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Abstract

Hospitals are highly complex and very cost-intensive systems. In 2017, the costs for hospitals in Germany were 105 billion Euros, and thus, accounted for over 20 % of the total health care costs (Statistisches Bundesamt, 2018). Different groups of people, such as medical, nursing, medical-technical, functional and facility management services have different values and interests, but pursuing a common goal: "healing and caring for the patient". This goal necessitates high-quality care at the lowest possible cost and always at the right time. In the light of the ever-increasing resource expenses, maintaining a stable and effective hospital management through a right allocation of resources becomes more and more important, but at the same time always more complex.

Meanwhile, operating rooms (OR) are one of the most expensive and most demanding areas of hospitals, but also the most important source of revenue. About 60-70% of hospital admissions are due to surgical procedures, generating 40% of the total costs (Lin et al., 2013). On this ground, hospital managers and specially OR managers are interested in optimizing the limited and cost intensive resource of OR time. Moreover, OR planning and resource allocation are difficult tasks, since they are plagued with multiple sources of uncertainty and variability.

OR planning usually takes place in a three level hierarchical process: strategic, tactical and operational. The strategic level is about long-term planning of capacity dimensioning as well as session planning and distribution. The tactical level is mid-term planning of allocation of capacity to each surgeon or medical specialty. The operational or short-term level addresses the daily schedules and staffing. An efficient planning should take place at the strategic level, and the resource management should take the preferences of individual stakeholders into account.

This thesis aims to contribute to the development of methods for session allocation at the strategic level and partially at the tactical level with the focus on surgeons' or specialty departments' preferences. As a result, fairness and productivity will be brought together in the process of OR time distribution and a stable state will be reached.

To realize the above-mentioned aim the following methods are developed in this thesis:

- The OR time allocation among surgeons/wards is formulated as a simple game. The proposed game approach assumes the wards to be players who consider the allocation of operating room sessions among themselves. The goal in this game is reaching a collective stability and finding a solution which is acceptable to all players. The concept in finding the stable solution is based on the power

concept from the economic literature. The power index method measures the power of the players in a game under a given set of strategies, based on which the most possible stable solution will be suggested.

- The resource allocation problem is formulated as a cooperative game and a distribution mechanism based on the Shapley value is proposed. The Shaply value suggests the most equitable distribution as a basis for further allocation negotiations. The individual players can form different coalitions each presenting specific values. The Shapley value divides the resources according to the marginal contribution of each player to the possible coalitions.

- The master surgical schedule (MSS) at the tactical level of operating room planning is addressed to develop a method to assign operating rooms, days and shifts to specialty departments in a defined planning horizon. A hybrid approach comprised of a bargaining method called fall-back bargaining and genetic algorithm is developed to solve the MSS problem as a combination optimization one.

- A dynamic system perspective is adopted to describe the system of operating rooms. In this approach, inspired by the control theory, the structure of the system is modeled and analyzed using Simulink® block diagrams. This approach provides a simple and user-friendly simulation environment to implement different management strategies into the system and analyze them to find out about the consequences of managerial decision in long-term.

The developed methods are applied to the real data from a case study in order to evaluate its practical applications. The collected data are from a German hospital in Baden-Württemberg for 24 months from January 2015 to December 2016. These data sets contain all the operations performed with information regarding departments, date, duration, operating room, surgeons and Diagnosis-related Groups (DRGs).

The results provide meaningful measures and insights into the OR planning and scheduling problem and identify areas for further improvement and investigation. It is desirable to further develop the proposed methods through applications to further real data and case studies. Nonetheless, the proposed methods provide suitable means to articulate and comprehend strategic plans. The game based approaches provide insights into the fair and acceptable distribution and allocation of operating room resources, namely OR time, among surgeons and specialty departments. The system dynamics approach provides an understanding about the operating room system behavior as responses to strategic and decisional inputs.

Kurzfassung

Krankenhäuser sind hochkomplexe und sehr kostenintensive Systeme. Die Kosten für Krankenhäuser lagen beispielsweise im Jahr 2017 in Deutschland bei 105 Mrd. Euro und bildeten somit einen Anteil von über 20 % an den gesamten Gesundheitskosten (Statistisches Bundesamt, 2018). Unterschiedliche Personengruppen, wie ärztlicher Dienst, Pflegedienst, medizinisch-technischer Dienst, Funktionsdienst und Facility-Management-Dienst haben verschiedene Werte und Interessen, aber ein gemeinsames Ziel: "Heilen und Pflegen der Patienten". Dieses Ziel erfordert eine qualitativ hochwertige Versorgung zu den geringstmöglichen Kosten und alles immer zum richtigen Zeitpunkt. Angesichts ständig steigender Ressourceninanspruchnahme wird die Aufrechterhaltung eines stabilen und effektiven Krankenhauses durch die richtige Zuweisung der vorhandenen Ressourcen immer wichtiger, aber auch immer komplexer.

Operationssäle (OPs) sind die kostenintensivsten und anspruchsvollsten Bereiche eines Krankenhauses, aber auch die wesentliche Einnahmequelle, da 60-70% der Krankenhauseinweisungen aufgrund chirurgischer Eingriffe stattfinden und dadurch 40% der Gesamtkosten erzeugt werden (Lin et al., 2013). Vor diesem Hintergrund ist das Krankenhausmanagement und insbesondere das OP-Management stetig an Optimierungsmöglichkeiten der knappen und kostenintensiven Ressource OP-Zeit interessiert. Darüber hinaus sind die OP-Planung und die Zuweisung der Ressourcen komplexe Aufgaben, da aufgrund der vielen Interdependenzen eine hohes Maß an Unsicherheit und Variabilität entsteht.

OP-Planung wird in einem dreistufigen hierarchischen Prozess vorgenommen: strategisch, taktisch und operativ. Auf der strategischen Ebene geht es um die langfristige Planung der Kapazitätendimensionierung sowie die Zeitslotplanung und -verteilung. Auf der taktischen Ebene geht es um die mittelfristige Planung der Kapazitätszuweisung an jeden Chirurgen oder jedes chirurgische Fachgebiet. Auf der operativen oder kurzfristigen Ebene werden die Tagespläne und die konkrete Personalbesetzung vorgenommen. Eine effiziente Planung sollte mit der strategischen Ebene starten und das Ressourcenmanagement sollte die Präferenzen der einzelnen Interessengruppen berücksichtigen.

Ziel dieser Arbeit ist es, einen Beitrag zur Entwicklung von Methoden für die Zuordnung von OP-Sälen und Kapazitäten auf strategischer und teilweise auch auf taktischer Ebene zu leisten. Hierbei werden die Präferenzen der Chirurgen oder der Fachabteilungen in den Mittelpunkt gestellt. Denn ein stabiler Zustand der Resourcenverteilung wird durch die Kombination von Fairness und Produktivität im Prozess der OP-Saal- und Kapazitätszuordnung erreicht.

Zum Erreichen des oben genannten Ziels werden in dieser Arbeit die folgenden Meth-

oden entwickelt:

- Die OP-Saal- und Kapazitätszuordnung unter Chirurgen/Fachabteilungen wird als Spiel formuliert. Der vorgeschlagene Spielansatz geht davon aus, dass die Fachabteilungen Spieler sind, die die Aufteilung der OP-Kapazität untereinander aushandeln. Das Ziel in diesem Spiel ist es eine kollektive Stabilität zu erreichen und eine für alle Spieler akzeptable Lösung zu finden. Das Konzept bei der Suche nach der stabilen Lösung basiert auf dem Machtindexkonzept aus der ökonomischen Literatur. Die Machtindexmethode misst die Macht der Spieler in einem Spiel unter gegebenen Strategien, auf deren Grundlage die stabilste Lösung vorgeschlagen wird.

- Das Kapazitätsplanungsproblem wird als kooperatives Spiel formuliert und ein auf dem Shapley-Wert basierender Verteilungsmechanismus vorgeschlagen. Der Shapley-Wert schlägt die gerechteste Verteilung als Grundlage für weitere Verteilungsverhandlungen vor. Einzelne Spieler können verschiedene Koalitionen bilden, die jeweils spezifische Werte haben. Beim Shapley-Wert werden die Ressourcen entsprechend dem marginalen Beitrag der einzelnen Spieler zu jeder Koalition aufgeteilt.

- Die Master-Operationsplanung (MSS) auf der taktischen Ebene der OP-Planung wird angewendet, um eine Methode zur Zuweisung von Operationssälen, Tagen und Schichten an Fachabteilungen in einem definierten Planungshorizont zu ermitteln. Zur Lösung des MSS-Problems als Kombinationsoptimierung wird ein hybrider Ansatz entwickelt, der aus einer Verhandlungsmethode namens Fall-back-Bargaining und einem genetischen Algorithmus besteht.

- Eine dynamische Systemperspektive wird angenommen, um das System der Operationssäle zu beschreiben. Bei diesem Ansatz, der von der Kontrolltheorie inspiriert ist, wird die Struktur des Systems modelliert und mit Hilfe von Simulink®-Blockdiagrammen analysiert. Dieser Ansatz stellt eine einfache, benutzerfreundliche Simulationsumgebung zur Verfügung, mit der verschiedene Managementstrategien in das System implementiert und analysiert werden können, um die Konsequenzen langfristiger Managemententscheidungen aufzuzeigen.

Die entwickelten Methoden werden mittels realer Daten auf ihre praktische Anwendung evaluiert. Die erhobenen Daten sind die vollständigen Jahre 2015 und 2016 eines deutschen Krankenhauses in Baden-Württemberg. Bei diesen Datensätzen handelt es sich um alle durchgeführten Operationen mit Angaben zu Abteilungen, OP-Ablaufzeiten, OP-Saal, OP-Datum, Operateuren und durchgeführten Prozeduren nach Diagnosis-raleted Groups (DRGs).

Die Ergebnisse liefern aussagekräftige Einblicke in das Problem der OP-Planung und der Terminierung und zeigen Bereiche auf, in denen weitere Verbesserungen und Untersuchungen erforderlich sind. Es ist wünschenswert, dass die vorgeschlagenen Methoden durch die Anwendung weiterer realer Daten und Fallstudien weiterentwickelt werden. Nichtsdestotrotz bieten die vorgeschlagenen Methoden aufschlussreiche Einsichten, um strategische Pläne zu verstehen und zu verbessern. Die spielbasierten Ansätze bieten Einblicke in die faire und akzeptable Verteilung und Zuweisung von OP-Ressourcen, d.h. OP-Zeit, zwischen Chirurgen und Fachabteilungen. Der systemdynamische Ansatz bietet darüber hinaus die Möglichkeit das Systemverhalten im Operationssaal als Reaktion auf strategische und entscheidungsrelevante Veränderungen zu verstehen.

Contents

Acronyms

ANE	Anesthesia
CDF	Cumulatiove Distribution Function
CV	Coefficient of Variation
DRG	Diagnosis Related Groups
DoA	Depth of the Agreement
Inf	Infimum
FB	Fall-back Bargaining
FI	Fairness Index
GA	Genetic Algorithm
GS	General Surgery
ICU	Intensive Care Unit
InEK	Institut für das Entgeltsystem im Krankenhaus
MOGA	Mutation Only Genetic Algorithm
NW	Normal Ward
OWA	Ordered Weighted Averaging
PI	Power Index
PSP	Perfectly Stable Point
SD	System Dynamics
SDL	Specialty Department Level
Sup	Supremum
TS	Trauma Surgery
THS	Thorax Surgery
OR	Operating Rooms
ORSL	Operating Room Suite Level
WPI	Weighted Power Index

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Declaration of Academic Integrity

Chapter 2: As the first author during her time as PhD student, Shiva Faeghinezhad developed and extended the methods, collected data and analyzed the results in Parts I and II. She wrote the entire articles with inputs from Kunibert Lennerts, Stefan Nickel and Justo Puerto (for Part II). The discussions with all co-authors contributed to the manuscripts in Parts I and II.

Chapter 3: As the first author, Shiva Faeghinezhad developed the method and applied the method to the collected data sets and evaluated the results. She wrote the entire articles with contributions from Kunibert Lennerts and Stefan Nickel. The discussions with all co-authors contributed to the manuscripts in this chapter.

Chapter 4: As the first author, Shiva Faeghinezhad developed the method and applied the method to the collected data sets and evaluated the results. She wrote the entire articles with contributions from Kunibert Lennerts and Stefan Nickel. The discussions with all co-authors contributed to the manuscripts in this chapter.

1 Introduction

The primary purpose of this thesis is to describe methods for planning and scheduling of operating rooms. The main focus is on the acceptability and fairness in the process of operating room planning and scheduling.

1.1 Motivation

In principle, the healthcare management is about organizing and planning of the right resources to deliver the highest quality of care at the lowest cost at the right time to the right patient (Van Riet and Demeulemeester, 2015). One of the most important areas within this sector to accomplish the aforementioned tasks is the surgical suite. However, the environment of operating rooms (OR) is one of the most expensive and most demanding areas of a hospital because of the following reasons: 1) surgical interventions constitute up to 60-70% of hospital admissions, which has been estimated to account for more than 40% of the total expenses (Lin et al., 2013); 2) a significant amount of high-cost equipment and energy is dedicated to the ORs; 3) 50% percent of the total number of doctors and 10% of the medical staff work in the OR (Balaras et al., 2007). Thus, in the light of these costs and resource demands, hospital managers are interested in finding effective ways to manage, organize and run ORs while ensuring high quality of care. Taking all the above mentioned facts into consideration, it is evident that planning of the OR department is a difficult task, as there are various conflicting objectives to be dealt with. This is due to not only costs and resources, but also presence and involvement of various groups of professional and semi-professional parties who have different orientations.

Moreover, as the population ages, some regions are facing a growing demand for providing more surgical services. All of these factors have motivated the researchers to increasingly stress out the importance of effective management and productive planning of operating room departments (Macario et al., 1995; Harper, 2002; Glouberman and Mintzberg, 2001).

1.2 Aims and Objectives

This research aims at planning OR schedules at the strategic and tactical levels. To this aim, in the proposed methodologies, satisfaction of surgeons or surgical specialties are put at the focal point to bring equity and fairness in the process of OR time distribution. In order to realize this issue, the OR resource allocation is formulated as a simple game. This means that different wards within a surgical department are considered to be rational players fighting for resources (e. g. OR sessions).

The rules that govern such games, guarantee a fair distribution of resources among wards, which satisfies all of them at the same level. This approach considers the optimality in the level of individual players rather than the whole system of the surgical department. The system level optimality may lead to dissatisfaction of some individuals and disturb the system stability because the satisfactions of individuals are sacrificed for the sake of the system optimality. In contrast, providing the individual level optimality maintains the system stability, as it considers keeping the individuals satisfied so that they don't tend to leave the system.

The **first** objective is to develop methods to allocate the OR capacity among participants (surgeons/surgical specialties) in a fair and equitable manner. For this objective the two following methods are developed:

- A method based on the power index concept from the economic literature is proposed, which measure the power of the participants in a distribution game. Afterwards, based on the measured power indices, the most stable solution is suggested.
- Another distribution mechanism based on the Shapley value, again from the economic literature, is proposed to solve the distribution problem as a cooperative game by creating coalitions of involved players and measuring their marginal contribution to each coalition.

At the tactical level, having already decided about the amount of OR capacity that each player receives, the next step is to assign days, rooms and shifts to the surgeons and surgical specialties. Therefore, the **second** objective is to develop a master surgical schedule which concerns with the pre-assignment of days, rooms and shifts to the surgeons and surgical groups, of course, based on their preference and values. The developed framework is also built on the game theoretic concepts. It takes the advantages of a method called fall-back bargaining to model the assignment process as a bargaining session. Since the solution space is a large one and searching the whole space in terms of the computing time is not a possible task, the fall-back bargaining is combined with a genetic evolutionary algorithm.

The **third** objective of this research is to study the OR department as a dynamic system. The OR is considered to be a dynamic system since it comprises interconnected elements, components and people, and changes over time. Therefore, the purpose is to understand and model the complexities and interrelationships among different elements in the OR departments. System dynamics tools simulate and quantify the behavior of the system and let the user to experiment with what-if scenarios. They are not very detailed models and are used at strategic and speculative levels. The advantages of this approach is that different strategies and settings incurred to the system can be simulated, tested and compared before their implementation in the real world.

1.3 Outline of the Thesis

The structure of this thesis follows the aforementioned objectives and is divided into four parts. Together, these chapters constitute the entire PhD thesis. The research tasks elucidating the research questions are provided in details in individual parts. Each chapter is finalized by conclusions.

- **Chapter 2** concerns the background, literature survey, and the mathematical concepts to develop the methods described for the first objective. The developed methods are described, and with the help of numerical examples, the efficiencies of the methods are illustrated.
- **Chapter 3** concerns the development of master surgical schedule. In this chapter, the background and the relevant literature are reviewed, and the proposed method is introduced and described. To show the capabilities of the method, numerical examples are provided.
- **Chapter 4** concerns the development of the system dynamics model. The background of system dynamics and its use in the OR literature are reviewed. Then, the method is elucidated and to demonstrate the value of the method, scenario analysis is carried out and discussed.
- **Chapter 5** summarizes how the research questions are addressed. Since, the relation to real-world situations is of great importance, the usefulness of the results and the practical impacts are discussed. The claimed contribution is stated and the recommendations for further research are discussed.

1.4 Published Parts of this Thesis

Submitted Manuscripts

Faeghi, S., Lennerts, K., Nickel, S., A System Dynamics Model Application to Operating Room Planning and Management, *Journal of Simulation*, under revision.

Faeghi, S., Lennerts, K., Nickel, S., Strategic Planning of Operating Room Session Allocation Using Stability and Acceptability Metrics, *Health Systems*, under revision.

Faeghi, S., Lennerts, K., Nickel, S., A Pre-assignment of Master Surgical Schedule with Focus on Surgeons' Satisfactions, Target journal: *Annals of Operations*

Research, under preparation.

Faeghi, S., Lennerts, K., A Fair Allocation of Operating Room Sessions Using the Shapley Value, Target journal: *Operations Research for Health Care*, under preparation.

Conference contributions

Faeghi, S., Lennerts, K., A system dynamics model for operating room capacity allocation, *CONFERENCE OF THE EUROPEAN WORKING GROUP ON OPERATIONS RESEARCH APPLIED TO HEALTHCARE SERVICES*, 18 July - 02 August, 2019 Karlsruhe, Germany

2 Resource Allocation and Capacity Dimensioning

2.1 Part I: Operating Room Session Allocation Using Stability and Acceptability Metrics

Abstract

Operating room (OR) resources are limited and the increasing demand for them may permanently outreach the supply. Hence, there is usually a competition among surgeons to win OR resources. However, the developed methods for OR session allocation are mostly based on system-wide optimization methods which compensate the preferences of individual surgeons in favor of productivity of the whole OR department. Such an approach neglects the equitable distribution among patient groups and leads to conflict and dissatisfaction among surgeons and may jeopardize their loyalty. To overcome this problem, a methodology based on the game theoretic solutions is presented in this work which formulates the allocation problem as a simple game. In this game, the individual surgeons or wards, as players, share the collective goal of reaching an overall stability. The stability is defined based on the concept of power from the theory of simple games and the weighted power index (WPI) method. In this method, the power of players in a game is measured for all possible strategies, and weighted by each player's performance leading to the choice of the most stable strategy. In order to deal with circumstances of uncertainty and lack of information in players' actual performances, the proposed method is combined with the Monte Carlo technique to obtain a stochastic problem-solving process. The suggested procedures are then applied to a case study from the literature and also a series of hypothetical scenarios whereby its ability to find the stable strategic solutions is presented and its features are discussed in detail.

2.1.1 Introduction

Operating room session allocation refers to allocation of operating room (OR) to various wards, which is particularly challenging due to the existence of conflicting interests between the people involved in it, and the limitation of the OR's typically high-cost resources (Macario et al., 1995; Harper, 2002; Glouberman and Mintzberg, 2001; Cardoen et al., 2010b; Bacelar-Silva et al., 2020). A great deal of theoretical work has addressed the allocation problem using complicated and detailed optimization methods, however, they are mostly case-specific research works which lack generalizability (Van Riet and Demeulemeester, 2015) and apparently lack insightful effects on real-life OR management practice (Zhu et al., 2019). An important issue in this regard is societal point of view: focusing on satisfaction of individuals so that the long-term collective efficiency could be guaranteed rather than compensation of individual preferences in favor of short-term success. OR session allocation is fundamentally a tool to reach an acceptable and equitable distribution not only among medical specialties (wards) but also among patient groups (Testi and Tànfani, 2009; Zhu et al., 2019).

Let us consider an operating room department with 20 operating room blocks and only two wards with different productivity rates. If one of them needs 12 and the other one 15 blocks to serve the patients on their waiting lists, the total demand will outreach the available amount and the OR manager will not be able to fully satisfy both of the demands. If she/he decides to entirely fulfill the demand of one of them, conflicts may arise; the other ward will find the allocation unacceptable because it leads to longer waiting times of its patient group. This, in turn, may put surgeons' satisfaction and loyalty at risk. A proportional distribution merely based on demand amount would also make no sense, because every ward has a different productivity rate and ignoring these rates may jeopardize the whole OR performance in favor of low performance wards. One possible approach to solve this problem is to analyze the acceptability and equability of feasible distribution possibilities from the ward's/surgeon's perspectives while considering their contribution to the whole surgical department.

2.2 Literature Review

Most of the relevant literature pursues to meet only some microeconomic goals such as the maximization of 1) patient throughput or case volume (Feldstein, 1967; Dowling, 1976; Baligh and Laughhunn, 1969; Blake and Carter, 2002; Dexter and Macario, 2002; Rohleder et al., 2005; Guido and Conforti, 2017), 2) profit (cost minimization) (Ma et al., 2009; Koppka et al., 2018) and 3) contribution margin (Brandeau and Hopkins, 1984; Hughes and Soliman, 1985; Robbins and Tuntiwongpiboom, 1989).

However, Blake and Carter (2003) argued that the acceptability of resource allocation by physicians and surgeons should be additionally considered. Zhang et al. (2009) also emphasized that the deficiencies between the assigned OR time to each surgical group and their desired target value should be minimized. The reason is that, on the one hand, when a hospital aims for profit maximization, it may result in a work overload on some surgeons, which might be undesirable and unacceptable to them and may have adverse impact on hospital revenues (Powell et al., 2012). On the other hand, the surgeons' targeted demand must be satisfied as much as possible, meaning that receiving too less OR time than demanded would also be unacceptable by them (Blake and Carter, 2003; Guerriero and Guido, 2011). An equitable distribution of OR time is also addressed by Testi and Tànfani (2009). They defined equity by “access based on need” and argued that equity is not compatible with efficiency.

Reaching a system-wide efficiency generally requires a “perfect cooperation” among players; this means a full agreement on rules that even lead to an unequal resource sharing. For this reason many of the developed methods such as mathematical programming like goal programming (Ozkarahan, 2000; Blake and Carter, 2002; Rohleder et al., 2005), stochastic programming (Denton et al., 2010), linear programming (Dowling, 1976; Hughes and Soliman, 1985), integer linear programming (Guido and Conforti, 2017; Testi and Tànfani, 2009), mixed-integer linear programming (Zhang et al., 2009), and meta-heuristics like genetic algorithms (Roland et al., 2006) and tabu search (Hsu et al., 2003) all require perfect cooperation. However, since in reality a full (and stable) cooperation between different wards at the expense of their overload or idleness is hardly expectable, the outcomes obtained by the aforementioned methods may often be unreliable. Therefore, when multiple players are present and a lack of perfect cooperation is likely, application of negotiative methods (i.e. game-theoretical approaches) can be of great advantage.

There have been many efforts in the field of game theory to develop methods for a quantitative description of various games with different properties; bargaining methods, bankruptcy allocation procedures, power-based and voting methods are some examples (Hipel and Obeidi, 2005). However, there are only a few studies which suggest the use of game theory and its solution concepts in OR scheduling. Ackere (1990), considered conflicting interests in the process of OR scheduling and developed a game to deal with conflicts such as those between the surgeon and the scheduler. Marco (2001) wrote about “game theory in the operating room environment” and discussed the advantage of game theory in describing human interactions in contrast to other decision making methods and argued how the interactions of staff and other stakeholders can be modeled as a game. McFadden et al. (2012) showed that a non-cooperative game theory can be appropriately applied to the operating room environment, and described how different types of games can be suitable to resolve conflicting situations in the OR environment.

2.2.1 Stability and Acceptability in OR Planning Problem

The OR suite is a symbiosis comprised of multiple wards in close interaction. They form a union (or alliance) committed to improve the quality and the efficiency of the OR suite and with a large impact on the whole hospital (Kheiri et al., 2020). In order to reach their collective goal of increasing efficiency, under the condition of limited resources, wards must restrict themselves to demand to be fully satisfied. However, since they all have a high tendency to optimize themselves and gain resources as much as they need, there is a strong competition among them. When individual wards have much more competition than self-limitation, the system, in which they exist, becomes unstable (Gui and Lou, 1994).

The problem of planning the allocation of resources for an OR suite is in fact a supply and demand **game** in a symbiosis, where the system stability is an important determinant of its successful development and evolution (Stepaniak and Pouwels, 2017; Wang et al., 2013). Generally, for the players in an allocation game, two concepts can be imaginable regarding the final solution: 1) minimizing the sum of the individual dissatisfactions; and 2) minimizing the maximum dissatisfaction of individuals (Tecle et al., 1998). The former incurs mutual objective compensation among individuals to reach the system-wide optimal solution while the latter allows no compensation which leads to stability by providing an acceptable solution to all individuals. The stability of an allocation scheme is hence to a great extent determined by the condition of equal satisfaction level for all players. This is based on the argument that when some players do not find a scheme acceptable, that scheme may be viewed as unfair by them, leading to instabilities in the overall system. As a result some players will then become liable to withdraw from the coalition of wards (Dinar and Howitt, 1997). Therefore, equal satisfaction of players is a crucial component to a have a synergistic system (Borkotokey and Neog, 2012) and guarantees success in a coalition of wards. The concept of equal acceptability and equitable distribution also affects patient groups in an indirect manner, who are waiting to be treated (Tap and Schut, 1987).

