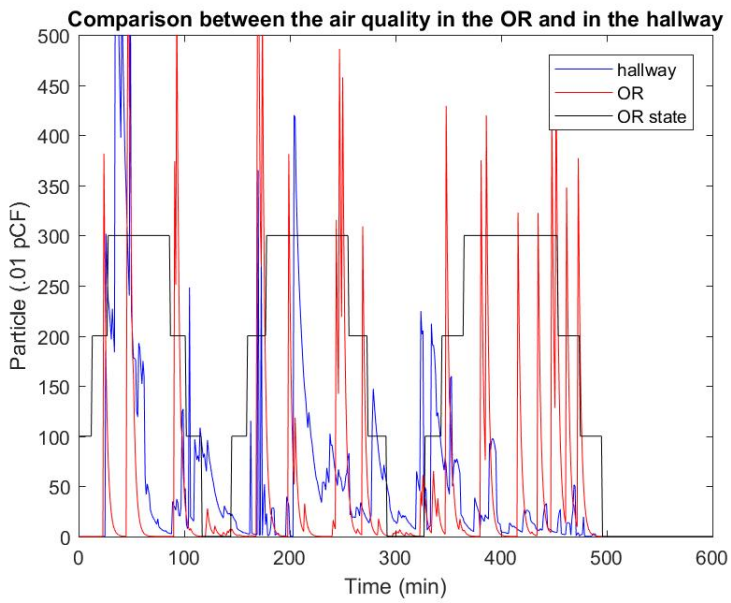


FIGURE 5.22: **IAQ simulation of one day in one OR and its adjacent hallway** using low decay estimate in the hall, low velocity estimate in the hall, and perfect transmission if door is opened from OR to hall.

5.3.6 Discussion

Our knowledge in engineering and the results from the CFD analysis underlined the importance and impact of leakages present in the OR as well as the number of door openings. Here, we build a system model to track particles inside the OR suite and that takes into account these leaks and the activity through mathematical functions that present diffusion and transmission coefficients taken from our clinical experiments seen in Chapter 3. Using the idea of a box model customized with delay parameter and PDEs, we are able to reconstruct the dispersion of the particles from the end point to their source. The backflow seen in the CFD model following the buoyancy driven airflow can also be modeled. The model focuses on rare effects such as contamination from one OR to another. The motivation and strength of this model are the ability to run the model on a large number of rooms and on a long period of time. Therefore, it can address the complexity of hundred of staff spatiotemporal behavior in a large OR suite as well as its complexity. A large part of the source of contaminations can be controlled by the better design of the door and temperature control, with a limitation of the door openings. This is why an indoor quality model should be coupled to the multi-scale model of surgical flow. Indeed, even if the whole airflow is strongly impacted by the architecture and design of the suite, its activity, which is the unknown and not monitored dynamic part of it, has also its part of responsibilities in safety and spreading of contaminants. The model can be coupled with a database gathering staff pulmonary related diseases to see the impact of these rare events on the health of the staff and provide quantitative agreements with the model. At the end, the model should be surgery specific, embracing the air quality level into our cyber-infrastructure of the OR suite. It would add another level of awareness to leverage the safety of the working environment.

5.3.7 Conclusion of the chapter

OR suites are a very special space inside a hospital and should be treated as one when designing it or maintaining it. Usually, its HVAC system is designed in such a way that air follows a path from clean to less clean and never reverse (with the exception of negative pressure ORs that are not studied here and usually are in a specific space of the hospital). This, when focusing on only one OR, seems to be the best solution, every room has its own ventilation system and everything is pushed out from the room. By doing some test in the clinical world and trying to understand better the airflow inside the ORs as well as outside we realized that, first airflow recirculate inside the room instead of being extracted right away, then, positive pressure can be the source of contamination from one OR to another. The architecture of the room, as well as its well-designed ventilation system, have to deal with an extremely dynamic and complex workflow that pushes the system to its limits very often and some regulation might not be respected all the time. By interviewing a couple of stakeholders in the field as well as a lot of surgical staff dealing with it every day, we understood that if their comfort is usually respected, their safety might not be. First, the potential spreading of nosocomial disease, with bacteria and viruses following the airflow due to the very light-weight of their particles. Second, the rising problem of surgical smoke plume linked to the increasing usage of electrosurgical instruments and that has been proved to be extremely toxic to the patient, who presents level of CO_2 and benzene higher than normal after a MIS procedure and for the staff who inhale the smoke every day, with the surgical mask proved to be inefficient for these very thin particles. We, then, wanted to understand these