2.2.2 Contributions of this Work and Outline

The allocation problem dealt with here corresponds to a classical allocation game (Rosenthal, 1973) in which selfish players (i.e. wards) should share limited resources (OR sessions) to accomplish their tasks (demands), i.e. complete treatment of their patients waiting list. Game theoretic solutions may provide, by their very nature, an appropriate basis for solving multi-player/multi-participant allocation and decision making problems, and equip the decision makers with valuable insights about perception of participants regarding final decisions. The limited application of game theoretic solutions in the OR scheduling area is the main motivation of this study. Although it is often encouraged to develop complicated heuristic approaches to solve practical problems, some exact and simple approaches have also proved to be powerful enough to solve real problems (Cardoen et al., 2010a) like the methods proposed by Testi and Tànfani (2009) and Rohleder et al. (2005).

Therefore, in contrast to the majority of approaches, the aim of this study is to demonstrate the applicability of simple game theoretic solutions to OR resource allocation problem. In the context of this theory the power index (PI) (Loehman et al., 1979) methodology is used to calculate the power of each player for potential allocation schemes and thus obtain a measure for the stability of the final solution. The problem is defined in Section 2.2.3 and the power index method is described in Section 2.2.4. Since no real data set which could suit the problem definition here was accessible, the capability of the proposed method is examined by means of a real example taken from the literature in Section 2.2.5 and a set of randomly generated hypothetical examples in Section 2.2.6. Furthermore, a deterministic (with no uncertainty) approach and a stochastic one (with uncertainty) based on Monte Carlo simulations are considered. Finally, Part I concludes in Section 2.2.7.

2.2.3 Problem Definition

OR planning and management is usually done in a three level hierarchical decision making process: the strategic (long-term) level, which is also referred to as session planning, deals with the number and type of surgeries to be performed. One of the main goals in this level is to distribute the time available to the OR unit among surgical services seeking an efficient case mix (Blake and Carter, 1997; Samudra et al., 2016; Guido and Conforti, 2017); the tactical (medium-term) level, which involves developing a surgical master plan determining surgeons that are to be associated with the time blocks defined by the strategic planning level (Beliën and Demeulemeester, 2007); and finally, the operational (short-term) level, which addresses daily schedules and staffing for individual OR units (Ozkarahan, 2000). With respect to these three levels, the current work falls under the strategic (session) planning level, and hence deals with the efficient management of the numbers and types of surgeries that are to be performed by the OR units. It should be noted, however, that the three mentioned levels are in fact not strictly separate from each other, but are rather inter-related and often overlap each other (Slack, 1999).

In this work, the OR suite of a hospital is considered as a system, with sub-systems each representing a surgical specialty, or ward. The OR suite system is defined by a limited number of OR sessions (total resources) that can be carried out in a unit of time, which then results in the number of treated patients (total patient throughput). Each ward is then modeled as a sub-system with a fixed performance, i.e. the average number of patients that the ward can treat in a single OR session. Each ward has then a demand of being allocated with a certain portion of the total resources available, which corresponds to the number of OR sessions that the ward will be allowed to perform. In turn, each ward's demand is itself based on the number of patients in its waiting list.

The methodology proposed here, seeks the most possible “stable” allocation scheme. For this purpose, a pool of possible allocation schemes is generated, and then, the stability of the allocation schemes are calculated with the help of power concept (see Section 2.2.4). The output would be then introduction of an allocation scheme which brings the most possible stability and is unlikely to be rejected by the wards. The study objectives cab be summarized as follows:

- to present a method for determining the stability of OR resource allocation by assuming the individual wards as players of an allocation game, and then compare to those obtained via conventional optimization methods;
- to identify the relative satisfaction of wards using stability analysis methods under uncertain conditions;
- to illustrate the importance of stability investigations by providing a series of real and hypothetical case studies.

2.2.4 Weighted Power Index Method

In the framework of the simple game theory, there is a group of methods collectively known as power index methods. Power indices are used to determine the impact of the players on the final results which is interpreted as the player's power in a simple negotiation game. Power index methods are designed to provide a fair division and a reasonable sharing of an overall value among the players (Bertini et al., 2018). When a particular division of values, resources or goods is fair enough and more likely to be responsive to the preferences of all players, then, that division is accepted as a stable solution to the game (Brams, 2008).

There are various types of power indices developed so far to deal with the measure of power in negotiation game processes: Shapley-Shubik (Shapley, 1953), Banzhaf (Banzhaf III, 1964), Johnston (Johnston, 1977), and Coleman (Coleman, 2011) indices are some examples. Loehman et al. (1979) developed also an approach which is similar to the Shapley-Shubik power index and it is chosen here because its features better suit the problem considered in this work. Loehman's Index is an approach to determine the relative power. The power index for a game player is calculated by comparing their individual payoffs with the total payoff gained by all players participating in the negotiation game. In the allocation problem discussed here, each ward's payoff is the share of resources it obtains. Hence, having N players and AS amount of total available resources in the game, the power index of player i, namely PI_i can be formulated as (Loehman et al., 1979):

$$PI_i = \frac{c_i - as_i}{\sum_{j=1}^{N}(c_j - as_j)} \tag{2.1}$$

where i and $j = \{1, 2, 3, .., N\}$ is the set of players, c_i is the demanded (or claimed) allocation for the player i, as_i is the amount of allocated share (or payoff) to the player i and $\sum_{i=1}^{N} PI_i = 1$. It should be noted that hereby the rule is that no ward receives more than it has demanded such that $0 \leq as_i \leq c_i$. The sum of all allocations is equal to the available resources ($\sum_{i=1}^{N} as_i = AS$). This constraint imposes the efficiency property which implies that no player can obtain a better allocated share without making others players' share worse off. This power index has also been suggested (Dinar and Howitt, 1997; Bertini et al., 2018) as a forecast to the stability of the results of a negotiation game. To this end, each player's PI_i is calculated for each allocation scheme and the balance in the distribution of power among the players is linked to the stability of the outcome. Conceptually, this means that a solution is more stable when the variation in the distribution of the power between players is smaller. To measure this stability, the coefficient of variation in the PI_i is calculated across all players for a given solution as:

$$CV = \frac{\sigma}{\bar{PI}}, 0 \leq S \leq 1 \tag{2.2}$$

where CV is the coefficient of variation of a particular solution, σ and $\bar{PI}$ are the standard deviation and the mean value of the set of the power indices of all players, respectively. A greater value of S hence represents a situation where a larger instability of the allocation solution is expected.

In Equation 2.1 the claims of different players can now be weighted (inspired by Holler (1981)) according to their capability to influence the game. These weights, which can help in obtaining realistic results, represent the share of each player in the game. In our OR problem, these weights represent the performance of the wards. Therefore, in order to take the weights into account Equation 2.1 is revised as follows:

$$WPI_i = \frac{(c_i - as_i)^{w_i}}{\sum_{j=1}^{N}(c_j - as_j)^{w_i}} \tag{2.3}$$

where WPI_i is the weighted power index of the player i, w_i is the weight of the player i calculated based on his/her performance, normalized and re-scaled to [0, 1] such that $\sum_{i=1}^{N} w_i = 1$ and $\sum_{i=1}^{N} WPI_i = 1$. A fixed OR capacity is assumed throughout this work. Among the three strategies of open (surgeons can choose any working day for their session), block (surgeons are assigned to a set of time blocks) and modified block (combination of open and block) scheduling approaches, the block strategy is applied here. The decision here is about the allocation of as_i of the total available OR sessions in a specific period of time (e.g. one week) to the ith ward. We also assume that these OR blocks are assigned to elective (in-patient) surgeries. Emergency cases are not taken into account.

2.2.5 Case study I

The case study is adopted from Testi et al. (2007) which is a surgical department in San Martino University Hospital located in Genova, Italy. The department is made up of six wards (players). Six surgery rooms are available from Monday to Friday for 6 hours daily, which constitute up to 30 OR sessions a week. Each ward has its own individual performance (weight) which is the average number of patients it can treat per OR session (see Table 1). There are also initial ward waiting lists, and each ward demands a certain number of OR sessions (demand) to clear its waiting list. The work by Testi et al. (2007) is a hierarchical approach with three levels for the weekly scheduling of operating rooms: session planning (number of sessions to be weekly scheduled for each ward), master surgical schedule (surgery room assignment to wards), and elective case scheduling (selection of patients to be scheduled in each session). Here, we are concerned with the first phase (session planning). Moreover, of the two scenarios dealt with herein, for which the total demand (1) equals and (2) exceeds the total number of resources, we are concerned with the latter. In order to allocate the OR sessions, Testi et al. (2007) calculated the “marginal benefit” of the kth session demanded by the jth ward. This marginal benefit accounts for the economic consequences of allocating more sessions to one ward or another in terms of the satisfied demand as follows:

$$d_{jk} = \frac{D_j - (k-1)}{\sum_j D_j} \tag{2.4}$$

where, d_{jk} is the marginal benefit of the kth session demanded by the jth ward, D_j is the total OR sessions demanded by the ward j, and k is the number of already assigned sessions. This equation gives more importance to the first session assigned to the jth ward, rather than to the subsequent ones. This means that the ward j's benefit is at the highest by receiving the first session (while it had already no sessions) compared to when it receives the kth session as it already has $k-1$ sessions. That is to say that the marginal benefit decreases as the number of received OR sessions increases. Since this equation divides the subtraction between the total demand of the ward j and the having already assigned $k-1$ sessions by summation of the demands of all wards, there more value is given to the ward with the bigger demand. This means that when a ward has more demands than the others, its marginal benefit will be higher as it has the bigger share of the total amount demanded by all wards. Testi et al. (2007) followed the aim of maximizing $\sum_j \sum_k d_{jk}$ as the objective function of the session distribution problem in the presence of constraints such as capacity and overrun hours. They didn't considered any cost constraints.

2.2.5.1 Deterministic Allocation Results Table 1 shows the details of the case study, the results and the coefficients of variation for the allocation schemes obtained by WPI and the method by Testi et al. (2007). Comparison of the coefficients of variation for both allocations shows that the one suggested by WPI is more stable than the one from Testi et al. (2007). Each ward's unsatisfied demand is given in Figure 1 obtained by WPI method and the method used in Testi et al. (2007). It can be seen that WPI method has allocated the available resources in a way that the disparities among the unsatisfied demands are lower. While the disparity in the solution of the method based on Testi et al. (2007) is equal to 3, it is 1 in the allocation given by WPI method. This arguably brings more stability among players. WPI method has not only reached at a more stable solution, but in fact, it has also improved the patient throughput slightly. The WPI solution offers an increase in the patient throughput – from 333 to 334 – and this is, however, obviously a side effect in this specific case and not an explicit objective of the presented method.

As the hospital management is always constrained by budget, and profit maximization has been always an objective function for resource distribution, we calculate here the total cost as a measure. Since for the case study taken from Testi et al. (2007) no additional data on cost and profitability was provided, therefore, we calculate the associated variable costs and payments for both optimal and stable allocation schemes using a method suggested by Diez and Lennerts (2009) as follows:

$$TC = 0.92t \tag{2.5}$$

where TC is the total variable cost of every surgery procedure to the hospital with the duration of t (minutes). The above-mentioned approach was suggested based on the data provided by German Institut für das Entgeltsystem im Krankenhaus (InEK) (DKG, 2018). Table 1 reports the total costs. It can be seen that there is only a slight difference between them (about 0.16%). It must be noted that the hospital and surgery costs vary among surgeons per unit of time of operating rooms (Macario et al., 2001), hence, obviously, this approach is not suggested here as a sound and exact way of calculating costs, but to provide a comparison. At a speculative and strategic level, such reductionist approaches can provide insights about decisions for the future, and there might be less need to utilize high-quality and precise data (Brailsford, 2008).

Table 1: Details of the case study form Testi et al. (2007).

				Proposed method by Testi et al.				Weighted Power Index method			
Ward	c[1]	w[2]	IWL[3]	as[4]	UD[5]	MPT[6]	WPI	as	UD	MPT	WPI
1	12	3.0	144	10	2	120	0.20	11	1	132	0.15
2	5	2.5	50	3	2	30	0.20	3	2	30	0.17
3	12	2.8	134	9	3	100	0.22	10	2	112	0.17
4	6	2.5	60	4	2	40	0.20	4	2	40	0.17
5	3	2.4	29	2	1	19	0.18	1	2	9	0.17
6	2	2.8	22	2	0	22	0	1	1	11	0.16
T[7]	40	2.7	440	30	10	333	-	30	10	334	-
Coeffiecient of variation (CV)				0.45				0.05			
Total costs (€)				39,574				39,637			

[1]Demand (weekly)
[2]Ward performnce
[3]Initial waiting list in one month
[4]allocated share
[5]Unsatisfied demand
[6]Monthly patient throughput
[7]Total

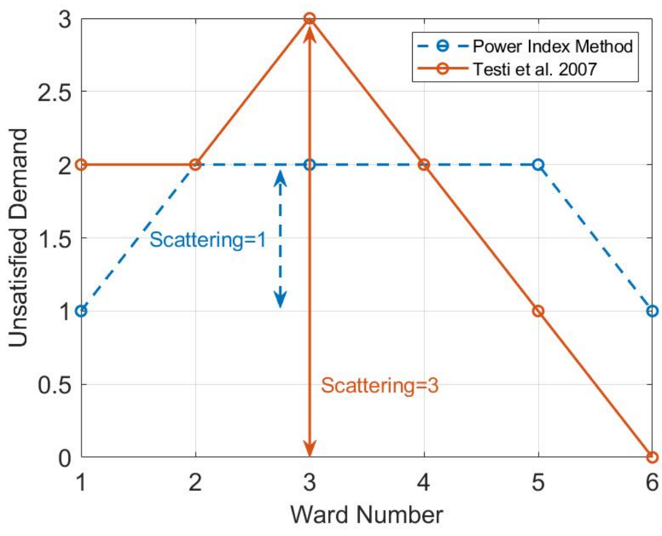


Figure 1: Scattering of the unsatisfied demands for power index method and results from Testi et al. (2007).

2.2.5.2 Perfectly Stable Point To have an insight about the stability of allocation schemes, a "perfectly stable point" (PSP) is calculated here at which the satisfaction of all players or their power indices are perfectly equalized such that the Equation 2.2 equals zero. Such a point is mostly achievable within a continuous decision space. The decision space of an OR session allocation problem, however, should be discrete corresponding to the cases in the real world. Nevertheless, the PSP can be found in a continuous space, and then used for measuring its distance from the obtained results.

Table 2 presents the PSP, the satisfaction ratio of individual players (wards) under the results obtained for the case study with respect to PSP, and the Euclidean distances between the results and the PSP. The satisfaction ratio of the ward i is defined as the division of its allocated share by the one suggested by PSP. The Euclidean distance is the most common distance measure and is used as a similarity measure (Strike et al., 2001) between the obtained allocation schemes and the PSP. As it can be seen, the satisfaction ratios for the results achieved by the WPI method are much closer together than those by Testi et al. (2007). However, the ratios for the Ward 6 are to some extent unusual. Since it has a demand of two sessions, there are just three possibilities for satisfaction ratios (0, 2.63, and 5.26). Among these numbers, 0 is unacceptable as it indicates a zero allocated share which increases the coefficient of variation among power indices and 5.26 is very large and indicates unfairness because it occurs when the ward's demand is fully satisfied. Any full satisfaction leads to the unsatisfied demand of 0, which also increases the coefficient of variation. Finally, the only possibility to fulfill the stability conditions is 2.63.

Table 2: Perfectly stable point and satisfaction ratios for San Martino University Hospital, Genova, Italy.

Ward	PSP	Satisfaction ratio	
	(as)	Testi et al. (2007)	WPI Method
1	10.43	0.95	1.05
2	3.28	0.93	0.91
3	10.38	0.86	0.96
4	4.28	0.95	0.93
5	1.25	1.74	0.80
6	0.38	4.87	2.63
ED[1]	–	2.33	1.04

[1]ED:Euclidean distance

2.2.5.3 Remedy for Uncertainty Surgical services are plagued with uncertainties that create major challenges with the development of faultless planning and scheduling. The previous section presented a deterministic solution to the OR management problem by using the average values for ward performances. While taking the average values can be an effective and fast way to reach to a solution, this approach will cause the elimination of some information and hence leads to uncertainties: omission of information is not much different from its lacking (Meyer, 1981; Johnson and Levin, 1985).

Ward performances or the average number of patients treated per session are difficult to predict, since they depend on various influencing factors such as the methods surgeons adopt, the accompanying teams and the characteristics of the patients themselves (Samudra et al., 2016). A Monte Carlo sampling method can be used to generate random values from probability distributions to all feasible situations for the game. In this way, possible situations that may arise can be accounted for beforehand. This approach hence transforms the stochastic problem to many deterministic ones that each can be solved using the approach described in previous sections.

We now solve Example I in a stochastic manner. In each iteration, 6 random numbers can be selected from six probability distributions for the ward performances (or weights). These 6 numbers are used to create a new deterministic OR allocation problem, and then it will be solved by WPI. The mean values and the standard deviations of the allocated shares are then updated so that the probability of winning a certain amount of allocated shares will be known for each ward.

In this study, triangular probability distributions are assumed, making it easier to further apply a three-point-estimation, a common approach when historical data are not accessible (like our case study). Triangular distributions have shown that can be used successfully in simulations in medical practices like in (Holm and Dahl, 2009; Arisha et al., 2010). The three-point-estimation can be generated by determining worse, most likely, and best conditions and then the triangular probability distribution can be derived by using the following equation:

$$f(x|a,b,c) = \begin{cases} 0 & for \quad x < a \\ \frac{2(x-a)}{(b-a)(c-a)} & for \quad a \leq x \leq b \\ \frac{2(c-x)}{(c-a)(c-b)} & for \quad b \leq x \leq c \\ 0 & for \quad c < x \end{cases} \tag{2.6}$$

where a, b, and c are the worse, most likely, and best values, respectively, for the variable $x \in R$. In our example, the variable x denotes the ward performance and it is assumed – based on expert judgments – that $a = w_i - 1$, $b = w_i$, and $c = w_i + 1$ (w_i is the performance of ward i form Table 1).

Figure 2 shows the changes in the share allocation during the Monte Carlo procedure. The number of iterations for the procedure is set to 1000. As it can be seen in Figure 2, the mean values and the standard deviations converge after a few hundreds of iterations. The probability of winning a specific amount of shares (Figure 3) can also be elicited, so that the decision maker can see all the probable outcomes. From Figure 3 it can be understood that for the Ward 1 the share of 11, the Ward 2 the share of 3, the Ward 3 the share of 10 and the Wards 5 and 6 the shares of 1 sessions are the most probable results. It can moreover be seen that it was not probable for any ward to win a share equal to its claim.

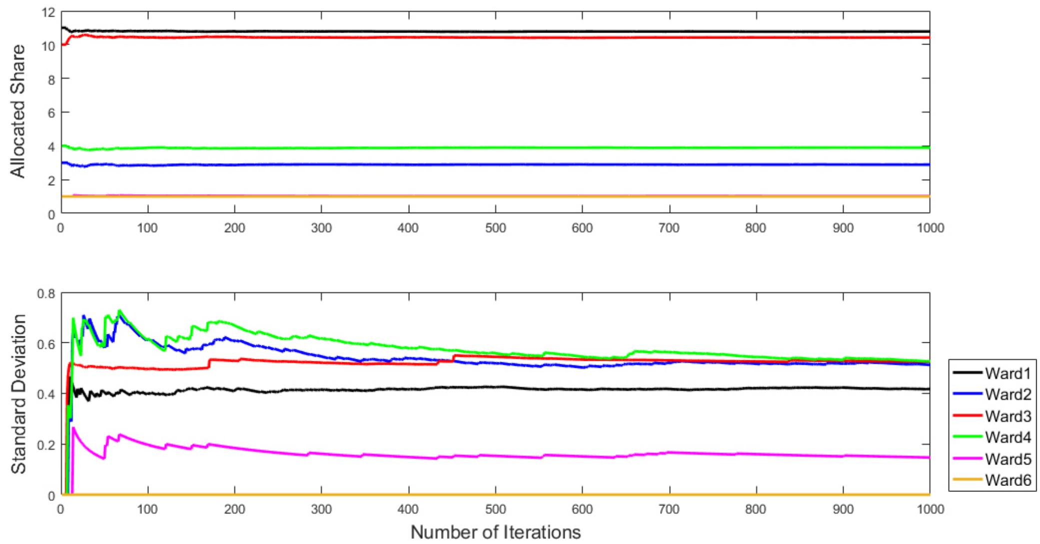


Figure 2: Mean values and the standard deviations of changes in allocated shares during the Monte-Carlo simulation.

The cumulative distribution function (CDF) for the patient throughput is also obtained from the results (Figure 4). Using these CDFs, the decision maker can estimate the probability of having a certain patient throughput. For example, Figure 4 indicates how the probability that the total patient throughput after one month will be less than 350, is calculated by assigning 350 to the horizontal axis of the CDF. It can be that the probability of having 350 treated patients is about 90%. An arbitrary quantile can also be used to find a contingency output. Figure 4 shows how the $80th$ quantile of the total throughput is calculated by intersecting the y-axis of the CDF at y=0.80. The results indicate that with 80% probability, a throughput around 344 will be the outcome. Using such CDFs, the decision maker can decide upon strategic approaches for the surgical department. He/she can additionally do experiments by adopting hypothetical strategies based on the desired expectations and choose the best one among them.

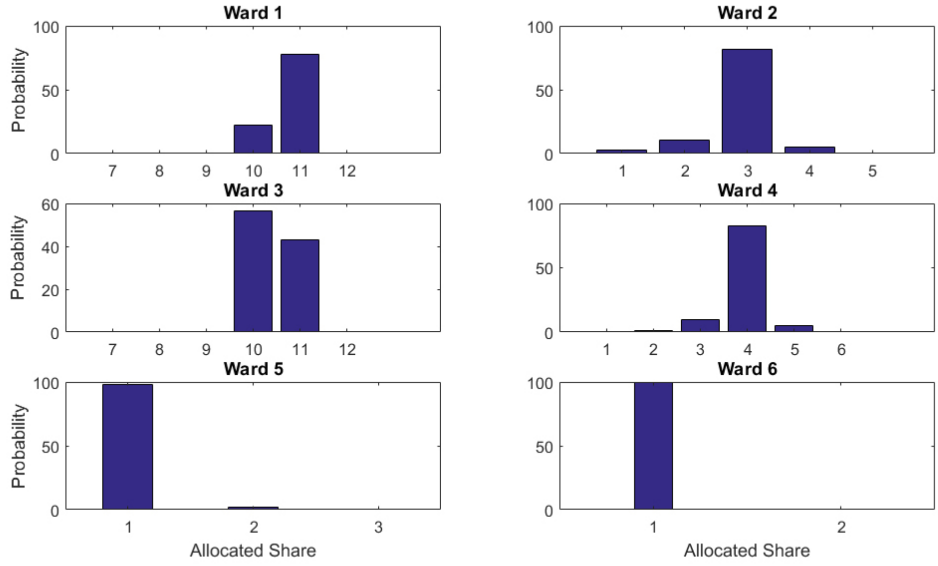


Figure 3: Probabilities of wining specific amounts of shares for each ward. These figures show that, for example, for Ward 1 the probability of wining 11 shares is about 80%, but the winning of 12 shares is 0%.

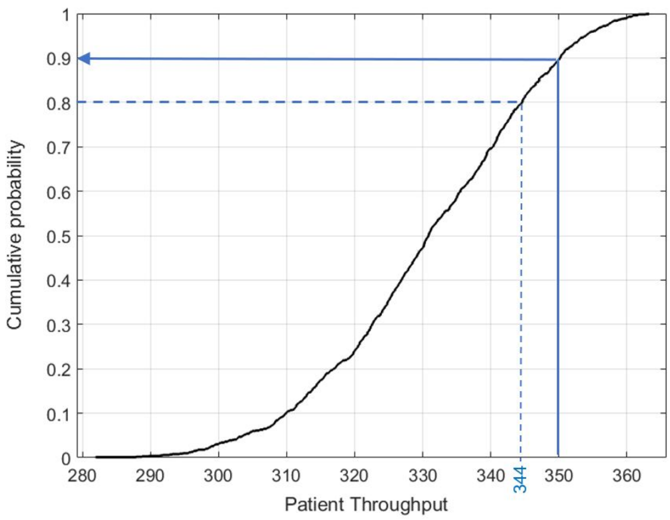


Figure 4: Cumulative probability distribution for patient throughput for stochastic problem solving of San Martino University Hospital. The solid line shows that the probability of having a patient throughput of 350 is about 90%; the dashed line shows that with 80% probability, the patient throughput will be around 344.

Moreover, the probability of being stable for the allocation schemes can also be elicited. Table 3 shows the first three allocation schemes with the highest probabilities to be selected as stable solutions. This probability calculation helps to identify the likelihood of the allocation schemes to be chosen as the most possible stable ones. The winning probability of the first allocation is much higher than the second and third ones. This shows the robustness of the arrangement of 11, 3, 10, 4, 1, and 1 for the Wards 1, 2, 3, 4, ,5 and 6, respectively. This result is in accordance with those from the deterministic approach. The reason is that the triangle probability distributions for performances here are formed based on the deterministic values from Section 2.2.5.1. Those values are taken as the most probable point of the three-point-estimation to generate the probability distributions. It is also worth mentioning that the allocation scheme obtained by the method suggested by Testi et al. (2007) is not among the schemes ranked as the three most possible stable ones.

Table 3: The first three allocation schemes with the highest probabilities of being selected as the stable solution for the stochastic problem solving of the San Martino University Hospital case.

Ward	1	2	3	4	5	6	Probability
Allocation Schemes	11	3	10	4	1	1	51.6%
	10	3	11	4	1	1	18.6%
	11	2	11	4	1	1	9.9%

2.2.6 Case study II: Hypothetical Instances

In this section, the presented method is applied to a series of hypothetical example cases of the OR session allocation problem, and its sensitivity to the various scenarios considered is analyzed. It is assumed that there is a surgical department comprised of 10 wards. The list of demands is generated randomly from the interval [1 15]. The number of available resources is calculated under the three circumstances of 1) 50%, 2) 60%, and 3) 80% of the total demands. For the performance of the wards, two scenarios are considered: random generation from the interval A) [1, 5] (for the circumstances under which the differences among performances are high), and B) [2 3] (for the circumstances under which the differences among performances are low). The PSP and the satisfaction ratios are calculated for all the resulting 6 scenarios (Tables 4 and 5).

It can be seen from the results (Figure 5), that the wider the range of ward performances is, the wider is the range of unsatisfied demands. Under A Scenarios, there are more differences between the highest and the lowest unsatisfied demand, for example, this difference for Scenarios A1 and B1 (also A2 and B2) are 5 and 4, respectively. Comparing Scenarios A3 and B3, it can be seen that as the performance range under B3 is smaller, the distribution of unsatisfied demand is much smoother than A3. It can also be seen that when the difference between available resources and the total demands is higher, the distance between the highest and the lowest unsatisfied demand becomes higher too. It can be concluded that when there is less and less resources to be allocated, more shares of resources go to the wards with higher demands and greater weights. When very scarce resources encounter excessive total demands, the system needs to pay more attention to satisfy the wards with higher productivity and higher needs so that it can keep working in an stable way.

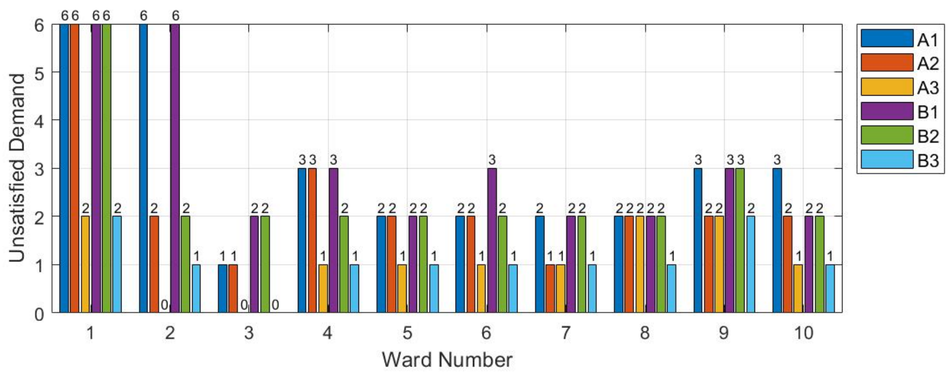


Figure 5: Unsatisfied demands for different wards under Scenarios A and B for the hypothetical case study.

There is an important and interesting issue that should be considered is the PSP. As the PSP is calculated in the space of real numbers, there exist also negative PSP values which imply that no resources should be assigned to the respective wards for the particular allocation. This means that the pertinent ward should wait to come up with a demand enough to fulfill the requirements of using one resource unit. For instance, consider Ward 3 under Scenario A: if we assign one OR session to this ward, despite the performance of 1.7 which delivers 1.7 patients per session, there will be just one patient treated, and the rest 0.7 of the assigned resources will be wasted. Therefore, for the overall performance it will be better for that ward to wait for the next allocation rounds in which it will have reached an enough demand.

Table 4: Details and results of Case Study II (Scenario A).

			Scenario A												
			Scenario A1				Scenario A2				Scenario A3			
Ward	c[1]	w[1]	as[1]	UD[1]	PSP[1]	SR[1]	as	UD	PSP	SR	as	UD	PSP	SR
1	6	1.6	0	6	1.38	0.00	0	6	2.31	0.00	4	2	4.15	0.96
2	10	4.2	4	6	8.24	0.49	8	2	8.59	0.93	10	0	9.30	1.08
3	1	1.7	0	1	-3.34	0.00	0	1	-2.48	0.00	0	0	-0.74	0.00
4	10	2.6	7	3	7.16	0.98	7	3	7.72	0.91	9	1	8.86	1.02
5	4	3	2	2	1.54	1.30	2	2	2.03	0.99	3	1	3.02	0.99
6	12	3.6	10	2	9.95	1.01	10	2	10.35	0.97	11	1	11.18	0.98
7	2	3.7	0	2	0.00	0.00	1	1	0.40	2.50	1	1	1.20	0.83
8	2	2.0	0	2	-1.69	0.00	0	2	-0.95	0.00	0	2	0.52	0.00
9	8	2.0	5	3	4.31	1.16	5	2	5.04	0.99	6	2	6.52	0.92
10	5	2.9	2	3	2.45	0.82	3	2	2.96	1.01	4	1	3.98	1.01
T[2]	60	–	30	30	30	–	36	24	36	–	48	12	48	–
A[3]	–	2.73	–	–	–	0.58	–	–	–	0.83	–	–	–	0.78
ED[4]					5.90				3.71				1.30	

[1] c: demand, w: ward performance, as: allocated share, PSP: perfectly stable point, SR: satisfaction ratio, UD: unsatisfied demand

[2]Total

[3]Average

[4]Euclidean distance between as and PSP

Table 5: Details and results of Case Study II (Scenario B).

			Scenario B											
			Scenario B1				Scenario B2				Scenario B3			
Ward	c[1]	w[1]	as[1]	UD[1]	PSP[1]	SR[1]	as	UD	PSP	SR	as	UD	PSP	SR
1	6	2.0	0	6	2.12	0.00	0	6	2.89	0.00	4	2	4.45	0.90
2	10	2.6	4	6	7.01	0.57	8	2	7.61	1.05	9	1	8.81	1.02
3	1	2.4	0	2	-2.23	0.00	0	2	-1.58	0.00	0	0	-0.29	0.00
4	10	3.0	7	3	7.41	0.94	8	2	7.93	1.01	9	1	8.96	1.00
5	4	3.0	2	2	1.41	1.42	2	2	1.93	1.04	3	1	2.96	1.01
6	12	2.6	9	3	9.01	0.10	10	2	9.61	1.04	11	1	10.81	1.02
7	2	2.8	0	2	-0.77	0.00	0	2	-0.22	0.00	1	1	0.89	1.12
8	2	2.6	0	2	-0.99	0.00	0	2	-0.39	0.00	1	1	0.81	1.23
9	8	2.3	5	3	4.62	1.08	5	3	5.30	0.94	6	2	6.65	0.90
10	5	3.0	3	2	2.41	1.24	3	2	2.93	1.02	4	1	3.96	1.01
T[2]	60	–	30	30	30	–	36	24	36	–	48	12	48	–
A[3]	–	2.65	–	–	–	0.54	–	–	–	0.61	–	–	–	0.92
ED[4]			4.59				3.38				0.91			

[1] c: demand, w: ward performance, as: allocated share, PSP: perfectly stable point, SR: satisfaction ratio, UD: unsatisfied demand

[2]Total

[3]Average

[4]Euclidean distance between as and PSP

2.2.7 Concluding Remarks

The system-wide optimization methods are based on collective-optimality and ignore the fact that the individuals have a strong tendency of self-optimization during any allocation process. Moreover, reaching a collective-optimality necessitates a perfect cooperation and a complete agreement upon the selected solution. It should be noted that individuals often have a stronger motivation in self-optimization rather than in social or group-optimization. This means, when they get unequal shares in a community, they may leave to find another community in which they can obtain greater utilities and higher shares.

This issue emphasizes the importance of the concept of stability, as opposed to the optimality alone. In hospitals, like many other communities, these considerations must be met too, where the physicians (and subsequently the patients) are the individuals involved in, say, the OR resource allocation problem. The acceptability level of the allocation schemes is hence of great importance. The physicians engaged in various surgical groups enter the game with a certain demand, to get a share of available but limited resources. How they will be happy and satisfied with the final solution depends on what they obtain compared to their demands and their levels of satisfaction compared to the other participants.

This work utilizes the concept of "power" to analyze stability and acceptability of feasible alternatives and finds the most stable solution possible for the OR session allocation problem. The power index method is used to this aim. This method calculates the power or potential tendency of individual players to leave the game and derives a score for allocation schemes based on this. Hence, it gives an insight into the stability level of an allocation scheme and investigates if that scheme will prevent individual wards to develop a tendency towards leaving the game. Moreover, although a great deal of theoretical comprehensive and detailed optimization methods have been developed to allocate OR capacity, this work shows that it is worth taking a look at game-theoretical solutions and solve the OR capacity allocation problem from another point of view. The seek after stable solution decreases the inequality in the individual wards' power to a possible minimum. In this study, also, the performances of the players in treating patients are considered. Hence, different criteria and indicators can be considered for this type of weights in future without changing the methodology presented here. Physician preferences or the criticality of conditions of a special group of patients are examples of such criteria.

A case study from the literature and a number of various hypothetical cases were solved using the proposed method. For the former, the results obtained using the presented method were compared with that of an optimization-only approach from the literature. It was shown that using the presented method based on the power indices, a smaller scattering exists in the unsatisfied demands leading to an overall more stable solution. In the hypothetical case study, the sensitivity of the results with respect to variations in performance and available resources were analyzed.

Furthermore, uncertainties encountered in real situations regarding the allocation process is also taken into account. The number of treated patients during each OR session is dependent on the duration and type of the surgery and are difficult to predict. A combination of a Monte Carlo simulation and the weighted power index was proposed to address this uncertainty. This combination calculates the probability of winning a specific share for each ward, and also that of an allocation scheme with regard to its stability.

2.3 Part II: Fair Allocation of Operating Room Sessions Using the Shapley Value

Abstract

The allocation problem – as an essential process in strategic planning of operating room management – is formulated as a cooperative game assuming the individual surgical services as players having different claim profiles, while seeking the objective of reaching an equitable resource distribution. In this sense, a mechanism based on the Shapley value is proposed, which suggests a fair and equitable distribution scheme as a basis for further allocation negotiations. Individual players can form different coalitions, which each having its own value. In order to calculate their values, bankruptcy and priority rules are utilized. These values, then, are used as inputs of the Shapley value which divides the resources according to the marginal contribution of each player. To make a performance judgment and examine the proposed mechanism, it is applied to an operating room planning problem selected from the literature and the results are compared from equability and fairness points of view. The method is also implemented to a real case study – elective admissions of surgical departments at a German hospital – and it is shown how an equitable distribution can influence the results.

2.3.1 Introduction

Surgical departments are, on the whole, lucrative and their revenue stream is vital. Being a remarkable aspect of hospital finances, the surgical cases constitute up to 40% of the hospitals' total revenue (HFMA, 2003). However, their profitability levels depend on how they are managed, and a faulty management could simply lead to unprofitability. This is mostly because of the ever-increasing expenses and limitations of the resources dedicated to the operating rooms (ORs) and the impact of their management on personnel, surgeons, nurses and other departments of the hospitals (Cardoen et al., 2010a; Ceschia and Schaerf, 2016). Hence, the careful distribution of these limited resources is profoundly important.

In the process of resource allocation, say OR time, among surgeons or surgical services, two important issues must be taken into account: the throughput of whole surgical suite, and equitable allocation of resources. To understand the importance of these issues let's take a different view to look at the surgical department. Here, system theoretic view is adopted and is assumed that the surgical department is a system (Georgopoulos and Matejko, 1967) within the bigger system of the hospital - having taken into account that life of the system of surgical department is utterly vital for continuation of hospital's economic life. The system seeks means to increase efficiency, decrease waste and allocate the resources to improve value (Fraser et al., 2008). This happens only if the system is able to interrelate its elements (say the surgical services or surgeons) appropriately, so that the goal of the system, which is a maximized throughput, could be achieved. The system has the duty to distribute its available resources among its elements in an equitable way. Equitable does not necessarily mean equal; it means “fair”. It must be considered that the concept of “fairness” is subjective.

Every element within the system has expectations regarding the resource distribution, but they don’t have the same contributions to the system. However, both contributions and expectations must be taken into account. Some levels of “fairness” are needed to be provided to keep the elements satisfied, so that they all can cooperate as a team and not withdraw the system (An et al., 2019). Unquestionably, a good teamwork is one of the remarkable factors that guarantees improvements in health care (Frankel et al., 2006).

Fairness has become a focal concept in the psychology of organizations. Kuppelweiser *et al.* (Kuppelwieser et al., 2018) discuss that fairness in any organization leads to employee loyalty, commitment, satisfaction, motivation and performance. They consider fairness as the endmost decisive factor of productivity and profitability. A resource allocation scheme can be seen as a fair one, when all resource receivers perceive it as acceptable. Blake and Carter (2003) argue that the acceptability of a resource allocation by physicians and surgeons should be additionally considered. On one hand, the surgeons’ targeted demand must be as much as possible satisfied; meaning that receiving very much less OR time than demanded would be unacceptable by them (Blake and Carter, 2003; Guerriero and Guido, 2011). On the other hand, the surgeons scramble to win the resources as much as they need; in this respect, the full satisfaction of surgeons (surgical services) cannot be implemented, because the resources are limited and can not be allocated to only a few of services, while some others are idle throughout the week. Work-overload is also unwanted, since it has a negative impact on the hospital revenue (Powell et al., 2012). A large body of studies has been conducted by the researchers to allocate the OR time with the objective of **maximizing the case volume** (e.g. Feldstein (1967); Dowling (1976); Baligh and Laughhunn (1969); Blake and Carter (2002); Dexter and Macario (2002); Rohleder et al. (2005); Jerić and Figueira (2012); Guido and Conforti (2017), **maximizing the profit/minimizing the cost** (e.g. Ma et al. (2009); Silva and de Souza (2020); Persson and Persson (2009)) or **contribution margin** (e.g. Brandeau and Hopkins (1984); Hughes and Soliman (1985); Robbins and Tuntiwongpiboom (1989)). However, none of the studies have taken the fairness concept into account.

As discussed, during the resource allocation from a fair point of view the efficiency of individual surgeons must also be considered. Macario et al. (2001) showed in a study, that efficiency per an OR block varies remarkably among surgeons and surgical services. Therefore, to increase the productivity of the whole surgical department, it is more important to pay attention to the productivity of individual surgeons, rather than merely increasing the surgical throughput.

A useful approach to this aim is game theory (Kaye et al., 2012) which is proven to be a helpful method to resolve the allocation conflicts (Dinar and Howitt, 1997; Wang et al., 2008; Hipel et al., 2013) and has the capability to be applied to a wide variety of situations involving human interactions. This theory uses the game form to represent the physical rules that govern strategic interactions between multiple players, whose decisions impact one another. These players could be either members of a team (coalition) having the same goals or opponents with different or conflicting objectives. The players have two choices: they can either cooperate with others or counteract them. Cooperation of all players would make them all win, but if one of them chooses to defect, that player's payoff would be much bigger than the others'. If all of them decide not to cooperate, this leads to the loss of everyone, or they may obtain a very little payoff (Kaye et al., 2012). Thus, there are, in general, two types of games: cooperative and non-cooperative. The former deals with coalitions, which are less complicated than the latter one, in which all the available strategies should be familiar to the players. Real-life situations can be better defined by coalitional forms. In cooperative games or better to say, in coalitions, the members need to shift their perspective from individualistic view to an altruistic one and focus on other members. This attitude would let the members evaluate what they can add to the game and help them to maximize the total benefit of the system.

The basic concepts of the cooperative game theory and their properties are introduced by von Neumann and Morgenstern (1944). Since then, many researchers have made efforts to develop various kinds of games and solution concepts. In the field of OR management, however, there are only a few studies that discuss the usefulness of application of game theory or related concepts. Ackere (1990) discussed the conflicting interests in the scheduling process of surgery rooms and developed a game to deal with conflicts such as those between the surgeon and the scheduler. Marco (2001) rationalized the advantages of game theory by comparing it to the more traditional decision making methods in describing human interactions and explained how such interactions could be modeled as a game. McFadden et al. (2012) argued that game theory can be successfully applied to the OR environment, and then, explained the advisability of different types of games for resolving conflicting situations in the OR.

In this sense, a mechanism based on the Shapley value is proposed, which provides a fair point to start the resource distribution process. The Shapley value represents a fair, equitable, neutral alternative for managers to help them to bargain over how the resources could be allocated. This would be achieved by ensuring that the participants have equitable positions during the bargaining process. The Shapley value is generally developed for economic applications and have been further used in other contexts; such as economic and social applications (e.g. van den Brink (2007)) environmental applications (e.g. Dinar and Howitt (1997); Sadegh et al. (2010); Abed-Elmdoust and Kerachian (2012); Petrosjan and Zaccour (2003); Liao et al. (2015); Naber et al. (2015)), and computer sciences (e.g. Iturralde et al. (2013); Kaewpuang et al. (2013)). As mentioned earlier, to the best knowledge of the authors, no reported research has applied game theory to the OR problems. The proposed mechanism illustrates how game theory, particularly its solution concepts like the Shapley, can be utilized in resource allocation problem in OR department. To achieve this purpose, the mechanism works by forming possible coalitions among players (surgical services), and then applies bankruptcy and priority rules to calculate the worth of coalitions as input to the Shapley value. Finally, it introduces a fair resource allocation. Therefore, in summary, the main objectives of this work are:

- to apply game theoretic concepts to the resource allocation problem to obtain a fair distribution of OR block times (resources) among surgical services;
- to evaluate and validate the proposed framework based on an operating room planning problem selected from the literature;
- to provide a real-world case study to illustrate the practical insights of application of the proposed method.

The Shapley value is to distribute the payoffs and benefits produced by the coalition of all players. But, the use of the Shapley method to distribute the resources among players according to their demands is inspired by Iturralde et al. (2013). Nevertheless, the specifications of this problem are different from that of Iturralde et al. (2013), which is in the context of telecommunication networks. In Iturralde et al. (2013), the distribution of resources is carried out by just considering the claim profiles, while in this work, the contribution and productivity of each player is taken into account as well. This purpose is fulfilled by combining the Shapley value with bankruptcy and priority rules. Part II presents a simple, systematic and careful allocation of resources to create satisfaction for all surgical services focusing on the fairness concept. To the best of knowledge of authors, this concept has not been carefully elaborated by the health care literature.

The remainder of the chapter is as follows: Section 2.3.2 briefly reviews the Shapley value. The proposed resource allocation method is described in Section 2.3.3. In

Section 2.3.4 an illustrative example is given to clarify the details of the method. The verification of the model is provided in Section 2.3.5. Section 2.3.6 is dedicated to deal with the uncertain conditions in which fuzzy technique is applied to generate fuzzy claims. The details of the case study, results and discussions are presented in Section 2.3.7. Finally, Part II closes with concluding remarks in Section 2.3.8.

2.3.2 Shapley Value

In this chapter, we cope with cooperative games, whose players are able to form coalitions. There are several solutions to the cooperative games like the Core, the Nucleolus (Schmeidler, 1969), the Shapley value (Shapley, 1953) and the Kernel (Davis and Maschler, 1965), among which, the Shapley value is a strong tool for an equitable distribution, as it considers the "marginal contribution" of each player. The Shapley value is a concept introduced by Shapley (1953) to the economic literature with the purpose of proposing the fairest allocation of cooperatively earned profits among the collaborative players of coalitions. It basically calculates the relative importance of every player considering their collaborative activities.

Suppose a cooperative game, in which $N = \{1, 2, ..., n\}$ is the set of players participating in the game and S is a subset of N, indicating a coalition. In this game, in order to calculate marginal contribution of each player, characteristic functions of all possible coalitions should be investigated. Characteristic function $v(S)$ of coalition S specifies the total payoff that the members of S can obtain by signing an agreement among themselves; this payoff is accessible to be distributed among the members of the group. If the set of all coalitions is denoted by $P(S)$, then the characteristic function $v(S)$ which maps the subset of players to real numbers, is as follows:

$$v : 2^N \to \mathbb{R}_{\geq 0} \quad satisfying \quad v(\emptyset) = 0. \tag{2.7}$$

Having the characteristic functions, based on the weighted average of the players' contributions to all possible coalitions, the Shapley value is calculated as:

$$\theta_i(v) = \sum_{\{S:i \notin S\}} \frac{(|S|)!(|n| - |S| - 1)!}{|n|!} [v(S \cup i) - v(S)] \tag{2.8}$$

where θ_i is the Shapley value or worth of the player i, N is the number of players, $|S|$ is the number of members in the coalition S, and $v(S \cup i)$ is the worth of the coalition S including the player i. The Shapley value of the player i can be interpreted as his index of power in each coalition.

2.3.3 Resource Allocation Framework

2.3.3.1 Problem Definition In this work, the OR suite of a hospital is regarded as a system, comprised of surgeons and surgical services as its elements. The interrelations among these elements within this system are modeled using mathematical formulations governing cooperative games. In this game, the system seeks the goal of distributing the resources among its elements in a fair manner. There is a limited amount of OR time, and each element has a particular performance in the sense of productivity per unit of resources (say OR sessions). Each surgical service has a list of patients waiting for surgery and demands to be allocated with a certain quota from the total available resources. Thereupon, each surgical service demand is itself based on the number of patients on its waiting list.

The proposed distribution scheme suggested by the proposed method can be used as the point of fairness, based on which the further decisions regarding the exact allocation of the OR session could be conducted. For this purpose, a mechanism comprised of four steps is introduced and described in what follows:

2.3.3.2 Step 1: Data Entry In this step, all data including the number of players, their claim profiles, and their productivities must be fed into the mechanism.

2.3.3.3 Step 2: Formation of Possible coalitions In the second step, possible coalitions are formed. Coalitions are groups comprised of one or more number of agents that gather together and make joint agreements to coordinate their actions. While the members are behaving cooperatively within the coalitions, they might interact non-cooperatively with the non-members. In a N-player game, the number of coalition members possibly ranges from 1 to N.

2.3.3.4 Step 3: Calculation of the Characteristic Functions In order to calculate the characteristic functions or worth of coalitions, a rule must be defined to determine the resource quota that each coalition receives and how this quota should be consumed by the coalition. For this purpose, a bankruptcy game is modeled, and the adjusted proportional rule of such games is taken to ration the distribution of limited resources among the players participating in possible coalitions. Bankruptcy games analyze the allocation of a number of perfectly divisible resources among a group of players according to their claim profiles, which in sum, exceed the amount to be allocated.

Our bankruptcy game is a triplet (N, E, c), where $N = \{1, 2, ..., n\}$ is the set of players, $C = \{c_1, c_2, ..., c_n\} \geq 0$, $0 \leq E \leq \sum_{i=1}^{N} c_i$. C represents the claim vector of players and E is the total available resources. Each coalition S obtains an amount of available resources that the other players – not participating in the coalition S – concede. Therefore, the number of resources brought to the coalition S is:

$$x(S) = max\left\{E - \sum_{i \in N \setminus S} c_i, 0\right\}, \qquad x(N) = E \tag{2.9}$$

Having determined the resource quota that each coalition receives, a rule must define how the coalition members should consume the resources. In this process, a priority rule is applied; that is, that first the capacity of the player with the highest productivity rate will be fulfilled, then, the remaining number of resources will be given to the player with the second highest productivity rate until his/her claim is satisfied as well, and so forth. This process continues until no adequate amount of resources remains to satisfy the players' requests. Macario et al. (2001) also proposed a method based on the priority rule to allocate a limited number of OR blocks to surgical services according to their productivity rate.

In order to compute the worth of a given coalition, the priority order of the members should be determined based on their productivity rates and the corresponding vector must be sorted in descending format. If a given coalition has m members, $W = \{w_1, w_2, ..., w_m\}$ is the productivity rates vector of its members and $C = \{c_1, c_2, ..., c_m\}$ is the claim vector. After sorting the productivity vector W, we have the new set of $\{z_1, z_2, ..., z_m\}$, whereby $z_1 \geq z_2 \geq ... \geq z_m$. The claims should be sorted as well according to the productivity based priority order of the members as the new set of $\{d_1, d_2, ..., d_m\}$, whereby, for example d_1 is the claim of the coalition member with the highest productivity rate of z_1. Afterwards, using the following algorithm the worth of coalition $v(S)$ could be calculated.

Calculation of $v(S)$
$v(S) \leftarrow 0$
$x(S)_0 \leftarrow resource\ quota\ of\ coalition\ S$
while $j \leftarrow 1$ **to** M **do**
  if $x(S)_{j-1} \geq d_j$ **then**
    $v(S) \leftarrow v(S) + d_j \times z_j$
    $x(S)_j \leftarrow x(S)_{j-1} - d_j$
  else
    $v(S) \leftarrow v(S) + x(S)_{j-1} \times z_j$
    terminate the loop
  end if
end while
  return $v(S)$

The objective of the above-mentioned process is to assure that each coalition uses its full capacity to contribute to the system. The purpose is to maximize the patient throughput out of each coalition given a certain number of resources. To clarify the details of the above-mentioned algorithm, a detailed calculation for the example mentioned in Section 2.3.4 is provided (Table 8).

2.3.3.5 Step 4: Calculation of Resource Allocation Based on the Shapley value

Based on the characteristic functions obtained in the previous stage, the Shapley value using Equation 2.8 and accordingly the percentage of resource share that every player receives, is calculated using the following equation:

$$P = \frac{\theta_i(v)}{\sum_i^N \theta_i(v)} \times 100 \tag{2.10}$$

This framework ensures that all players participating in the grand coalition (formed by all members) will receive a share of total available resources adjusted by their claim and contribution to the coalition. Moreover, this framework fortifies that the whole coalition will achieve the maximum contribution margin, while no claim will remain unanswered.

2.3.4 Illustrative Example

Herein, we illustrate the application of the proposed mechanism to a hypothetical game among surgical services. A surgical suite with the capacity of E =25 OR blocks is to be filled by allocating it to $N = 4$ different surgical services, named A, B, C and D. The claim (c_i) by the surgeon i is generated randomly from the interval [0, 10] under the constraint of $\sum_{i=1}^N C_i > E$. Their productivity per an OR block is also generated randomly from the interval [1, 5]. The claims of the surgical services and their productivity rates are shown in Table 6.

Table 6: Inputs of the illustrative example.

Surgical Service i	Claim c_i	Productivity rate w_i
A	12	2.8
B	7	4.7
C	8	1.5
D	3	3.5

The next step is to form the possible coalitions and determine the amount of resources, that they receive based on the bankruptcy rules (Table 7). Finally, based on the Equations 2.7 and 2.9 the number of resources allocated to each player can be calculated (Table 9).