pathways more clearly and see through modeling how these droplets were dispersing inside and outside of the room. We tried to answer multiple questions with two different numerical approaches, one was a CFD model of one OR, its adjacent hallway and the entry of an adjacent OR. The second was a multi-domain model using mathematical equations to simulate transport phenomenon and real activity at the doors of ORs in a large OR suite. In the first question, the goal was to show that a considerable number of particles leaves the OR through the leaks of the room and not only through the ventilation outlets. In our two models, we proved that it takes around 60 seconds for the particles to be spread in the entire room and that after this they start to leak at the door edges. The second question was to analyze how far these particles, leaving the OR, could go inside the hallway. Here again, we were able to simulate the flow with the CFD simulation and the system approach. The experimental measurements showed that there was a unidirectional flow inside the hallway, probably due to the U shape of the hallway in the whole OR suite (Fig. 5.14). The droplets, leaving one OR were then pushed by this airflow and continue their path along the hallway. The problem is that on this path there is also present the entry door of an adjacent OR. The next question was to understand if, under certain conditions that could temporary reverse the positive pressure at the doorway and let particles present in the hallway enter the room? This situation is less straightforward but comes from the activity of the OR suite and the gradient of temperature and thus, of density present between the cold air of the OR and the warmer air in the hallway. This creates buoyancy-driven flows and the CFD model showed a reverse airflow at the top of the doorway which lets particles from the hallway enter the OR. Then, the recirculating air inside the OR pushes the contaminants inside the room, up to the OR table in less than 2 minutes. Naturally, the last question is to see if particles emitted in one OR can get inside an adjacent one through the hallway? Once again our two models answered by the affirmative with the CFD modeling an open door in this adjacent OR and the numerical model was using a customized block system to pass from one space to another in the OR suite. It is now known that laminar flow is not a perfect solution in order to maintain infection rate of the surgical site [17] but here we are demonstrating that positive pressure linked to OR activities can lead to contamination from one OR to another which can have dramatic consequences on the safety of patients and staff in certain conditions. The last parameters we can track with our system is the distribution in the room of the surgical smoke plume and the quantity surgical staff can inhale during daily cases.

Chapter 6

Conclusion

As it is rather rare for an operation to proceed exactly as planned secondary to the variations in patient disease, surgical team performance, and staff availability, we propose an agent-based model framework that can incorporate all of these elements. In parallel, we built a mechanical model of airflow at the OR level, as well as the surgical suite level to monitor air contamination. In this thesis, we proposed the steps of the construction of these models, which has been enabled by the development of robust and non-obtrusive sensors around the OR suite while making sure no change from the surgical staff was needed. Optimizing management and environment of multiple ORs is a complex problem. A large hospital has a large number of different procedures performed every day, most of which need to be scheduled several weeks in advance. Each procedure requires the assembly of a surgical team lead by a surgeon. However, the actual procedure times can vary significantly, even for common procedures such as laparoscopic cholecystectomies. OR time is one of the most significant budget chapters in a modern hospital. Delays in OR procedures due to lapses in scheduling and/or delays in OR resources availability have been shown to be responsible for post-surgical complications. Additionally, the circulation in and out the OR during one day requires to keep up and running a very particular HVAC system. A proper and well-maintained airflow system to keep a safe but comfortable work environment is the key to a good surgical workflow.

Over the course of a one-year period, behaviors and events in and around the OR using a set of three sensors have been analyzed. For this initial project, key events that occur for each operation in the OR was segmented, identified unique steps that would signal the initiation/cessation of each event and created sensors that would target these. Since its installation in two ORs, the system has been running 24/7 and to date has captured and build statistics on data for over 1000 cases. Today the system is still up and running in five ORs gathering data every day.