Table 7: Possible coalition settings, their received amount of resources and characteristic functions.

Coalitions		$x(S)$	Value of the Coalition $v(s)$
Non-cooperative Coalitions	{A}	7	19.6
	{B}	2	9.4
	{C}	3	4.5
	{D}	0	0.0
Partial Coalitions	{A B}	14	52.5
	{A C}	15	38.1
	{A D}	10	28.0
	{B C}	10	37.4
	{B D}	5	23.5
	{C D}	6	15.0
	{A B C}	22	71.0
	{A B D}	17	63.5
	{A C D}	18	48.6
	{B C D}	13	47.9
Grand Coalition	{A B C D}	25	81.5

Table 8: Detailed calculation of $v(S)$ for the grand coalition from Table 7.

j	$x(S)_{j-1}$	d_j	$z_j \uparrow$	$x(S)_j \geq d_j$	$v(S)$	$x(S)_j \leftarrow x(S)_{j-1} - d_j$
1	25	7	4.7	True	7×4.7	$25 - 7 = 18$
2	18	3	3.5	True	7×4.7 $+3 \times 3.5$	$187 - 3 = 15$
3	15	12	2.8	True	7×4.7 $+3 \times 3.5$ $+12 \times 2.8$	$15 - 12 = 3$
4	3	8	1.5	False (terminate the loop)	7×4.7 $+3 \times 3.5$ $+12 \times 2.8$ $+3 \times 1.5$	–
						$v(S) = 81.5$

Table 9: The amount of share that each player receives.

Surgical Service	Shapley value	Received Share (%)
A	31.09	38.15
B	26.24	32.20
C	15.99	19.62
D	8.18	10.03

2.3.5 Case study I: Verification of the Proposed Mechanism

The purpose here is to verify that we have modeled what we aimed to do. In this regard, a decision making problem from the literature is selected to examine the performance of the proposed mechanism. Here, the case study discussed by Testi et al. (2007) is considered. The case, which is a surgical department in San Martino University Hospital located in Genova, Italy, has an OR department comprised of six surgical services regarded as players in this work. Six surgery rooms are available from Monday to Friday for 6 hours daily constituting up to 30 OR sessions per week. Each ward has its own individual productivity, which is the average number of patients it can treat per an OR session. The proposed method by Testi et al. (2007) is a three level hierarchical approach for OR scheduling on a weekly basis. These levels are comprised of session planning, master surgical schedule, and elective case scheduling. This work is concerned only with the session planning level, which is about assigning operating sessions to the wards. The objective function for Testi et al. (2007), to allocate the OR time between the surgical services, is to maximize the sum of "marginal benefits" of all surgical services defined by the kth session demanded by the jth surgical service as the following equation:

$$d_{jk} = \quad \sum_{j}\sum_{k} \frac{D_j(k-1)}{\sum_j D_j} \tag{2.11}$$

where, d_{jk} is the marginal benefit of the kth session claimed by the jth ward, D_j is the total number of OR sessions claimed by the ward j, and k is the number of already assigned sessions. This equation grants more significance to the first session assigned to the jth ward, rather than to the successive ones. This means that, when the ward j has already no sessions, after receiving the first one, its benefit is at the highest, compared to the state, in which it receives the kth session while it already has $k-1$ sessions. Namely, the marginal benefit drops as the number of received OR sessions rises. Consider that, in this equation the subtraction between total demand of the ward j and having already assigned $k-1$ sessions is divided by the aggregated demands of all wards, therefore, more value is received by the ward with the highest claim. That is to say that the more the demand, the higher the marginal benefit is. Testi et al. (2007) ran the allocation problem under constraints such as capacity and overrun hours without any cost constraints.

The results taken from Testi et al. (2007) and the results obtained from the proposed mechanism are shown in Table 10. Comparison of the results in Figure 6 demonstrates that the distribution percentages proposed by the Shapley-based method match the results from Testi et al. (2007). The differences between the results for the wards 1, 3, 4, and 5 are negligible. For players 2 and 6 there are slight differences between the results. The reason is that this method, unlike Testi et al. (2007), takes the performances of the players into consideration in the process of resource distribution, which provides a fairer approach. This motivates the players to improve their productivity and performance.

The fairness of solutions suggested by both methods is measured using the method proposed by Jain et al. (1984). This index measures the "equality" of a system which allocates resources to n players. If ith player receives an allocation x_i, then the fairness of the system is measured using the following formulation:

$$f(x) = \frac{[\sum x_i]^2}{n \sum {x_i}^2} \tag{2.12}$$

where $f(x)$ is the fairness index (FI). If $f(x) = 1$, then the system is 100% fair, and if $f(x) = 0$, it means that the system is totally unfair and only favors the demands of a few numbers of players. Here, this index is used in terms of unsatisfied claims. The reason is that, the unsatisfied claim is a remarkable factor in bringing dissatisfaction between surgical services. An unsatisfied claim means the numbers of procedures done in overtime. Here, unfair dissatisfaction levels are unwanted. This means that having surgical services which suffer from more overtime or have more patients on the waiting list than the others is not desirable.

By comparing the fairness indices calculated for both methods (Table 10), it can be understood that, the proposed method in Part II provides a fairer solution than the one from Testi et al. (2007) but the same throughput ($\sim$ 83 patients per week).

Table 10: Details of the case study form Testi et al. (2007).

			Testi et al. (2007)		Shapley value	
Surgical Service i	Claim (Weekly) c_i	Productivity (Patient/Block) w_i	Received share (%)	Unsatisfied claim	Received share (%)	Unsatisfied claim
1	12	3.0	33.33	2.00	32.81	2.16
2	5	2.5	10.00	2.00	11.32	1.60
3	12	2.8	30.00	3.00	30.84	2.75
4	6	2.5	13.33	2.00	13.64	1.91
5	3	2.4	6.67	1.00	6.68	0.99
6	2	2.8	6.67	0.00	4.71	0.59
Total	40	–	100		100	
FI				0.76		0.84
PT*			83		83	

* PT= Patient Throughput

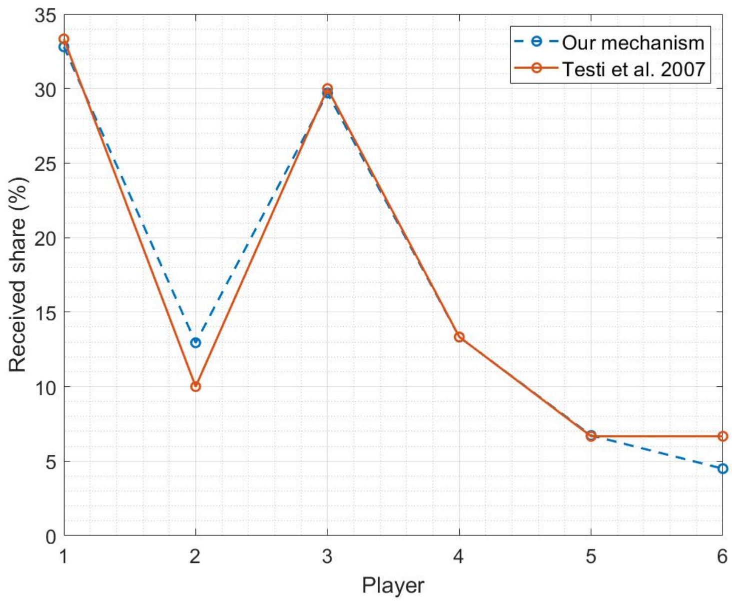


Figure 6: Comparison of the results obtained from the proposed mechanism and Testi et al. (2007).

2.3.6 Allocation Under Uncertainty: Fuzzy Claims

Surgical services are infested with uncertainties, and straight ways to measure surgical times are not generally available (Burgette et al., 2017). Uncertainty causes major challenges in faultless planning and scheduling. The previous section solved the OR management problem in a deterministic manner by using the average values for ward performances (contribution margin). Using the average values can be a quick way to obtain a solution; however, it requires the elimination of some information, and hence, creates uncertainties. This is because elimination of information is not much different from its lacking (Meyer, 1981; Johnson and Levin, 1985).

The contribution margin of wards or their claims are not easy to predict. There are different influencing factors such as the methods surgeons use, the quality of surgical teams, patient characteristics, and the frequency of patient arrivals for each service (Samudra et al., 2016). Therefore, in this section the uncertain parameters are considered to be fuzzy numbers and a fuzzy technique is employed to deal with these numbers. This is due to the capability of fuzzy techniques (Zadeh et al., 1965) in handling subjectivity and representing inherent vagueness caused by gaps in knowledge (Sadeghi et al., 2010). Here, some basic definitions of the fuzzy sets theory are reviewed.

Definition 1. X is a collection of objects represented by x. Then, a fuzzy set $\tilde{A}$ in X is defined as

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)|x \in X\} \tag{2.13}$$

$\mu_{\tilde{A}}$ is the membership function which maps X to the membership space M and takes values within [0,1].

Definition 2. A triplet (m_1, m_2, m_3) is called a triangular fuzzy number, when its membership function is given by follows:

$$\mu_{\tilde{A}}(x) = \left\{ \begin{array}{ll} (x - m_1)/(m_2 - m_1) & m_1 \leq x \leq m_2, \\ 1, & x = m_2, \\ (m_3 - x)/(m_3 - m_2) & m_2 \leq x \leq m_3, \\ 0, & \text{Otherwise.} \end{array} \right\} \tag{2.14}$$

Definition 3 An α-cut of fuzzy set X is a crisp set A_α that contains all the elements of the universal set X whose membership grades in A are greater than or equal to the value of α. This definition can be written as

$$[A]_\alpha = \{x \in X|\mu(x) \geq \alpha\}. \tag{2.15}$$

Table 11: Details of the case study form Testi et al. (2007) and the obtained results from the proposed mechanism.

Surgeon/Surgical Service	Fuzzy claim $(c_i - 2,\, c_i,\, c_i + 2)$	Fuzzy contribution margin $(w_i - 1,\, w_i,\, w_i + 1)$
1	(10, 12, 14)	(2, 3, 4)
2	(3, 5, 7)	(1.5, 2.5, 3.5)
3	(10, 12, 14)	(1.8, 2.8, 3.8)
4	(4, 6, 8)	(1.5, 2.5, 3.5)
5	(1, 3, 5)	(1.4, 2.4, 3.4)
6	(0, 2, 4)	(1.8, 2.8, 3.8)

c_i and w_i are the claims and contribution margins of players, respectively, taken from Table 10.

2.3.6.1 Fuzzy α-cut Technique This work uses fuzzy α-cut technique to address the confidence levels regarding fuzzy claims and elicit crisp values from fuzzy numbers to calculate the Shapley value. As mentioned earlier, the uncertain data are considered to be fuzzy to represent imprecision in data. According to the Definition 3, the wider the support of the α-cut, the higher the uncertainty and the less informative the parameter and vice versa (Li and Yen, 1995).

The process to consider the fuzziness in claims as well as contribution margin is as follows:

- Step 1: Select a value α of the membership function (a level of likelihood).
- Step 2: Calculate the Infimum (smallest) and Supremum (largest) values of each fuzzy number.
- Step 3: Calculate the share of each player for both Inf and Sup values based on the Shapley value described in Section 2.3.3.
- Step 4: Return to Step 1 and repeat Steps 2 and 3 for another α-cut (note: α can be increased step-wise from 0 to 1 every 0.1 increments). The fuzzy results (resource share of each player, total contribution margin, etc.) are obtained from the Inf and Sup values for each α-cut.

2.3.6.2 Case Study I Under Fuzziness In this subsection, for the case study from Testi et al. (2007) fuzzy claims and fuzzy performances are considered for each ward. Table 11 shows the triangular fuzzy numbers, which are generated based on the data from Table 10.

The percentage that each surgeon receives is presented in Figure 7. Figure 7 illustrate the outputs of the experiments for different values of α (0, 0.2, 0.5 and 0.8). It is obvious that as the uncertainty decreases, the gap between results for the Infimum (Inf) and Supremum (Sup) values gets narrower and narrower, and finally they share the same results for $\alpha = 1$. It depends on the risk attitude of the OR manager to choose a level of uncertainty and make decisions based on the obtained results. It is also possible to elicit a fuzzy result for each player. For example, see Figure 8 for Player 1. The manager is also able to elicit fuzzy contribution margin for the whole grand coalition of players (Figure 9), by which she/he can estimate the profitability of the OR departmentbased on her/his risk attitude.

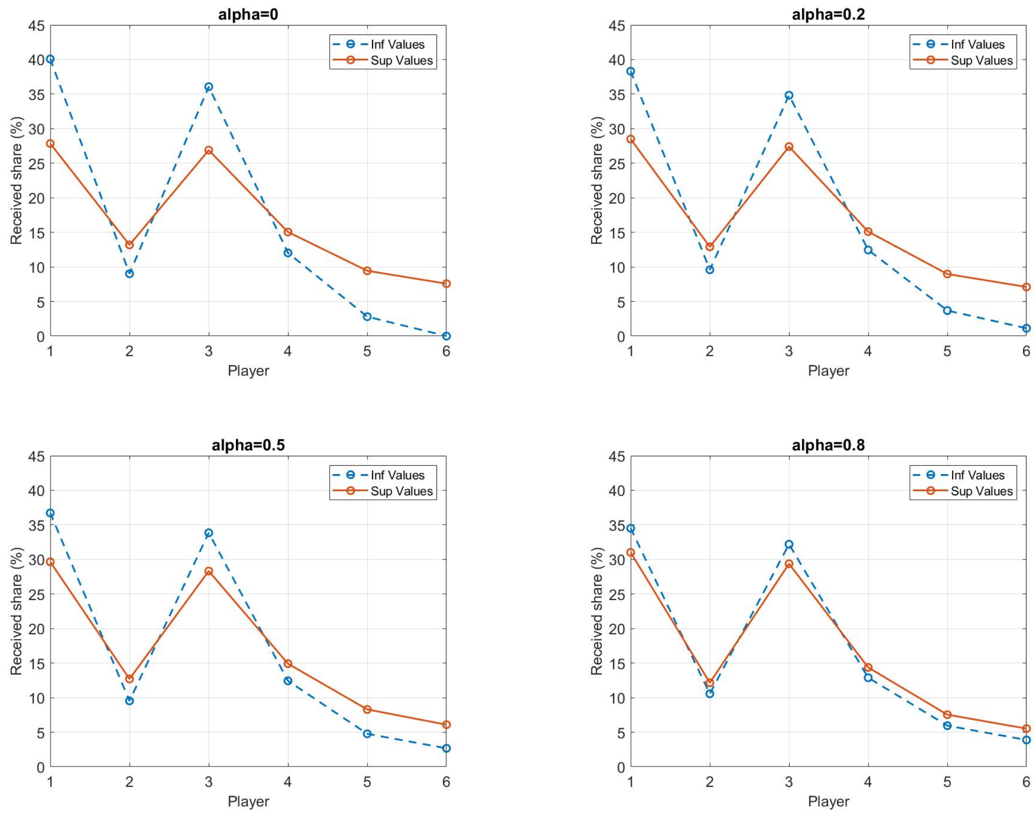


Figure 7: Received share of the players as percent for $\alpha = 0$ (top left), $\alpha = 0.2$ (top right). $\alpha = 0.5$ (bottom left), $\alpha = 0.8$ (bottom right) and The dashed line shows the results for Inf values and the solid one shows the results for Sup values.

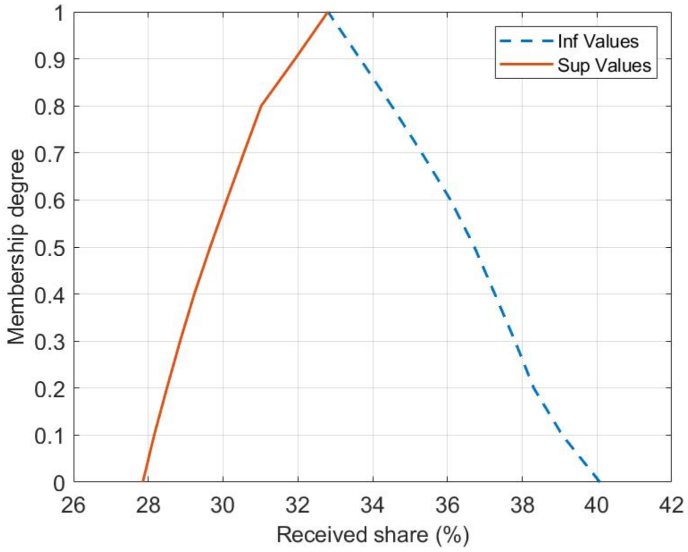


Figure 8: The fuzzy number of the received share for Player 1.

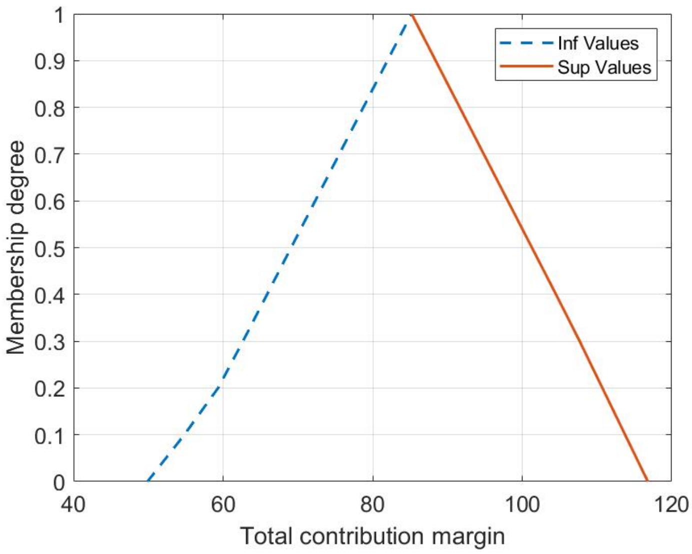


Figure 9: The fuzzy output from the Shapley based allocation mechanism for total contribution margin for the grand coalition (the whole surgical suite).

2.3.7 Case Study II

The case study here refers to one of the surgical departments in a general hospital in the state of Baden-Württemberg of Germany. This department is made up of three specialty departments of trauma surgery (TS), general surgery (GS), and thorax surgery (THS) which share 7 operating rooms. The operating rooms are available from Monday to Friday from 7:30 until 15:00, which means $5 \times 7 = 35$ sessions are available in a week. Overall 67 surgeons are involved in this department, which have various performances and productivity rates per an OR session.

The data for this department were collected for six months from January to June 2015. In this time-frame, 3,045 elective patients were admitted to this department. It is forecasted that the number of patients would increase in the upcoming years. According to the Statistical Office of Baden-Württemberg, the number of elective patients are expected to increase about 10% in 2030 with reference to 2015. This means that the hospitals in the region must adjust themselves to the demographic changes and patient increase.

The analysis of data showed that in this department averagely 23.4 procedures are carried out of the production window. OR overtime induces increase in surgical cost and brings dissatisfaction for surgical teams, and hospitals need to take effort to control the expenses and unhappy surgical teams. The purpose of this case study is, firstly, to estimate the performances of the individual surgeons, and accordingly, those of the surgical departments, to see how many procedures they can carry out per an OR session. Secondly, the current status is investigated to see how the situation for each department is; how many procedures are completed within the OR's production window and how many are done out of this window. Thirdly, the proposed mechanism is applied to the case study to see how the fair distribution can change the situation.

To evaluate the performances of surgeons and surgical services, the incision-suture duration is considered. In calculation of surgical service performances, the influence of overlaps during turnover times is also taken into account. For GS, the procedure duration for surgeons varies between 25 and 150 minutes. For THS and TS these values range between 25 and 107, and 20 and 108 minutes, respectively. Of course, there are duration variations in relation to diagnosis types, but it is assumed that – for the sake of simplicity – the average values could be representatively enough.

Further evaluations showed that the GS, THS and TS can carry out in average 2.8, 3 and 3.8 procedures per an OR session, respectively, and GS is suffering more from overtime than the other two departments (see Table 12). The data from these departments are fed into the proposed mechanism to see how consideration of fairness influences the situation. Since the emergency cases are also using these 7 operating rooms, according to the frequency of these cases during the day, it is assumed that 0.5 OR session on a daily basis during the production window is reserved for these cases. The available OR sessions in each month for elective cases are calculated based on the number of business days which are shown in Table 12. It can be seen from the results, that a fair distribution and consideration of contribution of each specialty department, may not dramatically increase the total patient throughput of the whole department but leads to more equitable distribution in terms of unmet demands and better outcomes with respect to fairness index. Comparison of the fairness indies shows that the Shapley method brings a comparative level of fairness between the specialty departments.

Table 12: Real data and proposed solutions for the case study over 6 months.

		Jan (123.5)*	Feb (136.5)	Mar (136.5)	Apr (136.5)	May (123.5)	Jun (143)	
	Dept.	Nr. of Procedures within (out of) Production Window						Mean
Real Measures	GS (2.80)	191 (55)	211 (62)	206 (52)	196 (64)	199 (50)	217 (65)	203.34 (58.00)
	THS (3.00)	39 (5)	53 (11)	48 (9)	48 (9)	49 (9)	55 (9)	48.67 (8.67)
	TS (3.80)	151 (37)	154 (29)	173 (24)	169 (21)	138 (35)	167 (35)	158.67 (30.16)
FI		0.71	0.72	0.71	0.64	0.77	0.71	0.71
Solution by Shapley value	GS (2.80)	194 (52)	220 (53)	208 (50)	212 (48)	198 (51)	226 (56)	209.67 (51.67)
	THS (3.00)	29 (15)	42 (21)	38 (19)	38 (19)	39 (19)	43 (21)	38.17 (19.00)
	TS (3.80)	168 (19)	165 (18)	188 (9)	183 (7)	151 (21)	183 (19)	173.00 (15.50)
FI		0.75	0.79	0.69	0.67	0.81	0.78	0.75

* Number of available sessions in month

2.3.8 Concluding Remarks

Hospitals as systems have the goal of being profitable to survive financially and to continue their services within the society. To reach this goal, an intra-system fairness must be constructed so that the system performance and its profitability could be guaranteed. The surgical department – as a vital component to the profitability of the whole hospital – must also sustain an intra-system justice and treat its key elements (surgical services) in a fair way. The productivity of the surgical suite – apart from the fairness concept – depends strongly on productivity of individual surgical services. These surgical services, despite the variations in their performances, are fighting for the resources to consummate their waiting lists. On the other side of the story, for each player, there is a minimum acceptable level, which if remains unsatisfied, it will be likely that the player withdraws the game. This issue highlights the importance of the concept of fairness.

Being "fair" in the process of resource distribution has become the motivation of this work. In this work, a fair resource distribution mechanism based on game theory, particularly, the Shapley value, is developed and implemented to allocate OR time to the surgical services according to their demand profiles and productivity rates. The mechanism introduced here, is comprised of several steps. Having considered the surgical services as players of a cooperative game (1) the possible coalitions are determined (2) based on the bankruptcy rules, the number of resources that each coalition receives is calculated, then (3) based on the priority rules, the value (characteristic function) of each coalition is measured, and finally (4) the percentage of resources that each player collects is calculated based on the Shapley value. An illustrative example is provided to clarify the process of resource distribution in the proposed mechanism. To judge the performance of the proposed mechanism, an operating room planning problem is taken from the literature. The deliberation of results using a fairness metric shows that the distribution scheme suggested by our Shapley-based method can provide a very good starting point for fair distribution negotiations, since it guarantees a relatively high level of fairness.

Furthermore, uncertainties encountered in real situations regarding the allocation process is also taken into account. The claim profiles and the contribution margins of the players are considered to be fuzzy numbers. With the help of the α-cut technique, the Inf and Sup values from the fuzzy numbers are elicited and utilized as the inputs for our mechanism. The outputs of the fuzzy integrated method are also fuzzy numbers, which can be interpreted according to the risk perceptions of the head decision maker or the OR manager.

Having ensured about the capability of the proposed method, it is also applied to real data collected from a surgical department in a German hospital. The results emphasized the influence of fair distribution on the overall productivity of the surgical department. The scenario analysis which focused on exclusion of the slowest surgeons, revealed that hospitals must align incentives among surgeons and surgical services to improve their facilities leading to increase in efficiency and productivity of the whole surgical department.

The scope of Part II pleads for further research in the field of master surgical schedules, to cope with the assignment of days, rooms and shifts at the tactical level. For example, developing a game theoretic process to allocate the resources considering surgeon preferences and patients priorities.

3 A Pre-assignment of Master Surgical Schedule with Focus on Surgeons' Satisfactions

Abstract

This chapter addresses the master surgical schedule (MSS) at the tactical level of operating room (OR) planning and control. This process focuses on assigning operating room time blocks to specialty departments and their associated surgeons in a finite planning horizon. The complexity of creating a MSS emerges from the fact that normally several surgeons and specialty departments share the same limited resources. Usually, surgeons have their own individual preferences regarding rooms, days and even shifts, and satisfying their preferences have not been necessarily the focal point of the methods have been developed so far. To overcome the complexities, a hybrid heuristic algorithm using bargaining methods, called Nego2Sked, is developed in this chapter, which solves MSS problem as a combinatorial one. The focus of Nego2Sked is on surgeon preferences as a key determinant of proper management of ORs. In this method, a feasible set of solutions is evaluated, scored and ranked by surgeons/surgical groups using ordered weighted averaging aggregation operator (OWA). Then, by assuming a virtual bargaining process, surgeons/surgical groups enter a bargaining process to bargain over the solutions and find the one upon which all surgeons have consensus. Since the problem is a large combinatorial problem, mutation only genetic algorithm is utilized to exploit and explore the solution space. To demonstrate the performance of Nego2Sked, computational results by solving a real case study are reported and analyzed.