In reviewing the results captured by the smartOR system, it was confirmed that the automatically detected turnover times were equivalent to what nursing and management were collecting and entering manually. Sensor data output was refined and noise filtering implemented, data from weeks and months were able to be processed over the course of a few days. With the ultimate goal of the system being a platform that could provide real-time OR state information, and serving as a system that may automatically notify OR manager if specific case types have exceeded expected time lengths, this was a big step. As the statistical analyses were completed, cases that deviated far from the mean (in excess of 6 standard deviations) were examined, and in nearly all situations, extenuating circumstances that resulted in excessive case lengths and/or delays were identified. To have the ability to track this, and notify OR management in real time as these events were occurring would allow for reallocation of OR resources more efficiently. Building a statistical model of OR behavior, case type lengths, and even personnel/resource allocation

based on data collected from the SmartOR system also allows for the creation of OR optimization techniques in the future. In parallel with this development, one sensor was added to the existing array to track OR suite air quality. The source of contamination and infection may come with the patient, endogenous or not, exogenous. Ventilation systems are rarely the source of pathogens but can become a reservoir. Exchanged air at the doorway, due to its activity with people coming in and out, is the largest source of contaminants. Researchers observed the foot traffic in the operating room and realized that the number of openings is proportional to case length and to the number of people in the OR, all of them compromising the sterility of the OR environment. To be able to track the movement of the OR door, we put an accelerometer/gyroscope on it in order to know the opening angle and at which velocity it is being open. The system underlined the correlation between OR activity and number of particles present in the OR, therefore its level of air quality. It even showed that there was a link between the particles emitted in the OR and the number of particles present in the hallway. Different sets of test inside the OR suite with controlled sources of contaminant introduced proved all these behaviors and gave lots of hints on airflow in the OR. Finally, the use of numerical and mathematical models helped to fully understand the complexity of such an environment. The flow of particles between the OR and the perioperative areas is affected by door opening and gradient of pressure and temperature. The mathematical model uses local source and sinks terms at the interfaces to connect all area components plus the number of door openings. The mathematical model is compared with the data from multiple laser particle counter that measure a number of particles at increasing distances from the source in a large OR suite. Then, using a CFD software we can have access to detailed information about thermal comfort variables as well as information on temperature, humidity, etc. But most importantly, the system is able to follow the concentration of a contaminant introduced inside the model. We can compute the volume of toxic gasses inhaled by staff depending on their position in the room and step of the procedure. Using this model and injected particles that have the same physical characteristics than the molecules present in the smoke or bacteria, we were able to follow particles in and around one OR and even between ORs with the door open or closed. The next step was then to be able to simulate this with the activity of the OR suite on a long period of time.

A staff-specific agent-based model intended to retain the key features observed in daily clinical practice was built. The proposed model specifically takes into account the OR staff and their communicational and technical skill levels. That model was then used to target efficiency improvement in the area that seems to be the most critical for the profession. The model framework is designed to be adaptively simplified or completed according to the detail of measures available in the clinical day activity. We used our own experience with a noninvasive tracking system of OR activity to provide an initial approximation of the range of the model parameters. The construction of the model is also used to improve the communication between computational scientists and surgeons who have, in general, very different perceptions of the problem, and determine what are the fundamental rules that might govern complex surgical flow.

Our long-term goal is to design a system that addresses these longer than usual cases that cost more, increase the risk of contaminations and that extend the exposition to toxic gasses. The system would decrease the lack of communication between all the involved parties including the surgeon, operating room staff, and patient at every level. Our understanding is that by monitoring and tracking all the processes involved in patient care and patient safety, these data can be fed into a system which

uses a multi-scale model that gives the hospital staff the ability to intervene and achieve the best organization and allocation of resources available at any time. If some of the resources are not available or if unhealthy working conditions are detected, the model built into the system alerts the users and recruits all available relevant employees. An ideal model should also calculate the probability of failures and alert OR management to take action when the system goes over acceptable levels of deficiencies. Eventually, by using operational research and other standard optimization techniques, our smart system should transition to becoming a truly intelligent and centralized OR management system. Nevertheless, the decision-making will always be the responsibility of staff in charge of OR coordination and management. Therefore, we need to continue our development of a solution for a cyber-physical OR system that provides all staff members with accurate and reliable real-time information to improve OR efficiency, safety, and ultimately patient care.

As mentioned earlier, we believe that algorithm development to optimize scheduling is well established but unfortunately the function to be optimized which actually predicts how long a surgery last is still very poorly understood. It is also clear that uncertainties are quite high and surgery does not necessarily work according to the plan, no matter how good the surgical team is. Having a model that can run various scenarios in real time to navigate efficient but safe options in the OR suite seems to be usefull for the whole organisation. We would advocate however the needs for big data to fix that problem: provided that every surgery, every environment, and every patient condition would be properly documented with detailed corresponding time series of events and consequences on outcomes, one may assume that good statistical model of surgery elapsed time and machine learning algorithm that provides adequate classification of patients can be set for each hospital system. There is indeed a general trend in surgery towards that direction because of the electronic patient record system adoption as well as the evolution of the health insurance reimbursement model that focus on quality outcome rather than volume, air quality being one reason of readmission rate [76] this safety concern cannot be left on the side either.