3.1 Introduction

Various groups of players are involved and coordinated in operating room (OR) suites to deliver highly specialized medical services to patients. Each player has a kind of selfishness, and their objectives do not necessarily correspond to others' (Weissman, 2005; Glouberman and Mintzberg, 2001). Hence, OR managers are constantly under pressure to manage these conflicting objectives. The most powerful group, which stay at the focal point of the ORs, are surgeons; they expect maximum convenience, easy and quick access to OR resources, and advanced equipment (Kaye et al., 2012). Every surgeon has its own preferences and waiting list, that may conflict with others', and hence, the OR manager must be able to respect all surgeons and OR constraints in order to maximize productivity, minimize conflict, maintain order and fairness. It must be mentioned, that not giving enough importance to surgeon preferences may decrease their satisfaction and consequently jeopardize their loyalty (Hosseini and

Taaffe, 2015). Therefore, it is rational to design a scheduling system which could properly manage surgeon preferences and priorities under consideration of resource limitations.

3.2 Relevant Sub-problems in the Literature

Operating room planning and scheduling is normally done in a three stage hierarchical decision process (van Oostrum, 2009; Guerriero and Guido, 2011): (1) strategic level or long-term (2) tactical level or medium-term (3) operational level or short-term. The first level is referred to as OR time distribution among surgical specialties or groups of surgeons seeking an efficient case mix (Blake and Carter, 1997). The second level referred to as master surgical schedule (MSS) which specifies surgeons to be associated with OR time (Beliën and Demeulemeester, 2007), and finally the operational level which deals with daily schedule and staffing for individual surgical groups. Surgeon preferences come first at the tactical stage and in the process of creating MSS to question. MSS is about deciding on how rooms and time blocks should be allocated to the surgeons. It is a cyclic timetable and must be adjusted according to strategical decisions and seasonal fluctuations.

Master surgical planning and its optimization has attracted more attention of researchers than the other stages. Various parameters and influencing factors are studied by researchers to generate MSS. Nevertheless, surgeon preferences were either halfway considered by these studies or were totally neglected. Marchesi and Pacheco (2016) considered minimization of unmet demand in terms of difference between allocated OR time and demanded one as their objective function. The minimization of deviations between realized utilization and targeted levels was regarded by (Adan and Vissers, 2002; Dellaert and Jeunet, 2017; Vissers et al., 2005; Cappanera et al., 2014). Instead, some other researchers (Beliën and Demeulemeester, 2007; van Oostrum et al., 2008; Beliën et al., 2009; Fügener et al., 2014; Santibáñez et al., 2007) studied the influence of OR schedules on downstream resource usage such as intensive care unit and normal bed utilization. They took leveling of these resources as their objective function into account. In a same manner, Testi et al. (2007) minimized the impact of MSS on downstream resources in terms of length of stay. Alongside resource leveling, Beliën et al. (2009) considered two more parameters to fine-tune their method. They tried to concentrate surgeons of the same group in a same room and maintain consistent weekly schedules. Keeping a consistent schedule was also scrutinized by Blake et al. (2002). They also ensured that the total OR time is assigned.

Maximization of the patient throughput as a conventional measure of productivity of health systems was also an attractive objective function in generating MSS, which was the focal point of studies by (Adan and Vissers, 2002; Santibáñez et al., 2007; Cappanera et al., 2014; Guido and Conforti, 2017). However, Guido and Conforti (2017) didn't consider a mere maximized patient throughput. They also took clinical and overall priority of patients into consideration to reduce the waiting times for patients who are in a semi-urgent status. The concept of longer waiting lists and penalizing longer queues was also appreciated by (Mannino et al., 2012).

Under-utilization and over-utilization as a cost burden to OR departments are also among the factors frequently studied by researchers. Minimization of these two factors and the associated costs was the focus point of (Ozkarahan, 2000; Hosseini and Taaffe, 2015; Guido and Conforti, 2017). The proposed approach by Marques et al. (2019) was slightly different, in which the authors considered several objective functions at the same time. They suggested minimization of four objective functions: number of assigned rooms, deviation of assigned shifts and those where most of the surgeons are available, deviation of weekly time from median value driven from historical data and workload variability at downstream units. To solve the MSS problem. Blake and Carter (2002) presented an algorithm comprised of two models. The first one determines a case mix and volume for each surgeon and the second one converts the determined case mix into equivalent set of practice changes for surgeons.

3.3 Model Preferences

Surgeon preferences as an objective function was partially by Testi et al. (2007) and Marques et al. (2019). However, they considered surgeon preferences in a binary way, which means they have considered either availability or not-availability of surgeons. Ozkarahan (2000) argued also about inclusion of surgeons satisfaction in scheduling process but views it as the least important determinant. Consideration of surgeon preferences in a binary way may not implement realistic implications. For example, if surgeons obtain the privilege to express different levels of preferences (in ordinal or cardinal manner), they can manage their own priorities such as patient priorities, operating room type and even consecutive shifts in order to avoid back-to-back working hours. Such an approach, which is of course not offered by hospitals, could definitely lead to more surgeons' satisfaction and loyalty. In this regard, Gendreau et al. (2006) consider four rules in scheduling problems: (a) supply and demand, (b) workload, (c) fairness and (d) ergonomics. Supply and demand is about assigning surgeons within their preferences and availabilities associated with prioritization of their patients or their availabilities due to involvement in other activities such as teaching, research or working for other hospitals. Workload is about not inducing overload or assigning less than desired. Fairness is about distributing the undesirable shifts in an equitable manner so that no surgeon feels discriminated, and ergonomics is about restricting consecutive working hours (Gendreau et al., 2006). However, satisfying these rules for all surgeons is relatively cumbersome and OR manger should use strong negotiation skills to carefully manage the assignment process.

Therefore, it seems sensible to negotiate distribution of OR time among surgeons or surgical groups and bargain over a solution which could reduce conflicts and maintain satisfaction and fairness especially among highly experienced and prestigious surgeons. For this purpose, bargaining games, in the game theory literature, which simulate the behavior of bargaining parties, could be a reasonable option. Bargaining methods are about how to make the bargainers involved in a conflict reach a consensus (Brams, 2003) and yield an optimal/near-optimal solution out of available alternatives. The use of game theoretic methods in OR planning has been considered by only few studies. Ackere (1990) developed a game to deal with conflicts between the surgeon and the scheduler. Marco (2001) and McFadden et al. (2012) highlight that negotiation and game theoretic methods are more advantageous than traditional methods in modeling interactions of different stakeholders in the OR environment.

3.4 Contribution of this Chapter and Outline

Taking the above-mentioned arguments, the focus of this chapter is on surgeon preferences in the first phase of generating MSS. Therefore, it is not about the detailed assignment of cases and patients. For this purpose, this chapter uses negotiation methods to maximize the minimum satisfaction of the surgeons regarding the assignment of OR time. In fact, the assignment process is considered as a bargaining process in which surgeons bargain over their preferences. Here, the fall-back bargaining (FB) method, developed by Brams and Kilgour (2001) is used to reduce the conflicts among surgeons and meet their expectations in creating OR schedules. The FB is a useful method to simulate negotiations involving multiple parties (Sheikhmohammady and Madani, 2008; Madani et al., 2015). The aim is to define the assignment of surgeons or surgical groups to the available operating rooms, days, and shifts in a way that the minimum satisfaction of the involved people are maximized. Such scheduling problems are difficult combination optimization ones and finding a feasible solution satisfying all conflicts is really burdensome. For this reason, different solution approaches and algorithms are developed to search the decision spaces such as genetic algorithm (Marchesi and Pacheco, 2016; Guido and Conforti, 2017; Dellaert and Jeunet, 2017; Marques et al., 2019), simulated annealing (Beliën et al., 2009; Fügener et al., 2014), branch-and-bound (Fügener et al., 2014), variable neighborhood search algorithm (Dellaert and Jeunet, 2017), linear programming (Hosseini and Taaffe, 2015), quadratic optimization (Beliën et al., 2009), goal programming (Ozkarahan, 2000; Blake and Carter, 2002), integer/mixed integer programming (Marques et al., 2019; Blake et al., 2002; Vissers et al., 2005; Beliën and Demeulemeester, 2007; van Oostrum et al., 2008; Mannino et al., 2012; Adan and Vissers, 2002; Santibáñez et al., 2007; Beliën et al., 2009; Cappanera et al., 2014) or simulation methods (Testi et al., 2007; Cappanera et al., 2014) are developed to explore the decision spaces and search for optimal/near-optimal solutions.

The solution approach to solve the negotiation model proposed in this chapter is a modified version of genetic algorithms (GA). This modification is a special case of GA called mutation only genetic algorithm (MOGA) (Zhang and Szeto, 2005; Ma and Szeto, 2004). The MOGA version, which is slightly modified here in comparison to its original one, suits better the proposed negotiation than traditional GA methods and almost no reported research has used it to solve MSS problems. The MOGA is chosen to show the validity and efficiency of this tool to deal with MSS problems.

This chapter is organized as follows: the problem description is provided in Section 3.5. Section 3.6 presents the theoretical basis of the proposed model, which includes description of the fall-back bargaining method, a short background of genetic algorithms, and the steps of the proposed hybrid approach. Numerical experiments including an illustrative example and several instances based on a real case study are reported in Section 3.7 and finally the chapter concludes in Section 3.8.

3.5 Proposed Management Approach for Weekly MSS

As already mentioned, this chapter concerns with the tactical level of planning and scheduling of ORs. This level deals with development of so called MSS timetables that defines the surgeons to whom the OR time is assigned. Normally, MSS timetables are created for a period of few weeks to few months based on the seasonal fluctuations and availability of surgeons, and can be classified into three types: (1) open (non-block) scheduling; aims to assign the OR time to the first surgeon requests it, (2) block scheduling; under this type, either individual surgeons or surgical groups are allotted a OR time in a periodic -weekly or monthly - schedule, and (3) hybrid scheduling which is a combination of both open and block scheduling. In an open system there is a competition among surgeons to win the OR time. They often result in high rates of cancellation, long waiting lists and variations in OR utilization rates among different specialties. This type could be advantageous for some specialties which can book the OR time far in advance, but for some others could result in under-utilization. To moderate these disadvantages, hospitals normally use the block scheduling. In block scheduling, the OR time is booked exclusively by a specific surgeon until a predefined time (cut off time) ahead before surgery, after which, if no final booking has been already carried out, the pertinent time will be made available for other surgeons (Ozkarahan, 2000). However, when the cut off time is too short, this approach may lead to idle OR blocks. Nevertheless, since surgeons perform a number of cases in a consecutive order, using a block system facilitates a better utilization of OR time in comparison to non-block system (Ozkarahan, 2000). This chapter, therefore, considers the block system in OR time assignment process.

Each MSS is a table of day-shift-room assignments to surgeons according to their demands and preferences. Figure 10 shows a schematization of an OR schedule where 4 ORs are shared among 4 surgeons on two days of the week. According to Figure 10, the representation of day-shift-room sequence for Monday can be written as $\{\{S1, S1\}, \{S3, S1\}, \{S4, S4\}, \{S2, S1\}\}$. Different permutations of this sequence can be seen as possible solutions for MSS. Therefore, for the MSS problem described, the search space is a space of permutations. Every feasible permutation can be evaluated differently from the viewpoint of individual surgeons. For instance, suppose that the preference sets of the S1, S2, S3 and S4 with respect to the above mentioned sequence are $\{\{1,2\},\{3,4\},\{5,6\},\{7,8\}\}$, $\{\{1,1\},\{1,1\},\{1,1\},\{1,1\}\}$, $\{\{1,1\},\{1,1\},\{1,1\},\{1,1\}\}$ and $\{\{8,7\},\{6,5\},\{4,3\},\{2,1\}\}$, respectively.

Day \ Room		OR1	OR2	OR3	OR4
Monday	Shift 1	S1	S3	S4	S2
	Shift 2	S1	S1	S4	S1
Tuesday	Shift 1	S2	S2	S4	S2
	Shift 2	S2	S3	S3	S4

Day \ Room		OR1	OR2	OR3	OR4
Monday	Shift 1	S1	S3	S1	S2
	Shift 2	S1	S1	S4	S4
Tuesday	Shift 1	S2	S2	S4	S2
	Shift 2	S2	S3	S3	S4

Figure 10: Upper: An example of an OR schedule, considering four surgeons of S1, S2, S3 and S4, two days (Monday and Tuesday), four rooms, and two shifts (Shift1=morning shift, Shift2=afternoon shift) and lower: a possible solution to maximize the minimum satisfaction of surgeons S1 and S4.

According to these preference sets, since all of the day-shift-rooms on Monday have the same score for S2 and S3, they are already happy with the schedule. The Monday-Shift1-OR1 is the ideal sub-block for Surgeons S1, and she/he has been assigned this block. However, the sub-block Monday-Shift2 -OR4 is at the bottom of her/his preference list, which is totally undesirable for her/him, yet, this sub-block is the first priority of the surgeon S4. It can be easily seen that if we switch the sub-block Monday-Shift1-OR3 and Monday-Shift2-OR4 between these two surgeons (S1 and S4), the satisfaction for both of them would be increased (see Figure 10). Such situations could be easily managed by negotiating the assignment alternatives which would lead to an increase the minimum satisfaction of surgeons.

The procedure suggested by this work aims at finding a sequence of day-shift-room, which maximizes the minimum satisfaction of surgeons. It takes the advantages of the fall-back bargaining procedure, which relies on the falling back of surgeons from their preferences until reaching a collective consensus. The proposed method which is a bargaining based MSS – hereafter Nego2Sked – uses a solution approach via genetic algorithm. The MOGA version, which is slightly altered here in comparison to its original version, is described in Section 3.6.2. The procedure to manage the surgeon preferences is presented in Figure 11 and could be briefly described in the following steps:

- Surgeons specify days or shifts that they want to dedicate to other activities beyond the OR (such as teaching, research, etc.). These days are excluded from surgeons' available days. Surgeons will accordingly assign a preference score to the available day-shift-rooms.
- A set of feasible solutions, namely sequences of day-shift-rooms assigned to the surgeons, are iteratively generated by GA.
- In every iteration the solution sets are evaluated and ranked by each surgeon using a fitness function based on ordered weighted averaging aggregation (OWA) operator.
- Then, based on the individual solution ranking orders, FB approach decides upon the final aggregated ranking of the solutions.
- Based on the outcomes from the previous step, the solutions are sorted, selected and mutated by GA to generate an evolved set of solutions for the next iteration.
- The iteration process goes on until a stopping criterion is reached. In the final solution set, the first ranked one is picked up as the winner assignment.

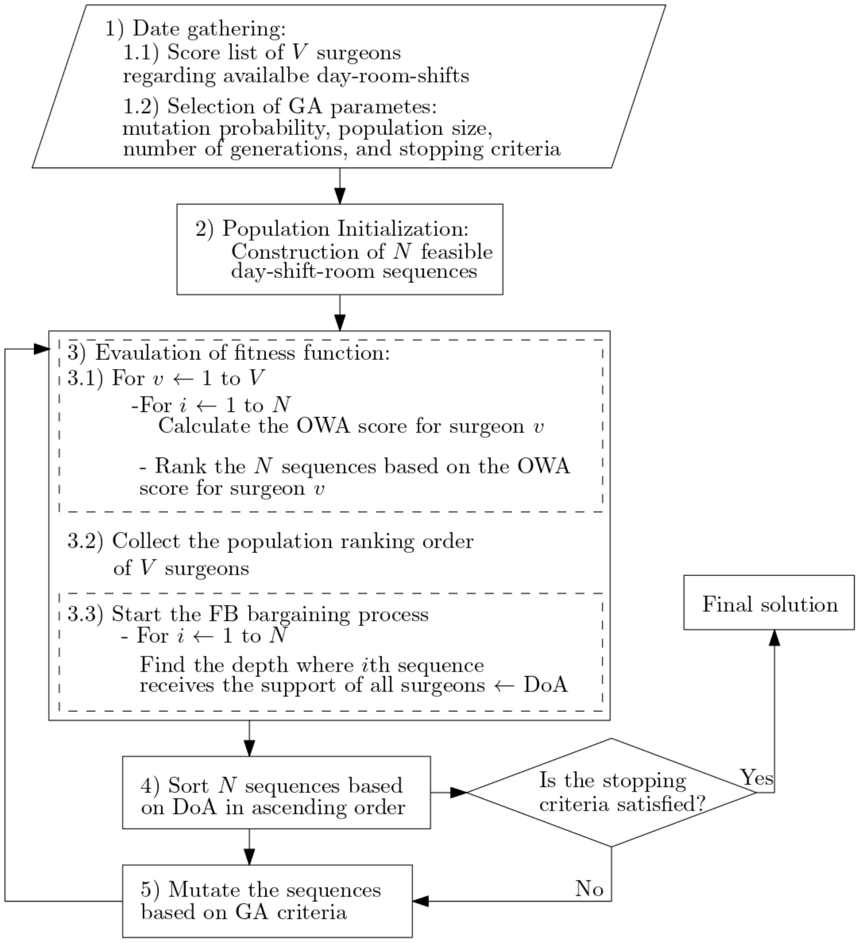


Figure 11: Flowchart of Nego2Sked.

The following assumptions and simplifications are considered in this work:

- Only elective cases are considered (non-elective and emergency cases are excluded). Handling every single case here is not important, because it is not about generating operational schedules.
- Multiple and multi-functional ORs are shared among surgeons of the surgical specialty.
- It is assumed that personnel (except for the surgeon) and instrumental resources either for anesthetic procedures or the surgery itself are available whenever they are required.
- Recovery room relevant restrictions are relaxed, and hence, only operating room constraints are taken into account.
- The only resource constraints are due to the opening hours of OR, the OR numbers and the availability of the surgeons.

- For the planning, the following data are available: a) number of OR sessions to be allocated b) number of surgeons, their availability and their preferences over day-shift-rooms.
- Shifts cannot be partially used and surgical teams are supposed to stay at the same room/sterile area and rely on the same team members so that no-one will be waiting for anyone, and therefore, the waiting times can be reduced or eliminated.
- A surgeon cannot obtain OR time blocks in different rooms on the same day or shift, or on a day or shift when they are not available.
- Surgeons have no priorities over each other.

3.6 Theoretical Basis of Nego2Sked Model

3.6.1 Fall-back Bargaining

The Fall-back bargaining (FB) (Brams and Kilgour, 2001) is a method for maximizing the minimum satisfaction of the bargainers. The bargainers are allowed to rank their preference rankings regarding the feasible alternatives. However, their preferences are usually not in accordance with the others', and therefore, conflicts may arise. Hence, to reach a compromise, they fall back from their preferences from the most favored one to the less and less preferred ones in a step-wise manner until an alternative is found, which receives the sufficient support and all bargainers agree upon it. The outcome of this process is a subset of alternatives which is called compromise set.

For instance, suppose that we have two bargainers who rank a set of alternatives A, B, C, D. The bargainer 1's preference order is D, C, B, A, while the bargainers 2's preference order is B, A, C, D. If they need to make a decision together, they cannot agree on their own very most preferred alternative (D and B). Therefore, they need to meet a compromise. They start to fall back from their first preferred alternative to their second choices; C and A for bargainers 1 and 2, respectively. However, there is still no common choice, and they continue to fall back to their third preferred alternatives; B and C. B is already chosen by the bargainer 2 as the most preferred alternative. Thereupon, B is a winning choice. Nevertheless, the bargainer 1 has already shown that C is his second choice. This means that C is a wining alternative as well. The lowest position of the winning alternative among the players is called "depth of the agreement" (DoA). In this case the depth of the agreement is three. The outcome of the FB procedure is a Pareto-optimal solution which, as mentioned earlier, maximizes the bargainers' minimum satisfaction (Brams and Kilgour, 2001).

There are three methods for the FB developed by Brams and Kilgour (2001):

- **Unanimity:** in this method the alternatives with unanimous support at highest possible DoA will be chosen.
- ***q*-Approval:** this method selects the alternative, which is supported by q number of bargainers at the highest possible DoA.
- **with Impasse:** in this method the bargainers are allowed to set an impasse in their rankings which implies that when the DoA falls below the impasse level, the bargainers would prefer not to make any agreement.

In this work, the unanimity method is chosen to make sure that the opinions of all surgeons are considered in the process.

3.6.2 Mutation Only Genetic Algorithm

Genetic algorithms (GA) and evolutionary computations are meta-heuristic searching methods applied to optimization problems with large searching spaces and are based on the survival of the fittest. Genetic algorithm was first developed by Goldberg and Holland (1988) and, since then, it has been employed in various disciplines. GA methods usually rely on selection, mutation, and crossover operators. However, in Nego2Sked, the crossover operator is left out and a version of the traditional GA is used, which is called mutation only genetic algorithm (MOGA). The reason to use this version of GA is the characteristics of the problem in question. Our scheduling problem is a combinatorial one and is represented by an order of elements. Hence, permutation representation is most suited technique and binary encoding is not used. For a permutation representation, the crossover operator in its traditional way does not make any sense.

THe mutation only genetic algorithm was first suggested to solve a type of combinatorial optimization problems called knapsack (Zhang and Szeto, 2005; Ma and Szeto, 2004) and it was claimed that the traditional genetic algorithm is a special case of MOGA. The MOGA introduces the mutation matrix concept which makes use of fitness information and loci statistics to determine the mutation probability in a dynamic way. It outperforms the traditional GA in terms of speed and quality of the solution (Szeto and Zhang, 2005; Law and Szeto, 2007).

Here, we consider using the mutation matrix and the MOGA concept and adapt it through slight variations to suit the characteristics of the problem in question. A population of N chromosomes, each represented by permutation of the L loci, which forms a $N \times L$ matrix $A(t)_{i\times j}$ for the population at a given time t, is considered. The

ith row of the matrix indicates the chromosome with the fitness of f_i and with the rank of i and jth column indicates the jth locus of the population matrix. In every iteration, the rows of $A(t)$ are ordered in terms of their rankings such that for every $i \leq k$, $f_i \leq f_k$. Then, the fittest chromosomes are exploited and, in order to explore the solution space, the mutation is performed on $A(t)$. For the exploitation purpose and decision over the survival of the fittest chromosomes, a mutation probability is calculated as $M_r = (i-1)/(N-1)$. Then, for a given row i, a random number c in the interval of $(0,1)$ is generated. If $M_r > c$, then mutation will be performed on this row, otherwise the chromosome will be copied to the next generation. If row i is to be mutated, the number of loci to be mutated should be determined (exploration of the solution space). Since the permutation representation is used in this problem, the swap mutation is chosen which suits better than other mutation types (Murata et al., 1996; Ruiz et al., 2006). In gene swap, two random loci in a chromosome will be selected. The genes at these two positions will be extracted, swapped and put back to the chromosome. Here, multiple swaps for the chromosomes to be mutated are performed. The number of swaps for the row i, N^i_{swap}, is calculated as $\lfloor (M_r \times L) \rceil$.

Mostly, real-world optimization problems are constrained ones. There are several methods to handle constraints in GAs, which can be generally classified as rejecting, repairing, modifying genetic operator, and penalty strategies (Gen and Cheng, 1996). The first three strategies make the generation of the infeasible solutions impossible. However, this approach makes the searching process difficult, since infeasible solutions constitute up a large quota of the population. Hence, penalty strategy is used to penalize the infeasible solutions and lead the searching directions towards the favorable solutions (Chang, 2008).

Penalizing the infeasible solutions transforms the constrained problem into an equivalent unconstrained one. The easiest way to penalize the infeasible solutions is adding a penalty to the fitness function for these solutions as follows:

$$F(x) = \begin{cases} f(x) & x \in \text{feasible region} \\ f(x) + p(x) & x \notin \text{feasible region} \end{cases} \tag{3.1}$$

where $p(x)$ is the penalty function. In Section 3.7.2 the penalty function to be applied to the problem in this chapter is described.

3.7 Framework of Nego2Sked

3.7.1 Population Initialization

Every surgeon has a number and an amount of already determined day-shift-room quota, which should be exactly fulfilled in every combination/chromosome. Every

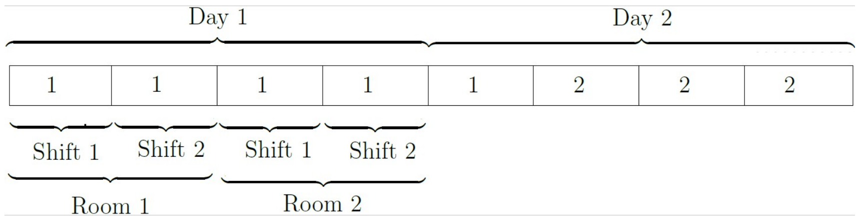


Figure 12: An example of chromosome of length $L = 8$ representing a stem assignment of loci (day-shift-room) to surgeons ($V = 2$) with $Q_1 = 5$ and $Q_2 = 3$. In this example, we have two days, two rooms and two shifts.

chromosome has L loci that equals the number of available days X multiplied by the number of available operating rooms Y and the number of available shifts Z ($L = X \times Y \times Z$). For initialization of the population of chromosomes, first, an assignment must be generated. Suppose that we have V number of surgeons (S_v) and each surgeon has a predetermined quota of Q_v such that $\sum_v^V Q_v = L$. The assignment of the day-shift-room (loci) starts with the first surgeon by fulfilling his quota in row. Afterwards, the second surgeon will be assigned to the day-shift-room and so forth. It should be noted that the surgeons have no priorities to each other and this process is just to generate a "stem chromosome" from which the initial population matrix will be created (see Figure 12).

To create the parent population matrix ($A(0)$) of size $N \times L$, N chromosomes as random permutations of the ordering of the stem chromosome are generated.

3.7.2 Fitness Function

In order to evaluate the fitness of the chromosomes, the FB method is applied. The aim of utilization of the FB is to rank the chromosomes according to depth in which they receive the support of all bargainers/surgeons. However, the prerequisite to start the FB procedure, is to obtain the individual preference order of chromosomes from the viewpoint of bargainers. To this aim, every generated combination needs to be evaluated, scored and ranked according to the preferences of bargainers. Evaluation of individual combinations is done based on the ordered weighted averaging (OWA) operator. The OWA operator can be used to model compensatory and non-compensatory preferences by adopting a degree of compensation among attributes/criteria. Based on the degree of compensation, the OWA Operator assigns order weights according to an ordered position, and therefore, this operator is different from other aggregation or multi-attribute/multi-criteria decision making methods (Reimann et al., 2017). The degree of compensation indicates the attitude towards satisfaction of attributes/criteria, either the purpose is satisfaction of all attributes or the risk of dissatisfaction of one or more of the attributes is accepted

(Zarghami, 2011; Heravi and Faeghi, 2012). In our problem in question, each and every locus on a given chromosome to be scored by a specific surgeon is an attribute to evaluate the whole chromosome.

As described in subsection 3.7.1 every block assignment combination or chromosome has a length of L. According to each chromosome for every surgeon a one-dimensional matrix $(1 \times L)$ can be elicited which its elements are either 1 (for assigned blocks) and 0 (for not assigned blocks). Every individual surgeons also constructs a $1 \times L$ matrix for his preferences. This matrix contains scores between 1 and 5, where 1 means that the pertinent block is the most preferred one and in contrary 5 means the block is less acceptable. When the surgeon can not by any means, perform any surgery the block is denoted by "NA". Having this preference matrix, the process to evaluate the whole set of assigned blocks is as follows:

We have N chromosomes in every population which are needed to be ranked by V surgeons.

Step 1: The assignment matrix for the surgeon v elicited from the chromosome n is as follows:

$$A_n^v = [a_{n,l}^v]_{1 \times L} \tag{3.2}$$

$$a_{n,l} = \begin{cases} 1 & \text{if block} \quad a_{n,l}^v \quad \text{is assiged to the surgeon } v \\ 0 & \text{otherwise} \end{cases} \tag{3.3}$$

Step 2: The preference matrix of the surgeon v is defined as:

$$P^v = [p_l^v]_{1 \times L} \tag{3.4}$$

where, $p_l^v \in \{[1,5], NA\}$

Step 3: The assignment matrix will be multiplied by the preference matrix to obtain the scored assignment matrix SM_n^v as follows:

$$SM_n^v = P^v.A_n^v = [sm_{n,l}^v]_{1 \times L} \tag{3.5}$$

Step 4: The next step is to aggregate the scored arrays, which is done using the OWA method. The entire process of the OWA for the surgeon v is as follows:

$$S_n^{v,min}(sm_{n,1}^v, \cdots, sm_{n,k}^v) \leq S_n^{v,OWA}(sm_{n,1}^v, \cdots, sm_{n,k}^v) \leq S_n^{v,max}(sm_{n,1}^v, \cdots, sm_{n,k}^v) \tag{3.6}$$

where $S_n^{v,OWA} : I^n \longmapsto I$ as follows:

$$S_n^{v,OWA}(sm_{n,1}^v, \cdots, sm_{n,k}^v) = \Sigma_{w=1}^k u_w^v b_w^v \tag{3.7}$$

where b_w is the wth smallest element in the set of inputs $sm_{n,l}$ for the alternative i. The coefficient $u_w^v \geq 0$, is the order weights such that $\Sigma_{w=1}^k u_w^v = 1$. According to Zarghami (2011) and Yager (1996) the OWA weights are calculated as follows:

$$u_w^v = (\frac{k^v - w + 1}{k^v})^{(\frac{1}{\beta})-1} - (\frac{k^v - w}{k^v})^{(\frac{1}{\beta})-1} \tag{3.8}$$

where $k^v = \Sigma_{l=1}^L a_{n,l}^v$ and β is the degree of compensation; the model is non-compensatory if $\beta = 0.001$ and vice versa if $\beta = 0.999$. Using these 4 steps every chromosome receives an OWA-Score from each surgeon, based on which the surgeon-specific score matrices could be built: the lower the score, the better the solution is.

In Nego2Sked a penalty function is considered to penalize the infeasible solutions. An infeasible solution in our problem is defined as a chromosome containing even one unacceptable assigned block (any locus denoted by NA). Hence, in the surgeon-specific score matrices for every locus with NA the fitness of the pertinent solution will be added by 100.

After penalizing the infeasible solutions, the ranking of chromosomes will be determined. This means, this time the surgeon-specific ranking matrices will be created, based on which, the FB process can be followed. In the FB process the depth on which the solutions receive the support of all surgeons for every one of them will be determined. According to these depths, the whole population will be sorted in ascending order and the matrix $A(t)_{n\times l}$ will be created.

3.7.3 Selection and Mutation

In this process, the fittest chromosomes are exploited, and it is determined whether the chromosomes survive or are to be mutated. As described in Section 3.6.2, for each chromosome in each generation the mutation probability M_r is calculated. Then, for a given raw (i) a random number $c \in (0, 1)$ is generated, and if $M_r \leq c$ then the corresponding chromosome will be duplicated to the next generation, otherwise they will be picked out for the swap mutation (see Section 3.6.2).

3.7.4 Iteration

The process of fitness evaluation, sorting, selection and mutation are iterated to let the population evolve by producing new generation of chromosomes. The iteration continues until a stopping criterion is met. In the presented algorithm the stopping criteria is defined as a fixed number of generations produced.

3.8 Numerical Experiments

In this section, the carried out numerical examples and the relevant results are described. Example I is a small combinatorial problem provided to give an insight into the method application and verify the efficiency of Nego2Sked. The numerical experiments in Example II are based on the real data coming from a hospital in Germany. However, since the received data sets were not detailed enough, a set of instances were generated based on the collected data. All experiments are run on a station with an Intel® Core™ i7-7500 processor at 2.70 GHz and 16.0 GB RAM under Windows® 10 environment. The formulations and algorithms were scripted in Matlab®.

3.8.1 Case I: Illustrative Example

Suppose that there are seven available blocks to be allocated to two surgeons $\{S1, S2\}$. The number of the blocks that each surgeon receives is 4 for $S1$ and 3 for $S3$. The preference matrices of the surgeons are defined as: $P^1 = [3, NA, 1, 2, 1, 2, 3]$ and $P^2 = [1, 3, NA, 2, 4, 2, 5]$. The compensation degree is set to 0.091. Table 16 shows the results of the proposed method. It can be easily understood that the ideal solution for S1 and S2 will bring the score sets of 1, 1, 2, 2 and 1, 2, 2 in ascending order, respectively. However, none of the surgeons can get their ideal solution, because their ideal ones do not correspond to each other's. The proposed solution brings the score sets of 1, 1, 2, 3 and 1, 3, 3 to surgeons S1 and S2, respectively. To evaluate the proposed solution, the whole decision space is searched for the exact solution. Considering the whole decision space the depth of agreement (Global DoA in Table 13) is 2.

3.8.2 Case II: Example Based on Real World Data

This case is a surgical suite with 7 operating rooms which are used jointly by three specialties: 1) trauma surgery (TS), 2) general surgery (GS) and 3) thorax surgery (THS). The operating rooms are available from Monday to Friday from 7:30 until

Table 13: Input data, proposed solution and scores for Case I.

Surgeon		Block Nr.						
		1	2	3	4	5	6	7
S1	Preference Matrix	3	NA	1	2	1	2	3
	Proposed solution			∗		∗	∗	∗
	Ideal solution			•	•	•	•	
	Score	1.09						
S2	Preference Matrix	1	3	NA	2	4	2	5
	Proposed solution	∗	∗		∗			
	Ideal solution	•			•		•	
	Score	1.14						
Global DoA		2						

15:00. The data for this department were collected for 24 months from January 2015 to December 2016.

Overall 67 surgeons are involved in this department each having different workloads. Yet not all individual surgeons are considered as bargainers; they are clustered to into two types: 1) a single surgeon with a sufficient workload (Type 1) or 2) a group of two or three surgeons with a collective sufficient workload (Type 2). Based on these rules 9 surgeons/surgical groups are considered for this example; 4 groups belong to GS, 3 groups belong to TS, and the remaining 2 groups to THS (see Table 14). In our case, the proportion of the OR time to be assigned to each surgeon/surgical group/surgical specialty is a decision that has been already taken at an upper level. Since the OR time assignment here is about elective cases, one of the 7 available operating rooms are reserved for the emergency cases. The opening hours are divided into two shifts: morning (from 7:30 to 11:00) and afternoon (from 11:00 to 15:00) and the planning horizon is considered to be one week. Therefore, overall $5 \times 6 \times 2 = 60$ day-shift-rooms are considered to be available within a week. The aim is just to arrange the order of OR block assignments to reach a point in the decision space where the conflict is at the lowest possible level.

In order to test the ability of Nego2Sked to produce satisfactory solutions, it is necessary to analyze the impact of changes in the final results. For this purpose five instances with variations in the proportion of OR time that each surgeon receives are generated. A scored list of day-room-shift room for every surgeon/surgical group is determined based on the data collected from the case study (see Appendix Table 19). For each instance the population size is 800 and the iteration number is 1000.

Table 14 shows the results of Nego2Sked for the suggested instances. At the first look it can be figured out, that no surgeon/surgical group has received any unacceptable day-shift-room. A detailed assignment plan is provided in Appendix Table 20. A closer look highlights that even no surgeon/surgical group has been assigned any block with the score 5 meaning the least acceptability. The total score of the every surgeon may not fluctuate a lot in response to small variations in quotas, because it is mostly dependent on the score matrix. For instance, for THS-2, the 91.7% are scored equal or greater than 3, of which around 20% is denoted by "NA". Therefore, his scores in 4 instances (except for instance IV) are the highest one. In instance V, where THS-2 has just one quota, his score is 1, which shows that the algorithm seeks to maximize the minimum satisfaction of individual bargainers. DoA for all instances varies around 11 (ranges from 10 to 12), which shows that the bargainers are able to come to an agreement at their $11th$ preference out of 800 possible solutions (population size).

Table 14: Results of Case II.

	Instances														
Surgeon	I			II			III			IV			V		
Nr.	Q	S	s_i	Q	S	s_i	Q	S	s_i	Q	S	s_i	Q	S	s_i
GS-1	7	1.76	0.81	8	1.84	0.79	7	1.49	0.88	5	1.96	0.76	7	1.82	0.79
GS-2	8	2.01	0.75	7	2.79	0.55	9	2.80	0.55	10	2.75	0.56	6	2.97	0.51
GS-3	7	2.91	0.52	8	2.23	0.69	6	2.56	0.61	5	2.86	0.54	9	2.21	0.70
GS-4	6	3.20	0.45	5	3.20	0.45	7	3.19	0.45	8	3.18	0.46	4	2.75	0.56
TS-1	8	2.22	0.70	9	2.00	0.75	7	2.25	0.68	6	2.50	0.63	10	2.26	0.69
TS-2	7	2.79	0.55	6	2.36	0.66	8	2.74	0.57	9	2.08	0.73	5	2.72	0.57
TS-3	10	2.91	0.53	11	2.97	0.51	9	2.95	0.51	8	2.98	0.51	12	3.05	0.49
THS-1	3	1.89	0.78	2	3.50	0.38	4	2.19	0.70	5	2.60	0.60	1	1	1
THS-2	4	3.75	0.31	4	3.75	0.31	3	3.89	0.28	4	2.94	0.52	6	3.28	0.43
DoA	–	12	–	–	11	–	–	11	–	–	11	–	–	10	–
Ave	–	2.60	–	–	2.73	–	–	2.67	–	–	2.65	–	–	2.45	–
CV	–	0.24	–		0.23	–	–	0.24	–	–	0.15	–	–	0.27	–
FI	–	–	0.93	–	–	0.93	–	–	0.93	–	–	0.97	–	–	0.94

To demonstrate the effectiveness of Nego2Sked in solving this example, two parameters are calculated. The first one is the coefficient of variation (CV) between the surgeon scores. CV is, per definition, a measure of the extent of variability in relation to the mean of a data set, and yields a value between 0 and 1. The greater the CV value, the more the variability is. The CV values of the obtained results are between 0.15 and 0.27, which shows a low variability in surgeon scores. The second parameter to estimate the effectiveness is a fairness index (FI) which is measured using the method proposed by Jain et al. (1984). This index measures the "equality" of a system which allocates payoffs to its n elements (here surgeons). If the ith player receives the payoff s_i, then the fairness of the system is measured using the following equation:

$$f(s) = \frac{[\sum s_i]^2}{n \sum {s_i}^2} \tag{3.9}$$

where $f(s)$ is the FI. If $f(s) = 1$, then the system is 100% fair, and if $f(s) = 0$, it means that the system is totally unfair and only favors the demands of a few number its elements. The payoff, here, is calculated as the similarity of the obtained score to the worst possible score, using the following equation:

$$s_i = \frac{d_{iw}}{d_{iw} + d_{ib}} \tag{3.10}$$

where d_{iw} and d_{ib} are the absolute values of distances between the score i and the worst (5) and best (1) possible scores, respectively. The FI values show that the results and score distribution in system has in average 5% difference from an ideal system. This demonstrates the efficiency of Nego2Sked in distributing the OR time in a fair manner.

3.9 Concluding Remarks

The main motivation of this chapter is to reduce possible conflicts may arise in the process of creating master surgical schedules. Hence, this work considers the master surgical planning problem as a negotiation process and develops a heuristic method, called Nego2Sked, to take the surgical preferences in creating MSS into account. To this aim, every surgeon or surgical group is regarded as a bargainer which bargains over their preferences with other surgeons in a bargaining process. To model this process, the fall-back bargaining method from negotiation and decision making literature is adopted. In the process of fall-back bargaining, the bargainers rank the proposed solutions based on their preferences which may not necessarily match with others'. Then, they start to step back from their most preferred alternatives to the less favored ones, until finding a solution which receives sufficient support. The process of solution evaluation from the surgeon's viewpoint is done using the ordered weighted averaging operator, which is considered as a useful method to gain realistic judgments over solutions. The reason is the possibility that this method gives the user to adjust the degree of compensation.

Since the MSS problem is a large combinatorial problem, searching the whole solution space is not feasible. Therefore, the advantage of evolutionary algorithms, in this case genetic algorithms, is used to search and explore the solution space. In this sense, considering the fact that the problem in question is a combinatorial one, a special case of GA without crossover function is used. This version which is called mutation only genetic algorithm, according to the literature, outperforms the traditional GA algorithms in terms of speed and quality.

The proposed hybrid algorithm is then applied to two examples to give insights into the method and demonstrate its capabilities and efficiency. Example I, which is a small example, shows that the algorithm can find the optimal solution in small solution spaces. Example II, which is based on the real data from a hospital in Germany, shows that the algorithm is efficient in maximizing the minimum satisfaction of the surgeons.

Like any other methods, Nego2Sked has its own limitations. This method focuses only on the pre-assignment of day-shift-rooms to the surgeons/surgical groups, and does not take the details of every single case or patient into account to generate detailed and operational schedules. The purpose was mainly to show the applicability of bargaining methods to solve MSS problems. However, the results provide a sound ground for further operational schedules.

4 A System Dynamics Model Application to Operating Room Planning and Management

Abstract

Operating room (OR) management is an essential task which has remarkable impacts on the efficiency of not only operating room departments themselves but also other functions of hospitals. On this ground, evaluation of long-term adequacy of specific decisions and policies regarding the planning of OR departments is of a notable importance. Since hospitals deal with a varying environment, every long-term analysis must investigate and predict hospital responsiveness to the relevant variations and changes. However, static models which just consider a limited time-frame have gained more attention in OR management than dynamic models such as system dynamics. System dynamics models are not dependent on detailed and high-quality data and because of this advantage they can be applied to aggregate data at a strategic level. Using a system dynamics approach, this chapter aims to consider OR departments as multi-product systems, comprehend the interactions of their different influencing parameters and study their dynamic hypothesis. The proposed model is based on a mesoscopic approach, which represents the system flow processes through piecewise constant rates. The novelty here is that the proposed model is generic, modular and easy to extend. The model is described by means of MATLAB/Simulink® software, and validation of its effectiveness and demonstration of its capabilities are done through an application to a real case study.

4.1 Introduction

Hospitals and particularly operating room (OR) suites are fast-changing and complex environments in which different groups of individuals are involved and coordinated to deliver highly professional operations. This is analogous to production systems; they are both built around a set of interconnected processes to transform inputs to outputs with two major differences:

- Since the real business of hospitals is to treat individual patients, the offered **products** are specific sets of pure **services** and physical products play no role (Fetter and Freeman, 1986). These sets of services are referred to as diagnosis related groups (DRGs) and hospitals offer different DRG related **products/services** to their customers/patients. Thus, their production lines are multi-product ones. The OR department obeys the same pattern: a multi-product production line within which each surgery type is a product. In contrary to production lines, which are mostly comprised of one-directional material flows, in surgical suites patients flow in diverse directions, which brings about more complexities (Wolstenholme and McKelvie, 2019).

- Additionally, there are always various ethical and methodological factors influencing the organization and management of surgical suites (Sobolev et al., 2008). Each of the involved stakeholders has their own interests that may not necessarily correspond to the others'. Therefore, every OR manager must be able to balance the needs of these different groups in order to maximize **productivity**, minimize **conflict** and maintain **order** and **fairness** (Kaye et al., 2012). On this account, managing of OR departments is often cumbersome.

Some may argue that comparing a hospital or an OR suite to a production system might not be a right analogy, because hospitals are plagued with uncertainties and deal with human beings. However, conceptualizing of OR suits as multi-product systems helps in better understanding of their efficiency and productivity (Palmer, 1991). The idea behind such an assumption is to simplify the process of modeling of OR suites, study their system structure and understand the patient flows between different processes. Additionally, from a strategic point of view, this kind of simplification would be satisfactory enough to understand how decisions and plans could support the strategic goals of the hospital in the long-term without being captivated by unnecessary details.

To explore and investigate healthcare system structures and assess their behavior under decisional changes, computer simulations are frequently recommended by the literature (e.g. Salleh et al. (2017); Wolstenholme (2020); Lattimer et al. (2004)). Simulation models can be classified into static or dynamic models. In static models the outcomes normally belong to a particular point in time. In contrary, dynamic models simulate systems as they evolve over time. Since healthcare systems deal with changing environments because of variations in patient types, they should be modeled as dynamic systems. One of the useful methods to study the structure of dynamic systems, is system dynamics (SD). SD techniques (Forrester, 1997) have been used by numerous researchers to investigate a wide range of healthcare decision problems. They are grounded in control theory and are mathematical modeling techniques to characterize the behavior of complex systems over time. They specify the interrelations of the system's elements and their interactions with each other. In this approach, systems are structured as causal-loop (influence) diagrams which represent the flow of resources over time through different states as specified by rates (Baines and Harrison, 1999).

One possible SD application, as mentioned above, is studying the OR department structure, its management at a strategic level and improving the patient throughput.

Generally, the aim of this chapter is to develop a SD model – by assuming OR suits as multi-product systems – in order to investigate the long-term consequences of decisions like increase/decrease in resources (OR room, opening hours, surgeons, etc.), demand responsiveness, and specialty coverage of hospitals concerning changes in future demands. Figure 13 demonstrates the results of a simple simulation example, exploring the long-term demand responsiveness of a single-specialty OR department in two years' time and shows how the increase in resources can shorten the length of waiting lists.

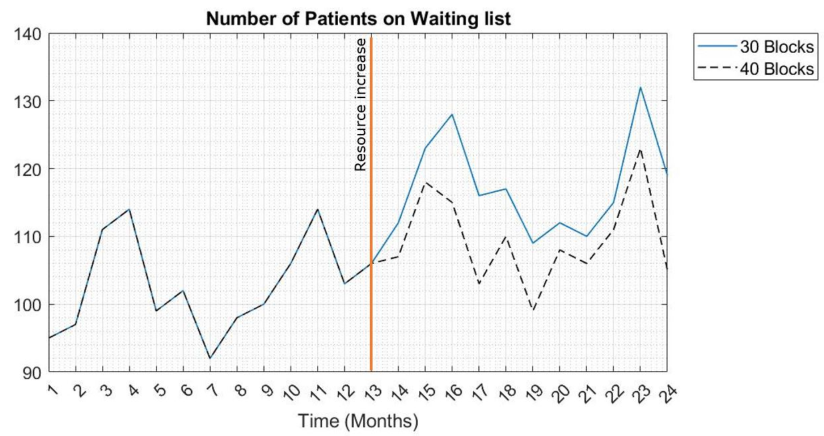


Figure 13: Example of two yearly OR department behavior in response to demand increase after one year. Suppose that an OR department has a monthly demand for new surgeries as random selection from $U(55, 70)$ with a 10% demand increase in monthly amounts after one year. The OR department has a total amount of 30 OR block per month and a productivity rate of three patients per every block. At the end of every month, the unprocessed surgery demands would be postponed to the next month. If the manager decides to increase the time blocks by 40 after 12 months, the demand responsiveness would be enhanced (the dashed line). The solid line shows the behavior of the waiting list without employing any changes.

4.1.1 Relevant Literature

In general, system dynamics approaches have been widely used and advised in healthcare decision and policy making (i.e. Taylor and Lane (1998); Royston et al. (1999); Brailsford et al. (2004); Wolstenholme and McKelvie (2019)). The literature in this area could be generally classified into two branches: a) epidemiological studies (i.e. (Dangerfield et al., 2001; Dangerfield, 1999)) and b) healthcare management and planning studies which mainly tend to concern patient flows (i.e. Lane and Husemann (2008); Maliapen and Dangerfield (2010); Taylor et al. (2005); Van Ackere and Smith (1999); Sedehi (2001); Ravn and Petersen (2007); Mahachek (1992)). For a detailed review about the different system dynamics (SD) applications to the healthcare problems in a general context, readers are referred to (Lyons and Duggan, 2015; Davahli et al., 2020).

In the particular field of operating room management there are also research studies employing the systemic dynamics view. González-Busto and García (1999) applied a SD approach to analyze waiting lists in Spain and study the effectiveness of policies like subcontracting on the length of waiting lists. They categorized the waiting lists into outpatient and surgery lists. However, because of higher costs and more managerial concerns, they put a particular focus on the surgery lists. Anderson et al. (2002) adopted a dynamic simulation approach to analyze and comprehend the factors affecting costs and outcomes of a single department of cardiovascular surgery. They also suggested that their model can be used to answer clinical questions to cardiologists and cardiovascular surgeons. Lane and Husemann (2008) analyzed the acute patient pathways using a qualitative mapping derived from SD. Their maps considered patients scheduled for elective surgery. They demonstrated that SD could be useful for elucidating the functioning of healthcare systems. Grida and Zeid (2019) developed a re-configurable SD model for multi-department operating room settings and implemented the Theory of Constraints to identify the system bottlenecks. However, only the performance of the whole system was traceable in their system, and the behavior patterns of individual departments and surgeons could not be extracted.

Review of existing literature reveals that the developed system dynamics methods are not generic enough to be applied to different hospital settings. Choosing the right level of details is of great importance. The reason is that the greater the level of detail, the less the chance that a model will be considered as generic. On the contrary, the more simplified the model, the greater the possibility that the model could not represent the reality (Gunal, 2012; Brailsford, 2005). Another point that should be noted is that normally the SD applications are aimed at reaching and maintaining a steady state condition (Brailsford, 2008). However, high variability and demand fluctuations in healthcare systems call for the system's ability to recover from these changes at every time step (i.e. dynamic stability) rather than reaching an unchanging equilibrium situation. Therefore, the SD approach in healthcare has many unexplored ideas for research, such as the standardization of generic models in healthcare (Vázquez-Serrano and Peimbert-García, 2020) and contemplating the dynamic behavior of healthcare systems.

4.1.2 Contribution of this Chapter and Outline

In contrast to the majority of models which are case-specific approaches and concern reaching a steady state condition, the underlying research question here is: what is the structure of a modular and generic framework for a dynamic model which allows easy reconfiguration and application to any OR setting and facilitates studying long-term policy consequences? And how the quality of dynamic stability can be incorporated in such a model? The model resulting from this research provides a mean of easy modeling at a suitably aggregate level by assuming specialty departments and surgeons as production units. Its most interesting feature is modularity; using a block construction, the model allows integration of different systems, subsystems, and components as blocks, and enables easy reconfiguration of the model according to desired OR settings and corresponding specifications. This approach is innovative since no other similar model has been reported in the literature. Since many healthcare settings are not necessarily rich in useful data (Brailsford, 2008), the focus here is on **semi-continuous** models (see Section 2.3). To address the uncertainty, a **stochastic** aspect, by incorporating random variables, is added to the model.

In recent years, many user-friendly SD software packages have been developed which make the modeling process easier. However, these software packages lack flexibility to deal with explicit mathematical representations or employ complicated algorithms for optimization purposes inside models. MATLAB/Simulink® has been also demonstrated to be able to simulate and optimize dynamic models (Morcillo et al., 2018; Fanti et al., 2018) and moreover, offers the advantage of embedding algorithms and complicated functions. Hence, MATLAB/Simulink® is utilized in this chapter to describe the modeling process. To the best of the knowledge of the authors, Simulink® has not been applied to operating room management problems.

This chapter commences with a systemic view on operating room and describes the methodology in Section 4.2. Then the modular description of the OR system is given in Section 4.5. In Section 4.6 a real case study is described where the modeling approach is applied and then follows by a scenario analysis to demonstrate the advantages of the proposed method. Finally this chapter concludes in Section 4.7.

4.2 Methodology and Modeling of OR Systems

4.2.1 General Approach

In this chapter, a broader meaning of system dynamics is intended. The combination of the definition of "system" as an assemblage of elements/components/activities and "dynamic" as a time-varying situation. Hence, here the term "system dynamics" refers to studying the time-varying behavior of connected components/activities. Generally, any system can be defined as **Input-Transformation-Output**; a flow of information from input to output, which evolves through the passage of time.

Here, the whole system of the operating room suite is treated as a continuous flow, which basically contains one flow: the patient flow. In this model, resources – namely operating room sessions – are referred to as any inputs, while patients are referred to as any outputs from the transformation units. This definition requires a simple feedback loop which delivers information about the outputs to the inputs. The model can be broken into sub-systems based on the type of transformation units and the relationship of input and output flows into and out of these units. In the current context, the transformation unit refers to any element of the system which offers services. These units are surgeons at the lowest level, at a middle level are specialty departments, and possibly at the highest level could be any aggregation of specialty departments. An operating room department system can thus be modeled as one or more of such transformation activities and queues connected together in series or parallel manners.