In conclusion, it seems that optimizing surgical flow from the individual staff scale to the OR suite scale requires a highly interdisciplinary work and a long-term effort, where multi-scale modeling can play an important role. Leveraging the workflow of the OR suite without neglecting the safety of hospital occupants should be the goal of everyone. Embracing all staff into the system for high acceptance and usage rates of such a system requires a human-centered design of its application as well as its interaction. This work is already in progress with the help of engineers from the air civil industry who master in human interaction systems with the design of cockpits and control towers.

Appendix A

Introduction to MCPS

RE-ENGINEER OPERATING ROOM DATA ACQUISITION AND TRANSMISSION FOR IMPROVING SURGICAL SUITE AWARENESS AND MANAGEMENT

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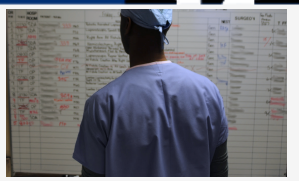
Introduction

Large surgical suites are more flexible than small ones in terms of daily adjustments of surgery cases scheduling. However, most of the surgical suites data acquired and transmitted through different technology channels of the hospital to the staff are not real-time information and can be inaccurate. Organizations need measurement systems in order to detect where inefficiencies are and to compare with the new one. Our system studies the relevant data acquisition and transmission to the right terminals of the surgical suite to improve efficiency for large surgical suites. In this project, we aim at answering two questions: How to measure and understand the efficiency of a surgical suite? Which tools should we give to the staff to help them improve surgical suite efficiency?



Results of observations within the surgical suite

Problem : limited real time information

We studied the surgical suite activity through interviews and pictures of the whiteboard. We identified the case-scheduling whiteboard as the central collaborative tool to follow the surgeries and anticipate modifications. The multidisciplinary surgical team uses the whiteboard as a support for exchanges and collaboration. This **whiteboard reflects limited status** of the cases, contains adds-on emergency cases, modification of scheduling etc. As seen on Fig. 3, the staff uses a local symbol language to communicate faster. Because this is manual input and the large workload of the whole staff, **there can be delays between the real events and the moment the information has been written on the whiteboard.**

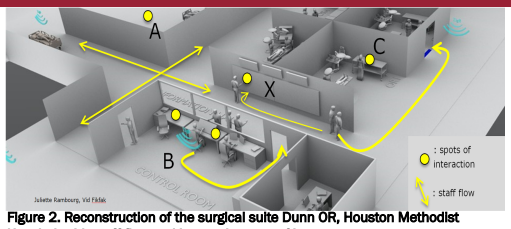


Figure 2. Reconstruction of the surgical suite Dunn OR, Houston Methodist Hospital, with staff flow and interactive area of interest.

Comparison white board – OR status results :

- 5 ORs installed
- 42 cases compared
- 8000 pictures processed
- 20+ interviews

[nurse]
As soon as we have time: when a patient arrives in PreOp, we cross out the time of his case line so that everybody can know he is in here. We cross it then a second and third time, as a star, when the surgery has begun.

Figure 1. Extract of interview

Event	Average Delay	Standard Deviation
Patient enters the OR	15 min	22 min
Patient exits the OR	13 min	29 min

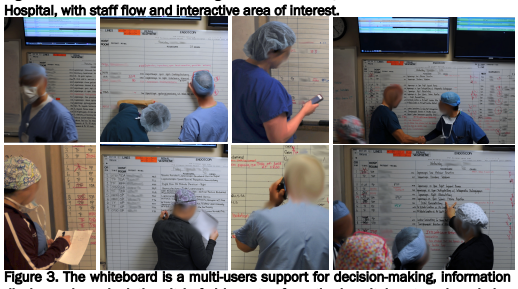


Figure 3. The whiteboard is a multi-users support for decision-making, information display and manipulation. It is fed by notes from the hospital system, knowledge and updates from the staff.

Track OR activity - SmartOR

We started by **sectioning OR workflow** and identifying **key actions or activity** that indicated when each part began and/or concluded. We then determined dedicated sensors to capture and track the parts of the surgical. The hardware and software solutions include a small PC and a distributed TCP network of sensors. Our system has to be robust, wireless and non-invasive. We use 3D printed cases for all the parts. The computer collect and analyze data coming from multiple ORs through a 4G server covering at least 3 ORs. This also allows us to do 24/7 maintenance on the system without needing to physically enter the OR.

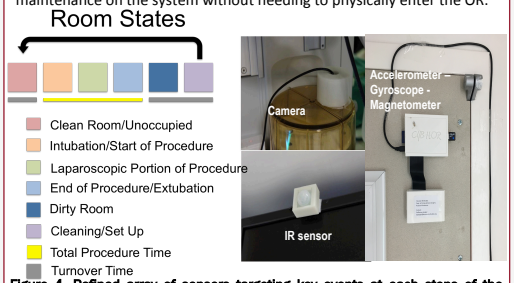


Figure 4. Refined array of sensors targeting key events at each steps of the procedure .

The system is currently installed in 5 ORs of our home institution and is running for almost 2 years. We analyzed more than **1000 cases** and **identified inefficiency and outliers** at different steps. This allowed targeted cases reviews and determination of potential causes for extended procedure lengths. We found that there were opportunities for **efficiency improvement** in all segments of the OR cycle.

Solution : spread real time information

BoardProbe is a whiteboard-like multi-touch screen application. It copies the traditional case-scheduling whiteboard of the surgical suite and offers additional features enabled by the computer-assisted system. Our purpose is **to link BoardProbe to the SmartOR** in order to combine interactions and visualizations of OR status. By doing so we can cross-check information and prevent miscommunication and mistakes as well as **smoothen the workflow**.

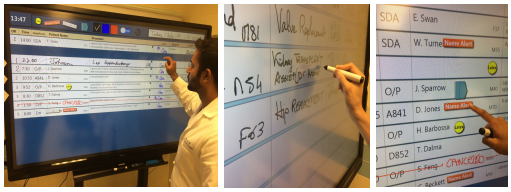


Figure 5. Example of use of BoardProbe with test users and simulation of surgeries

Future Work

- Clinical tests of the connection between the 2 systems
- Adaptation to other surgical suites (vascular, GI...)
- Keep the users in the loop to design future features

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Appendix B

Noticable publications and presentations

- Publication in the journal of Surgical Endoscopy : A robust and non-obtrusive automatic event tracking system for operating room management to improve patient care, 2015 (Chapter 2)
- Poster of the same work at the conference Society of American Gatrointestinal and Endoscopic Surgeons 2015, Nashville, TN (Chapter 2)
- Publication in the Journal of Computational Surgery : An intelligent hospital operating room to improve patient health care, 2015 (Chapter 2)
- Publication in the journal of Surgical Endoscopy : The SmartOR: a distributed sensor network to improve operating room efficiency, 2016 (Chapter 2)
- Presentation of the same work at the conference SAGES 2016, Boston, MA (Chapter 2)
- Poster and presentation at the 4th IEEE International Conference on Biomedical and Health Informatics 2017, Orlando, FL : Re-engineer operating room data acquisition and transmission for improving surgical suite awarness and management (Chapter 2 and 4)
- Publication of the same work in Proceedings of IEEE-Engineering in Medicine and Biology Society, BHI (Chapter 2 and 4)
- Poster at the conference SAGES 2017, Houston, TX : A novel Surgical Suite Management Technology including Automatic Surgery Steps Tracking and a Large Collaborative and Informative Display (Chapter 2 and 4 and Appendix A)
- Paper under second review in the journal Association for Computing Machinery Transaction on Cyber-Physical System : A Cyber-Physical System to Improve the Management of a Large Suite of Operating Rooms (Chapter 2 and 4 and Appendix A)
- Presentation the International Conference on Computational Science 2017, Zurich, Switzerland with publication in Procedia Computer Science : Multiscale Modeling of Surgical Flow in a Large Operating Room Suite: Understanding the Mechanism of Accumulation of Delays in Clinical Practice (Chapter 4)
- Submission to PlosOne of the paper : Multiscale Modeling of Surgical Flow Explains Lognormal Distribution of Surgical Time and Occurrence of Large Delays

- The project Coordinated Operating Room Network (CORNET) is funded by the NSF center I/UCRC for Cyber-Physical Systems for the Hospital Operating Room (CyBHOR)) center since 2013 (Chapter 2 and 4 and Appendix A)

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Modélisation multi-échelle assistée d'un système de détection d'évènements : optimisation du fonctionnement et de la sécurité au sein des blocs opératoires

Résumé :