4.3 System Stability

Within a system, **stability** is an important determinant of its successful development and evolution (Stepaniak and Pouwels, 2017; Wang et al., 2013). Stability in the area of operations research is normally considered as returning to a steady state after being imposed to disturbances (Luhmann, 1995). Here, stability means **dynamic stability** defined as the ability to recover from small disturbances and changes in a longer time frame. From the perspective of systems theory, the goal in dynamic stability is to increase the degree to which changes and disturbances can be regulated in the most peaceful and fair way (Luhmann, 1995). In healthcare systems changes in patient types, either hourly, daily, weekly or seasonally, are usually high, while the resource capacities to be distributed among the system elements remain constant. Therefore, stability in terms of OR management could be considered as a fair distribution of resources among specialty departments or surgeons. Details of incorporation of a fair distribution process in the proposed model are given in Section 4.5.1.

4.4 Level of Detail

Since the objective here is to aid the long-term strategic decision making, detailed information are not a prerequisite and aggregate data would suffice. In terms of detail level in simulation modeling, three classes can be identified (Schenk et al., 2010): 1) macroscopic, 2) mesoscopic and 3) microscopic. Macroscopic models are continuous and based on differential equations. They mostly work with aggregate data and are incapable of accurately representing of numerous objects flowing through the system. On the contrary, microscopic simulations are discrete models which mostly refer to the discrete-event simulations. These types of models are very complicated, their creation is time consuming and often the obsession with details might cause losing the sight of the big picture (Penn et al., 2020; Brailsford, 2008). What falls between these two types are mesoscopic models which normally facilitate quick and effective analysis and planning. Mesoscopic models represent flows through piecewise constant flow rates and use mathematical formulas for recalculating the system state variables (Schenk et al., 2010). In the healthcare context, it is recommended to balance the data requirements in modeling processes and concentrate on main problems (Gillespie et al., 2014). Therefore, the proposed method belongs to the mesoscopic class. Here, the reaction of the system to a single surgical order is not of importance, rather the consequences of variations in orders and policies are of interest. Additionally, the input and output values are not calculated as average values over a long period. For a mesoscopic modeling it has to be substituted with a piecewise constant flow and the simulation step size depends on the length of planning horizons which could be weekly or monthly.

4.5 Modular Description of the System

A block representation (Kailath, 1980) is used to decompose the system into subsystems. On this basis, the generic system is formed by interconnecting of corresponding blocks. The whole system is essentially comprised of three categories of modules: 1) **sub-production units**, 2) **resource distributor** and 3) **measurement**. In this section, the generic system structure is firstly introduced based on a block representation, without giving details on the internal structure of the individual sub-systems. Then, three forming modules are described in details. Subsection 4.5.1 discusses the resource distributor module. The measurement module and the surgeon subsystem as the smallest sub-production unit are explained in Subsections 4.5.2 and 4.5.3, respectively.

In control theory, a systems is characterized by a block with input vector (u) and the output vector (y). The outputs are determined by function (fcn):

$$y = fcn(u) \tag{4.1}$$

which could be an operator or an algorithm and thoroughly determines the behavior of the system (Figure 14). Different sub-systems are connected to each other using input u and output y terminals and on the basis of information flow principles.

The interdependencies between the three OR system modules are shown in Figure 15. As it can be seen in Figure 15, at the surgical suite level, every specialty department

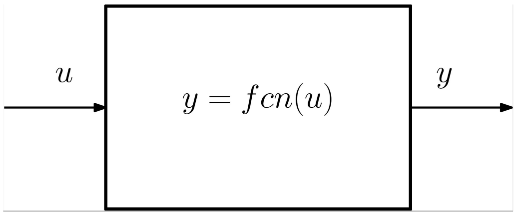


Figure 14: Block representation of a subsystem.

is modeled as a separate sub-production sub-system, which has the task to process its own orders according to the resources it receives. The resource distributor module is responsible for distribution of available resources at a given system level (e.g. available resources for the whole surgical suite) and the measurement module is required to provide measurements. The sub-production units have themselves the capability to be considered as production systems at a lower level, comprised of their own sub-production (sub-sub-production) units - i.e. surgeons. Hence, the above-described structure could replicate itself inside each sub-production unit (Figure 15). Therefore, the performance of each sub-production unit is dependent on its sub-sub-production units, and accordingly, the performance of the whole system depends on the performances of individual sub-production units. The model represents the patient flow as a piecewise constant flow rate and a sequence of impulse-like surgical orders.

The processing of orders is done based one the following procedure:

- P1) At every time step, the surgical orders are laid by individual surgeons (sub-sub-production units).
- P2) Every ward or surgical specialty collects the orders of its surgeons/surgical groups and passes them to the OR manger at the upper level.
- P3) At the operating room suite level (ORSL) the OR manager, according to the collected orders, distributes the available but limited resources, namely OR time, among wards.
- P4) At the specialty department level (SDL) the received quota of resources is distributed among its surgeons/surgical groups.
- P5) Then, the received resources will be processed by the surgeons/surgical groups and the outputs of the system in terms of processed orders, associated costs, and possible overtime will be calculated. These outputs will also be accumulated over time in the measurement module.
- P6) The remaining unprocessed surgical orders at the time step t will be added to new surgical orders at the time step $t + 1$ using a feedback mechanism.

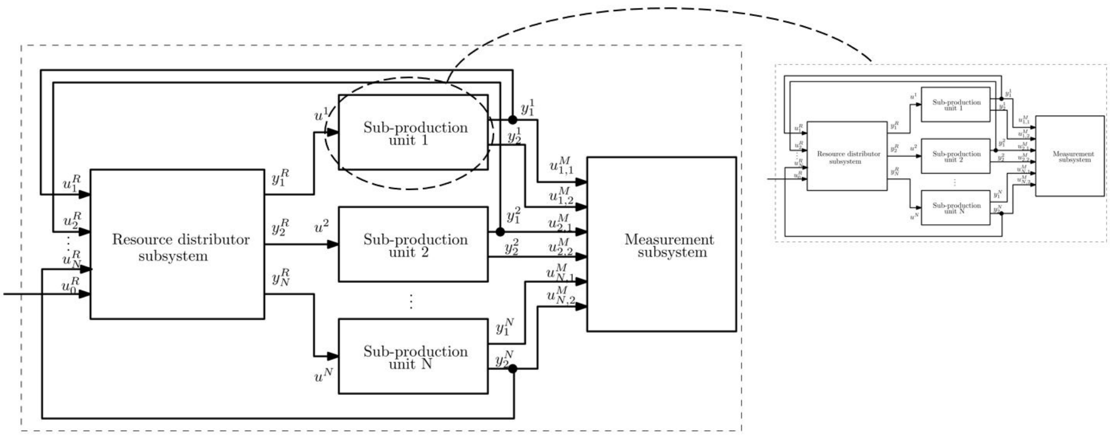


Figure 15: The structure of the generic system and model layout. Every sub-production unit has the same structure.

Figure 16 shows the Simulink® model parts which are built up based on Figure 15. The number of wards/specialty departments in this model corresponds to the case study described in Section 4.6. In the following subsections, the structure of the system, the relevant parameters and the governing equations are explained in details. The type and number of parameters are chosen in a way to fulfill the condition of being generic. This degree of details corresponds to the requirements of the strategic decision making which concerns mainly the size of the OR department (number of rooms and surgeons), the amount and types of surgeries for each specialty and general cost calculations.

4.5.1 Resource Distributor Module and Distribution Rules

As already mentioned, the resource distributor is defined at two levels: 1) the whole surgical suite (P3), 2) sub-production units (specialty departments, P4). The purpose of the resource distributor is to allocate the available resources among the wards and accordingly the surgeons depending on the level it is responsible for. This subsystem is the heart of the system, and the performance of the whole system is decided here. Distribution of OR time blocks is an allocation problem, which corresponds to the classical allocation game (Rosenthal, 1973) in which selfish players should share limited resources. In the allocation problem in question, the specialty departments/surgeons, should share limited OR blocks to consummate their waiting lists of patients.

It must be noted that the distribution of the resources is a task which needs specific considerations. Surgeons normally stay at the focal point and their acceptance level regarding resource distributions should be always taken into account. Moreover,

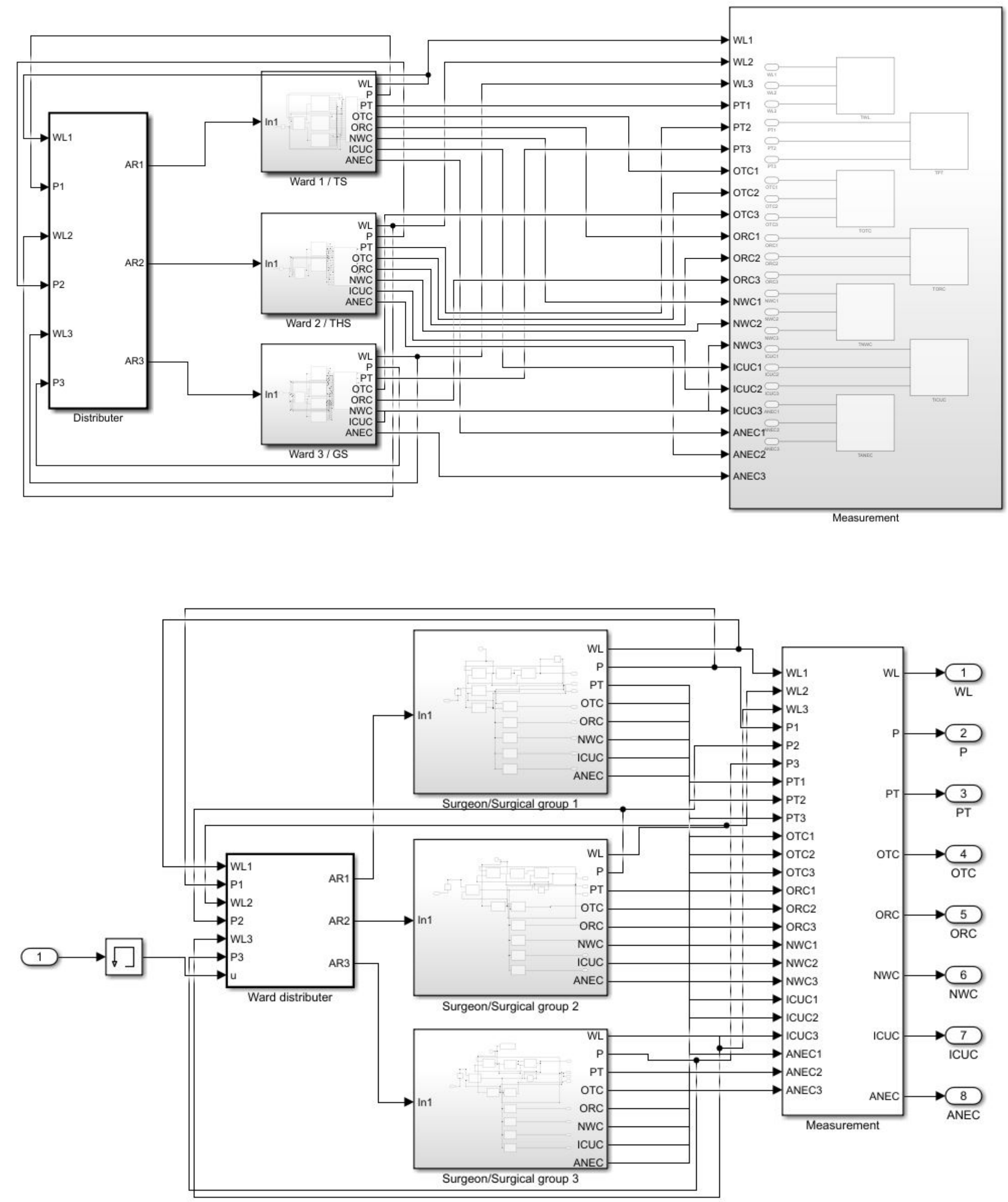


Figure 16: Example Simulink® model of the whole operating room suite (upper) and the ward (lower). This model corresponds to the case study with three specialty departments, which is described in Section 4.6. The ward sub-system "Ward1/TS" shown in this figure is comprised of three surgeons/surgical groups.

each surgeon or ward has a waiting list of patients and any distribution mechanism would indirectly and subsequently impact the patients. Therefore, a fair distribution at every simulation time step brings acceptability and satisfaction to the system and ensures the dynamic stability. In this sense, the power index method, taken from the game theory literature, is considered to be a suitable method to gauge the acceptability of feasible resource distributions. The reason is that the power indices are designed to provide fair division and reasonable sharing of an available value among participants (Bertini et al., 2018) by determining the impact of participants on the final results. This impact is interpreted as a power which indicates how much power the participants would receive as the result of a proposed solution.

There are various types of power index methods. In this chapter, the power index proposed by Loehman et al. (1979) is adopted. Loehman et al.'s Index is an approach to determine the relative power for participants by comparing their individual payoffs with the total payoff gained by all participants. In the allocation problem discussed here, each participant's payoff is the share of the resources she/he obtains. This version of power index is formulated as the following equation:

$$PI_i = \frac{CL_i - AR_i}{\sum_{j=1}^{N}(CL_j - AR_j)} \tag{4.2}$$

where i and $j = \{1, 2, 3, .., N\}$ are the sets of participants, CL_i is the claimed amount of resources for the participant i, AR_i is the amount of the share allocated to the participant i and $\sum_{i=1}^{N} PI_i = 1$. It should be noted that no participant receives more than her/his claim by applying this constraint: $0 \leq AR_i \leq CL_i$. This power index has also been suggested (Dinar and Howitt, 1997; Bertini et al., 2018) as a forecast to the stability of resource distributions. To measure the stability, each participant's PI_i is calculated for each allocation scheme. It must be noted that the balance in the distribution of power among the participants is linked to the stability of the outcome. A solution is more stable when the disparity in power distribution among the participants is smaller. This disparity is measured using coefficient of variation in PI_i across all participants for a given solution as:

$$S = \frac{\sigma}{\bar{PI}}, \quad 0 \leq S \leq 1 \tag{4.3}$$

where S is the coefficient of variation of a particular solution, σ and $\bar{PI}$ are the standard deviation and the mean value of the set of power indices of all participants, respectively. A greater value of S, thus, represents a situation where a larger instability of the allocation solution is expected.

In Equation 4.2 the claims of different participants can be weighted (inspired by Holler (1981)) according to their capability to influence the outcome. These weights help in obtaining realistic results and, in our OR problem, represent the performance of the wards. The weighted power index for the participant i (WPI_i) can then be written as:

$$WPI_i = \frac{(CL_i - AR_i)^{WP_i}}{\sum_{j=1}^{N}(CL_j - AR_j)^{WP_i}} \tag{4.4}$$

where WP_i is the weight of sub-production unit i calculated based on its performance and $\sum_{i=1}^{N} WPI_i = 1$. This performance is measured based on the production rate per unit of allocated resources, which in our case is the number of patients per OR block.

Back to the system, the resource distributor at ORSL has already information regarding the performance rates (WP_i). Once it collects the waiting list information (WL_i) at every time step from the specialty departments, it calculates the required claims (CL_i) as the following equation:

$$CL_i = \frac{WL}{WP} \tag{4.5}$$

Having calculated the claims and gathered information regarding the available OR blocks, a pool of possible block allocations is generated, and then, their stability degrees are calculated with the help of the above-mentioned power concept. The system then picks the allocation scheme with the highest stability. Hence, the outputs of this sub-system would then be the amount of OR blocks each sub-production unit is allowed to receive.

The same procedure holds true for the lower level resource distributors (SDL) inside the sub-production units, with a small difference that the input of these sub-systems are the outputs of the higher level (ORSL) resource distributor. Figure 16 provides closer pictures of how distributors are connected to the other sub-systems at SDL and ORSL levels.

4.5.2 Monitoring Module

The measurement sub-system accumulates data from the individual production units to monitor the whole system during the passage of time at the levels of ORSL and SDL. The structure of this module is compatible with the cost categorization defined by the German Institute für das Entgeltsystem im Krankenhaus – Institute for the Hospital Remuneration System – (InEK) which is responsible for the DRG data and pricing system. The InEK system divides expenses of hospitals into eleven cost centers: 1) normal ward, 2) intensive care unit, 3) dialysis department, 4) operating room, 5) anesthesia, 6) delivery room, 7) cardialogical diagnosis and therapy, 8) endoscopic diagnosis and therapy 9) radiology department, 10) laboratories and 11) other diagnostic and therapeutic areas. For each cost center, three categories of costs are considered: 1) personnel, 2) material and 3) infrastructure costs. The proposed model, collects information regarding the most cost-intensive areas of "operating room (OR)", "intensive care unit (ICU)", "normal ward (NW)" and "anesthesia (ANE)". In addition, the "total patient throughput" and the "total waiting list" are also calculated. Overtime is also another parameter which is monitored in this model. Suppose that we have N sub-production units or specialty departments in our surgical suit. The equations governing the measurement sub-system are as presented in Table 15. The same equations hold true for every specialty department with N surgeons. In Figure 16, it can be seen how the measurement modules at ORSL and SDL take inputs from the specialty departments and surgeons.

Table 15: Equations governing the measurement module.

Equation	Description
$TORC_t = \sum_{i=1}^{N} ORC_i$	$TORC_t$= total operating room cost at time t ORC_i= operating room cost of sub-production unit i
$CTORC = \sum_{t_0=0}^{t} TORC_t$	$CTORC$ = cumulative total operating room cost
$TICUC_t = \sum_{i=1}^{N} ICUC_i$	$TICUC_t$= total intensive care unit cost at time t $ICUC_i$= intensive care unit cost of sub-production unit i
$CICUC = \sum_{t_0=0}^{t} TICUC_t$	$CICUC$ = cumulative total intensive care unit cost
$TNWC_t = \sum_{i=1}^{N} NWC_i$	$TNWC_t$= total normal ward cost at time t NWC_i = normal ward cost sub-production unit i
$CTNWC = \sum_{t_0=0}^{t} TNWC_t$	$CTNWC$ = cumulative total normal ward cost
$TANEC_t = \sum_{i=1}^{N} ANEC_i$	$TANEC_t$= total anesthesia cost at time t $ANEC_i$ anesthesia cost sub-production unit i
$CTANEC = \sum_{t_0=0}^{t} TANEC_t$	$CTANEC$ = cumulative total total anesthesia cost
$TPT_t = \sum_{i=1}^{N} PT_i$	TPT_t= total patient throughput at time t PT_i= patient throughput sub-production unit i
$CTPT = \sum_{t_0=0}^{t} TPT_t$	$CTPT$ = cumulative total patient throughput
$TWL_t = \sum_{i=1}^{N} WL_i$	TWL_t= total waiting list at time t WL_i= waiting list sub-production unit i
$CTWL = \sum_{t_0=0}^{t} TWL_t$	$CTWL$ = cumulative total waiting list
$TOTC_t = \sum_{i=1}^{N} OTC_i$	$TOTC_t$=total overtime cost at time t and OTC_i = overtime cost sub-production unit i
$CTOTC = \sum_{t_0=0}^{t} TOTC_t$	$COTC$ = cumulative total overtime cost

4.5.3 Surgeons as Sub-sub-production Units

In this section, the details of the surgeon sub-systems are described. Figure 17 shows the details of its Simulink® model. The surgeons are the smallest production units responsible to process their own orders. The orders to be processed by the system are laid by these units at every time step. The list of orders is comprised of the new patients (NP) at time t, and the orders (patients) that were not processed at time $t-1$ and were consequently transmitted to time t as the remaining waiting list (RWL). Summation of these two variables yields the surgical order of the sub-sub-production unit. Every surgeon requires a specific amount of OR resources to consummate its order list, which is determined based on her/his performance (P). Having been assigned the OR resources (after P2, P3 and P4), the orders will be processed based on the received quota of resources and the patient throughput (PT) for the time t will be calculated as follows:

$$WL = NP + RWL \tag{4.6}$$

$$PT = P \times AR \tag{4.7}$$

$$P \sim \mathcal{N}(\mu_p, \sigma_p^2) \tag{4.8}$$

$$RWL = WL - PT \tag{4.9}$$

where, WL= waiting list; NP=new patients; RWL= remaining waiting list; AR= allocated resources; PT= patient throughput; and P= performance of the pertinent surgeon which is selected randomly out of a normal probability distribution calculated based on the surgeon's historical performance data.

Regarding cost calculations, as described in Subsection 4.5.2, the adopted approach is based on the German InEK system. Hence, inside every surgeon unit, the pertinent OR, normal ward, intensive care unit, and anesthesia cost blocks are provided. To this aim, inside every block random values per surgical procedure are generated. These random values are sampled from normal probability distributions fitted to the cost information provided by the InEK system. The probability distributions are calculated based on the data of the most frequent diagnoses. To overcome the problem of production of negative values by normal distributions, a positivity constraint is applied to the sampling process rejecting negative values and re-sampling until getting a positive one. This process corresponds to the definition of rectified normal distributions.

$$ORC_i = \sum_{j=1}^{PT} ORCs_j \quad \text{where} \quad ORCs_j \sim \mathcal{N}(\mu_{ORCs_j}, \sigma^2_{ORCs_j}) \tag{4.10}$$

$$NWC_i = \sum_{j=1}^{PT} NWCs_j \quad \text{where} \quad NWCs_j \sim \mathcal{N}(\mu_{NWCs_j}, \sigma^2_{NWCs_jv}) \tag{4.11}$$

$$ICUC_i = \sum_{j=1}^{PT} ICUCs_j \quad \text{where} \quad ICUCs_j \sim \mathcal{N}(\mu_{ICUCs_j}, \sigma^2_{ICUCs_j}) \tag{4.12}$$

$$ANEC_i = \sum_{j=1}^{PT} ANECs_j \quad \text{where} \quad ANECs_j \sim \mathcal{N}(\mu_{ANECs_j}, \sigma^2_{ANECs_j}) \tag{4.13}$$

Each surgeon has a specific time slot to treat a certain number of patients. However, the performance amounts are not always integer numbers. Therefore, there is always a remaining time, which is not enough to complete a procedure. If the surgeon could complete a given procedure within 60 minutes of overtime, then, this amount of time would be granted to her/him, otherwise the remaining time would be considered as idle time. To calculate the overtime cost a method suggested by Diez and Lennerts (2009) is taken, which suggests assigning a 0.92 € per minute of surgery according to the InEK system. Therefore, overtime cost for surgeon i, OTC_i, is calculated as the following algorithm:

Calculation of $OTCOTC_i$
while $k \leftarrow 1$ **to** PT/AR **do**
    if $OT_k(S) \leq 60min$ **then**
        $OT \leftarrow OT_k$
    end if
end while
$OTC_i = \leftarrow OT \times 0.92$
    return OTC_i

The surgeon sub-system could represent one surgeon or a group of surgeons who have common characteristics or approximately the same level of performances and could cooperate with each other. At every time step, all of the calculated parameters for surgeons are collected by the ward measurement module to monitor the state of the system.

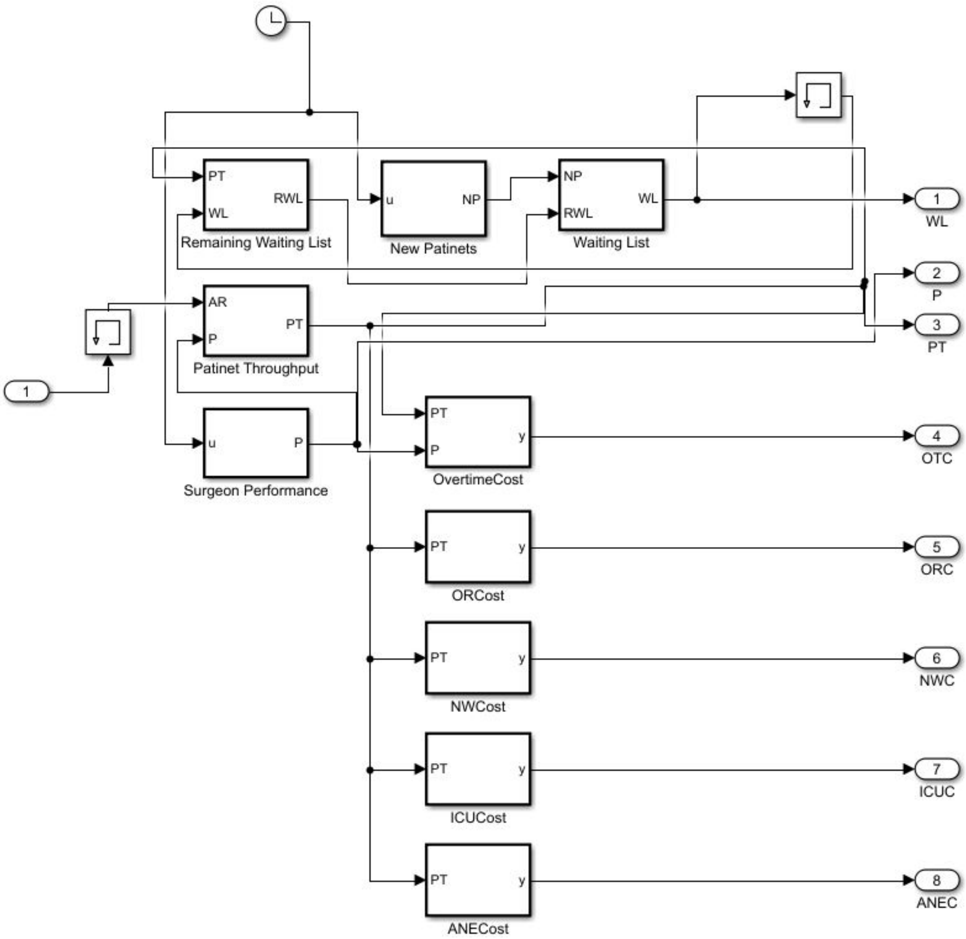


Figure 17: The Simulink® model of surgoen/surgical group.

4.6 Case Study

The case study here refers to one of the surgical departments in a general hospital in the State of Baden-Württemberg of Germany. This department is made up of three specialty departments of trauma surgery (TS), general surgery (GS), and thorax surgery (THS) with case mix indices of 1.16, 3.63 and 2.46, respectively. There are seven jointly used operating rooms available from Monday to Friday from 7:30 until 15:00 o'clock, which means $5 \times 7 = 35$ sessions are available in a week. Overall 67 surgeons are involved in this department each having a different performance rate.