Améliorer la gestion et l'organisation des blocs opératoires est une tâche critique dans les hôpitaux modernes, principalement à cause de la diversité et l'urgence des activités impliquées. Contrairement à l'aviation civile, qui a su optimiser organisation et sécurité, le management de bloc opératoire est plus délicat. Le travail ici présenté abouti au développement et à l'installation de nouvelles technologies assistées par ordinateur résolvant les problèmes quotidiens des blocs opératoires. La plupart des systèmes existants modélisent le flux chirurgical et sont utilisés seulement pour planifier. Ils sont basés sur des procédés stochastiques, n'ayant pas accès à des données sures. Nous proposons une structure utilisant un modèle multi-agent qui comprend tous les éléments indispensables à une gestion efficace et au maintien de la sécurité dans les blocs opératoires, allant des compétences communicationnelles du staff, au temps nécessaire à la mise en place du service de nettoyage. Nous pensons que la multiplicité des ressources humaines engagées dans cette structure cause des difficultés dans les blocs opératoires et doit être prise en compte dans le modèle. En parallèle, nous avons construit un modèle mathématique de flux d'air entre les blocs opératoires pour suivre et simuler la qualité de l'environnement de travail. Trois points sont nécessaires pour la construction et le bon fonctionnement d'un ensemble de bloc opératoire:
1. avoir accès au statut du système en temps réel grâce au placement de capteurs
2. la construction de modèles multi-échelles qui lient tous les éléments impliqués et leurs infrastructures
3. une analyse minutieuse de la population de patients, du comportement des employés et des conditions environnementales
Nous avons développé un système robuste et invisible qui permet le suivi et la détection automatique d'événements dans les blocs. Avec ce système nous pouvons suivre l'activité à la porte d'entrée des blocs, puis l'avancement en temps réel de la chirurgie et enfin l'état général du bloc. Un modèle de simulation numériques de mécanique des fluides de plusieurs blocs opératoires est utilisé pour suivre la dispersion de fumé chirurgicale toxique, ainsi qu'un modèle multi-domaine qui évalue les risques de propagation de maladie nosocomiale entre les blocs. La combinaison de ces trois aspects amène une nouvelle dimension de sensibilisation à l'environnent des blocs opératoires et donne au staff un système cyber-physique capable de prédire des événements rares impactant la qualité, l'efficacité, la rentabilité et la sécurité dans l'hôpital.

Mots clés : modélisation multi-échelle, modèle multi-agent, organisation des blocs operatoires, workflow dans les blocs operatoires, sécurité, qualité de l'air, chirurgie assistée par ordinateur, mécanique des fluides numériques

Multiscale Modeling and Event Tracking Wireless Technologies to improve efficiency and safety of the surgical flow in an OR suite

Summary :

Improving operating room management is a constant issue for modern large hospital systems who have to deal with the reality of day to day clinical activity. As opposed to other industrial sectors such as air civil aviation that have mastered the topic of industry organization and safety, progress in surgical flow management has been slower. The goal of the work presented here is to develop and implement technologies that leverage the principles of computational science to the application of OR suite problems. Most of the currently available models of surgical flow are used for planning purposes and are essentially stochastic processes due to uncertainties in the available data. We propose an agent-based model framework that can incorporate all the elements, from communication skills of the staff to the time it takes for the janitorial team to go clean an OR. We believe that human factor is at the center of the difficulty of OR suite management and should be incorporated in the model. In parallel, we use a numerical model of airflow at the OR suite level to monitor and simulate environment conditions inside the OR. We hypothesize that the following three key ingredients will provide the level of accuracy needed to improve OR management:
1. Real time updates of the model with ad hoc sensors of tasks/stages
2. Construction of a multi-scale model that links all key elements of the complex surgical infrastructure
3. Careful analysis of patient population factors, staff behavior, and environment conditions.
We have developed a robust and non-obtrusive automatic event tracking system to make our model realistic to clinical conditions. Not only we track traffic through the door and the air quality inside the OR, we can also detect standard events in the surgical process. We propose a computational fluid dynamics model of a part of an OR suite to track dispersion of toxic surgical smoke and build in parallel a multi-domain model of potential nosocomial contaminant particles flow in an OR suite. Combining the three models will raise the awareness of the OR suite by bringing to the surgical staff a cyber-physical system capable of prediction of rare events in the workflow and the safety conditions.

Keywords : Multiscale Modeling, Agent-based Model, Operating Room Management, Operating Room Workflow, Safety, Indoor Air Quality, Computational Surgery, Computational Fluid Dynamics.

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