The structure of the generic model has already been described in Figure 16 in Section 4.5.1. To ease the modeling procedure not every single surgeon is modeled as a sub-sub-production unit. They are categorized into two general groups: 1) a single surgeon who has a sufficient workload, 2) a group of two or more surgeons who have together enough workload to be modeled as a joint-production unit. In this regard, nine sub-sub-production units for the whole of the mentioned surgical department are created, therefrom, four groups belong to GS, three groups to TS, and the remaining two groups to THS. Table 16 shows the model input data regarding the

Table 16: Model inputs regarding surgeon information, their performances and related costs.

Surgeon	Performance	ORC (€)	ICUC (€)	NWC (€)	ANEC (€)
1-GS	$\mathcal{N}(3.75, 0.1^2)$	$\mathcal{N}(1770, 1618^2)$	$\mathcal{N}(1252, 610^2)$	$\mathcal{N}(2605, 1238^2)$	$\mathcal{N}(737, 538^2)$
2-GS	$\mathcal{N}(2.6, 0.1^2)$	$\mathcal{N}(1770, 1618^2)$	$\mathcal{N}(1252, 610^2)$	$\mathcal{N}(2605, 1238^2)$	$\mathcal{N}(737, 538^2)$
3-GS	$\mathcal{N}(3.4, 0.1^2)$	$\mathcal{N}(1770, 1618^2)$	$\mathcal{N}(1252, 610^2)$	$\mathcal{N}(2605, 1238^2)$	$\mathcal{N}(737, 538^2)$
4-GS	$\mathcal{N}(3.0, 0.1^2)$	$\mathcal{N}(1770, 1618^2)$	$\mathcal{N}(1252, 610^2)$	$\mathcal{N}(2605, 1238^2)$	$\mathcal{N}(737, 538^2)$
5-TS	$\mathcal{N}(5.25, 0.1^2)$	$\mathcal{N}(1437, 849^2)$	$\mathcal{N}(1270, 588^2)$	$\mathcal{N}(93, 45^2)$	$\mathcal{N}(516, 143^2)$
6-TS	$\mathcal{N}(4.5, 0.1^2)$	$\mathcal{N}(1437, 849^2)$	$\mathcal{N}(1270, 588^2)$	$\mathcal{N}(93, 45^2)$	$\mathcal{N}(516, 143^2)$
7-TS	$\mathcal{N}(3.0, 0.1^2)$	$\mathcal{N}(1437, 849^2)$	$\mathcal{N}(1270, 588^2)$	$\mathcal{N}(93, 45^2)$	$\mathcal{N}(516, 143^2)$
8-THS	$\mathcal{N}(3.75, 0.1^2)$	$\mathcal{N}(2696, 1283^2)$	$\mathcal{N}(3327, 1196^2)$	$\mathcal{N}(3702, 2370^2)$	$\mathcal{N}(1091, 446^2)$
9-THS	$\mathcal{N}(3, 0.1^2)$	$\mathcal{N}(2696, 1283^2)$	$\mathcal{N}(3327, 1196^2)$	$\mathcal{N}(3702, 2370^2)$	$\mathcal{N}(1091, 446^2)$

surgeons/surgical groups, their related specialty departments, their performances and the department-related costs.

Surgery costs per hour of operating room time can differ significantly among surgeons, according to their performances (Macario et al., 2001), but because of data gaps and for the sake of simplicity, the probability distribution for different categories of costs are considered to be the same for the whole of a given specialty department.

The data for this department were collected for 24 months from January 2015 to December 2016. In this time-frame, 11,424 elective patients were admitted to this department. It is prognosticated that the number of patients would increase in the upcoming years. According to the Statistical Office of Baden-Württemberg, the number of elective patients is expected to increase about (as an average amount for all disciplines) 10% in 2030 with reference to 2015 (Landesamt, 2005). This means that the hospitals in the region must adjust themselves to the demographic changes and demands. In this regard, it is indispensable to define reasonable "what-if" scenarios, evaluate them and experiment with the system prior to making any decisions and changes.

4.6.1 Simulation Scenarios

The long-term policy orientation is the objective of SD models (Barlas, 1994). In this regard five scenarios/policies are defined to examine the system behavior and the quality of its dynamic stability. Scenarios 1 through 3 are mostly dealing with changes in input management parameter values such as opening hours and operating room numbers. Scenarios 4 and 5 are mainly dealing with examining the modularity and reconfigurability of the model. Scenario 4 is about exclusion of one of the specialty department sub-systems, and Scenario 5 is about the exclusion of surgeons sub-systems. Table 17 lists a short description of each scenario. The simulations are run for a period of 10 years from 2020 to 2030 based on monthly rates.

Table 17: Different scenarios and their model inputs.

Nr.	Scenarios	Input to the Model
1	Business as usual (BaU)	The OR department continues its function under the current conditions, demand increase in 10 years is expected to be 8.80% for TS, 7.60% for GS and 15.30% (according to Landesamt (2005)).
2	Increase in number of operating rooms (IOR)	The number of OR rooms will be increased from 7 to 8, demand increase same as BaU.
3	Increase in opening hours (IOH)	The opening hours will be increased from 7.5 to 8 hours, demand increase same as BaU.
4	Service elimination (SE)	The specialty department with the least demand (in this case TS) amount is eliminated, demand increase same as BaU.
5	Dismissing low performance surgeons (DPS)	At each specialty department one surgeon/surgical group with the least performance will be dismissed, demand increase same as BaU.

4.6.2 Simulation Results

The simulation results for each scenario are shown in Table 18. One can extract results for the individual surgeons or specialty departments, however, only the results for the whole system are presented here. Figures 18, and 20 and 21 in the Appendix A2 elucidate the state and sensitivity of the studied operating room suite to the changes in scenario variables. According to the results, the behavior patterns of different variables show that:

- If the operating room department continues its function under the current conditions, it could not be able to provide enough services to meet the increasing demand for surgery. Despite the 30% of increase in the number of patients in 2030 with respect to 2020, the monthly patient throughput stays relatively unchanged.

- Patient throughput variable shows a better behavior in Scenario 2 and has the highest amount (about 11.5% increase with respect to Scenario 1). Although the costs are almost in direct relationships with the number of total patient throughput, the ICU and normal ward costs show 14% (instead of 11.5%) of increase with respect to Scenario 1. This shows that more GS and TS patients, who need more ICU resources, were treated. Adding an extra operating room to the department increases not only the patient throughput, but also the responsiveness of the system to the demand increase. The fitted trend-line slope to the patient throughput (14%) is higher than those in the other scenarios. The productivity ratio, calculated as the average number of patient throughput to the average number of patients in waiting list, is also higher than the other scenarios. However, it should be mentioned that the total cost of this scenario, because of consumption of more resources, is also higher than the others.

- In Scenario 3, patient throughput shows a 5.6% increase with respect to Scenario 1, however, increase in normal ward costs is about 8%. This means that more THS patients, who need longer stays in normal ward, are treated.
- Regarding Scenario 4 which is about the elimination of a service which would be less demanded, one might be conservative in interpreting the outputs. Since the demand amount in this scenario is decreased and the operating department has to deal with less patients, all outputs show reduction with respect to Scenario 1. Nevertheless, the overtime may not necessarily improve. It means that the eliminated service is less responsible for overtime than the other departments.
- Despite dismissing low performance surgeons in Scenario 5, the results show more overtime. The reason is that the surgeons are faster than the other scenarios, and hence, they are more allowed to complete unfinished procedures within 60 minutes of overtime.

(For more result details please refer to Figures 22 to 25 in the Appendix.)

The simulation results show how changes in different variables can affect the whole system. The assessment of the model results for different scenarios presents a good perspective of the interconnected and dynamic nature of the system. However, the main purpose of this study is to comprehend the interactions of different variables. This study offers a quick approach for integrating, exploring, adapting, and understanding the consequences of policies and decisions. Even if wrong, the developed model can be still useful in the early investigations of system behavior. The scenario analysis is conducted to just comprehend the system behavior patterns, and hence, the generated numbers are merely to provide comparisons and may not speak for any absolute realistic future.

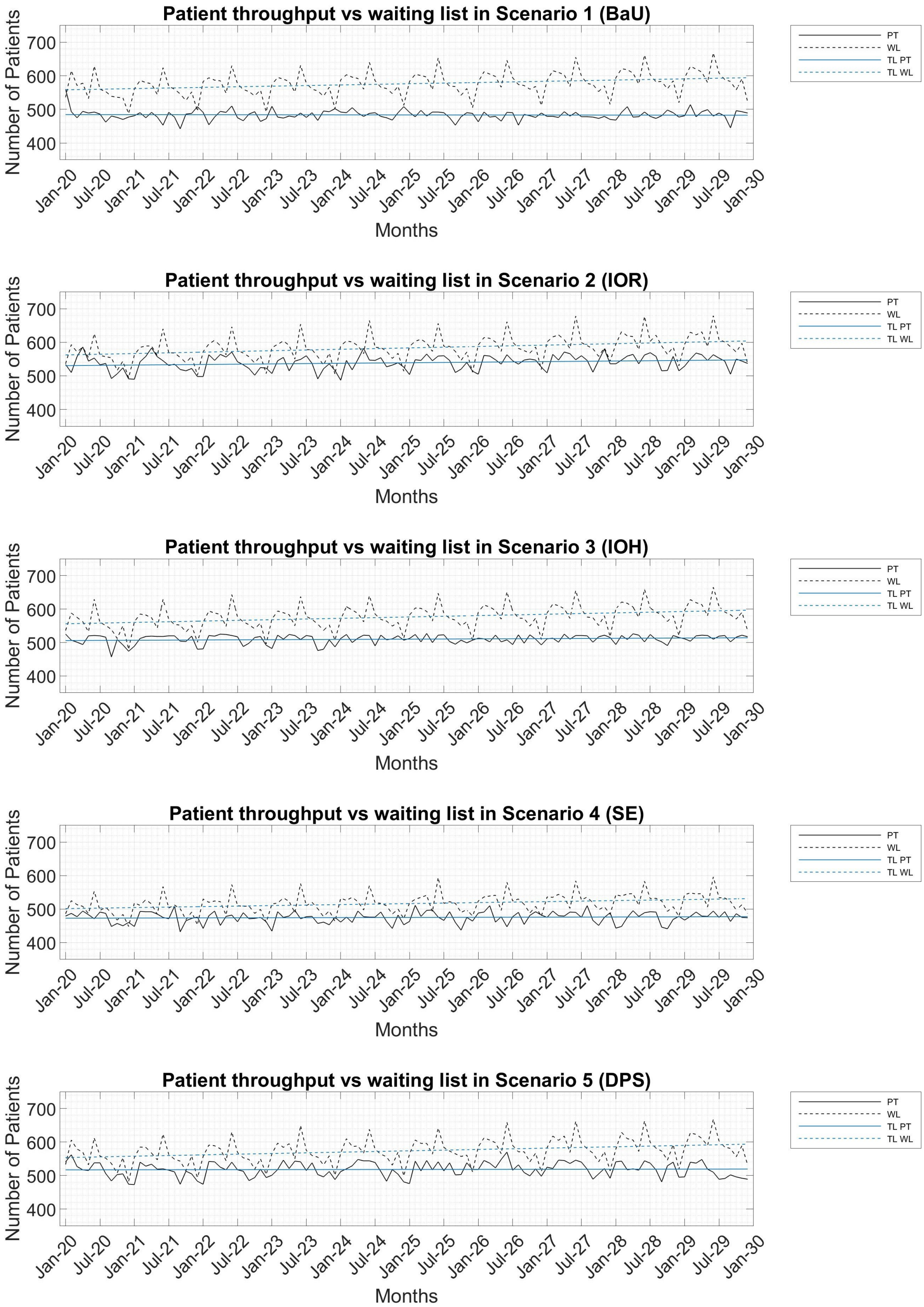


Figure 18: Behavior of patient throughput and waiting list of the whole surgical suite. “TL PT” and “TL WL” are fitted trend-lines to total patient throughput and waiting list, respectively

Table 18: Outputs of the different scenarios

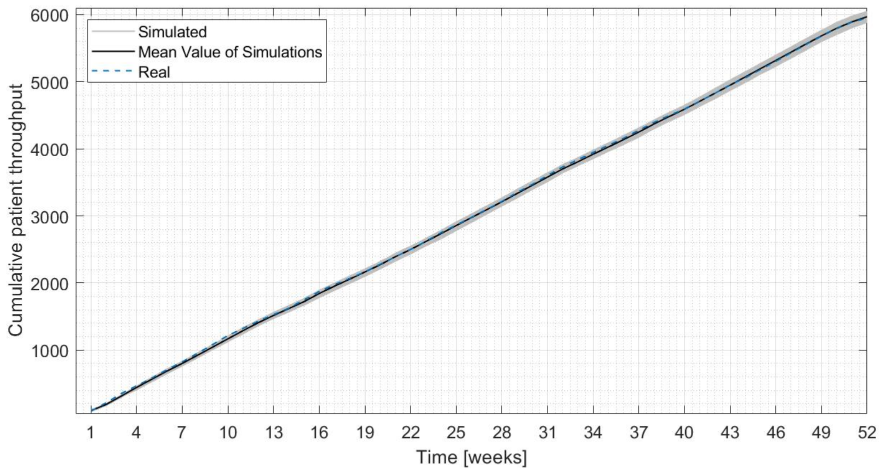
Scenarios	Model outputs										
	PT∗	TPT	PT/WL∗	TORC∗ ($\times 10^5$ €)	Overtime∗ †	TNWC∗ ($\times 10^5$ €)	TICUC∗ ($\times 10^5$ €)	TANEC∗ ($\times 10^5$ €)	TOTC∗ ($\times 10^4$ €)	TC∗ ($\times 10^6$ €)	RR $\frac{\text{Slope of TL PT}}{\text{Slope of TL WL}}$
(BaU)	483	58015	0.88	7.42	2.04	4.03	6.41	2.50	1.60	2.06	$\frac{0.00}{30.00}$
(IOR)	539	64685	0.92	8.30	2.03	4.69	7.48	2.80	1.80	2.35	$\frac{14.00}{30.00}$
(IOH)	510	61202	0.88	7.81	2.20	4.35	6.83	2.63	1.70	2.19	$\frac{6.00}{30.00}$
(SE)	475	56987	0.92	7.15	2.24	3.49	5.28	2.37	1.73	1.85	$\frac{4.00}{30.00}$
(DPS)	518	62421	0.90	7.93	3.85	4.30	7.05	2.66	2.98	2.23	$\frac{2.00}{30.00}$

∗based on monthly average amounts
† hrs/(room × day)

4.6.3 Model Validation

To validate a simulation model, it is necessary to determine how sharply the model is able to simulate the real systems. Therefore, it is crucial to test the model or perform a sensitivity analysis to determine the accuracy of the model behavior. In the validation process of SD models, the focus should be on behavior pattern prediction rather than numerical sensitivity and point prediction (Barlas, 1994). To this aim, the considered case study is analyzed during a period of 52 weeks from January to December 2016. Using this data first a calibration is conducted to adjust the model. For the validation, a multivariate analysis concerning surgeon performances (P) with 100 simulations is conducted. The weekly new patient arrivals remained the same as those in the real data for all simulation runs. Figure 19 shows the simulation results, their mean value and the real data. Since long-term and midterm behavior predictions are of importance here, the cumulative (Figure 19 upper) and the 4-weekly (Figure 19 lower) patient throughput results are taken into consideration. The average relative error and the root mean square error for the cumulative results are about 1.4% and 22.3 and for the 4-weekly predictions are about 2.7% and 6.7, respectively. The difference between the simulated and the real total patient throughput is only about 0.3%. The results demonstrate that the model can represent a satisfactory back-casting of the real system in midterm and long-term. Although it does not perfectly reproduce the historical data at each time step, but adequately reflects the behavior patterns and the total outcomes.

Since the received data sets were not detailed enough and no cost data from the real case was available, the only comparison possibility was the behavior of patient throughput. The model could, of course, be extensively validated in terms of overtime and cost estimations in case of availability of relevant reliable data.



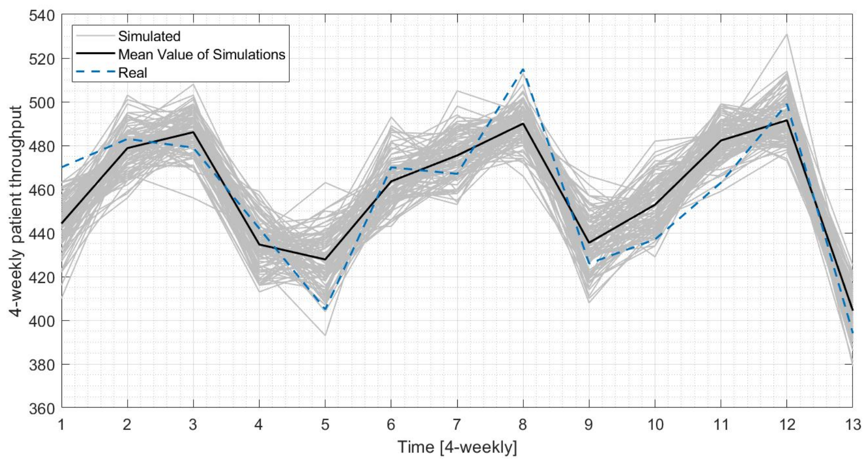


Figure 19: Comparison of the simulated and the real data over 2 years (52 weeks), upper: cumulative patient throughput (mean simulated total: 5967, real total: 5950); lower: 4-weekly patient throughput.

4.7 Concluding Remarks

It is well-known that experimentation with real systems is not possible in most cases given undesired consequences or high costs. Particularly, in the case of management and planning, system dynamics simulations are the basis for policy design and regulation improvements (Morcillo et al., 2018) and it must be mentioned that they are learning laboratories (Forrester, 1997) and are not optimization tools.

Therefore, the purpose of the approach presented in this chapter is to provide an experimental simulation model to analyze consequences of decisions and policies at strategic levels and address the issues of demand dynamics and demand management. The proposed model, which is developed in MATLAB/Simulink® environment, provides a sound perspective of operating room suite dynamism by suggesting a modular and generic design and illustrating the interconnected relations between various components. Being aware of these relations and having a holistic view of an OR system, the hospital administration and OR manager can harmonize the current management affairs and predict the behavior patterns of various variables of the system over time. By considering the probable behavior of system variables in response to various strategies and policies, hospitals can prepare themselves early enough for the future changes and demands. Moreover, the suggested model is one of the few works which offers a generic approach to deal with the OR planning and management problem from the perspective of control theory.

The proposed approach is applied to a real operating room suite in Germany through the simulation of five different scenarios. Using this scenario analysis the system behavior according to future changes is analyzed and comprehended. It must be noted that the generated numbers are not of interest, but the relative differences and system reactions with respect to inputs are important.

Similar to all models, the proposed model has some limitations too, which should be taken into account when interpreting the results. The model is built and calibrated based on the limited available data sets. If more data would be available, inclusion of more parameters in the system could be possible in future work. Accordingly, for such an extended model a systemic sensitivity analysis of model parameters would be useful to examine, for example, the significance of the input parameters and correlation of the input parameters with the outputs. However, the main objective of studies like this is to investigate the system's reactions to different plans, and understanding, comprehending and exploring the dynamism of the OR system.

5 Overall Conclusions

The purpose of this study has been to describe methods for planning and management of operating rooms and to further improve the understanding of how game theoretic and bargaining methods can be used for supporting OR management and decision making. Moreover, what also can be very useful in decision making and management is a systemic view, which is adopted in this research to comprehend the behavior of operating rooms as systems.

There have been two main motivations in designing this study. The first motivation stems from the fact that values, orientations and objectives of different stakeholders involved in operating rooms departments may conflict with each other. This issue makes the OR management task and resource distribution between different claimants a challenging task. One of the important groups of stakeholders, which stay at the center of operating room departments are surgeons who metaphorically fight for the OR time. The preferences of surgeons and their pertinent specialty departments have been the motivation of developing two methods to dimension the OR capacity at the strategic level in Chapter 2 and one further method to generate master surgical schedules based on negotiation and bargaining methods in Chapter 3.

The second motivation is to consider the OR department as a system; a system which is in a constant interaction with its surrounding environment and there is a natural flow of information from input to output. The idea is to break down the operating room departments into sub-systems and comprehend the interrelations between these sub-systems and study the behavior of them through the passage of time. This idea led to development of a system dynamics model which is represented in Chapter 4.

Chapter 2 reviews the literature related to OR management and planning, and describes the theoretical bases for the power index methods and the Shapley value. The problem of OR capacity allocation is formulated, and the suggested methods are described. This study attempts to define the acceptability and stability mechanism of resource allocation among resource users in operating room management context. The proposed methods are evaluated based on a case study taken from the literature. Comparison of the results obtained from the proposed methods to those from the literature shows that, using the power index method, there is a less disparity between the claimed and received resources for individual claimants in the final solution, which implies that no claimant is discriminated in the name of others. Regarding the second method based on the Shapley value, evaluation of the results using fairness metric shows that distribution scheme suggested by the proposed Shapley-based method can provide a sound starting point for fair distribution negotiations, as it ensures a relatively high level of fairness between participants.

Chapter 3 concerns the details of the proposed model for creating master surgical schedules. This chapter first gives an introduction about master surgical schedules and reviews the related literature. Then, after describing the relevant theoretical basis, the suggested framework is explained. The core of the proposed method is based on a bargaining method called fall-back bargaining in which individual bargainers – in our case surgeons – first rank the existing solutions and then enter the bargaining process. In the bargaining process they step back from their first choice until they can find a solution upon which they all can agree. Bargaining methods guarantee the maximization of minimum satisfaction of the bargainers. The process of solution evaluation from the surgeon's viewpoint is carried out using the ordered weighted averaging operator, which is a useful method in obtaining realistic judgments over solutions. To search and explore the large solution space, a special case of genetic algorithms called mutation only genetic algorithm is used. Application of the method to two examples – one illustrative and the other one based on a real case – shows that the proposed method is efficient in maximizing the minimum satisfaction of the surgeons.

Chapter 4 concerns the system dynamics model and first starts with providing a discussion on how to view the hospitals and accordingly operating room departments as systems. Then, the chapter reviews relevant literature, which is followed by the methodology and modeling descriptions. The model is developed based on the principles of dynamical systems and control theory. The three modules of (1) wards, (2) resource distribution and (3) monitoring equip the user with possibilities to characterize the model according to their expectations. The proposed approach is used to model and simulate a real operating room suite in Germany. A scenario analysis is also run to demonstrate the capabilities and capacities of the model. It must be noted that the generated numbers are not of interest, but the relative differences and system behavior under different scenarios are of importance.

5.1 Contributions of the Study

The following contributions are claimed by this study:

- Although the surgeon preferences and acceptability of the resource allocations are addressed by the literature and are considered in developing planning and scheduling methods, no reported research has used game theoretic and negotiation methods to solve the allocation problem concerning surgeon preferences. Therefore, a novelty of this study is to use and employ these kinds of methods to solve the resource allocation and scheduling problem.

- The results suggested by the developed method may not be considered to be directly implemented in real management and planning of operating rooms. The idea here is to provide a starting point grounded on fairness and acceptability, based on which further decisions can be made.

- The system dynamics model developed in this study is a generic model which offers modularity, eases the modeling process and can be simply modified and extended. This model facilitates scenario analysis and studying the behavior of the system under different settings.

5.2 Limitations and Recommendations for Further Research

Like any other research study, according to the scope within which it is defined, this thesis has also limitations. The following items, among others, are not resolved by this thesis. However, they are recommended for further research:

- The proposed methods based on the power index and the Shapley value only suggest starting points for further planning and may not have direct realistic implications. Naturally, the methods must mature through the application in practice and receiving feedback from practitioners, OR managers, and most importantly surgeons.

- The bargaining-based method to create MSS focuses only on the pre-assignment of days, shifts and rooms to the surgeons or surgical specialties, and does not take details of every single case or patient into account. However, the results provide a sound basis for further operational schedules. Therefore, further development to create detailed operational schedules considering patient priorities based on the suggested results could be recommended.

- The system dynamics model is built and calibrated based on the limited available data sets. Obviously, when more data are available, inclusion of more parameters and variables in the system will be possible, and the model could reflect a more realistic future.

A Appendix

A.1 Detailed results of Chapter 3 for Case II

Table 19: Score list of surgeons/surgical groups.

		OR1		OR2		OR3		OR4		OR5		OR6	
Surgeon	Day	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2
Surgeon 1	Mon	2	N	2	N	2	N	2	N	2	N	2	N
Type 1	Tue	1	4	1	4	1	4	1	4	1	4	1	4
Dept. GS	Wed	1	4	1	4	1	4	1	4	1	4	1	4
	Thu	2	N	2	N	2	N	2	N	2	N	2	N
	Fri	2	4	2	4	2	4	2	4	2	4	2	4
Surgeon 1	Mon	2	3	2	3	2	3	2	3	2	3	2	3
Type 2	Tue	2	3	2	3	2	3	2	3	2	3	2	3
Dept. GS	Wed	2	2	2	2	2	2	2	2	2	2	2	2
	Thu	3	3	3	3	3	3	3	3	3	3	3	3
	Fri	3	3	3	3	3	3	3	3	3	3	3	3
Surgeon 1	Mon	3	4	3	4	3	4	3	4	3	4	3	4
Type 2	Tue	3	3	3	3	3	3	3	3	3	3	3	3
Dept. GS	Wed	2	2	2	2	2	2	2	2	2	2	2	2
	Thu	2	2	2	2	2	2	2	2	2	2	2	2
	Fri	2	2	2	2	2	2	2	2	2	2	2	2
Surgeon 1	Mon	4	3	4	3	4	3	4	3	4	3	4	3
Type 2	Tue	4	4	4	4	4	4	4	4	4	4	4	4
Dept. GS	Wed	5	4	5	4	5	4	5	4	5	4	5	4
	Thu	3	3	3	3	3	3	3	3	3	3	3	3
	Fri	2	2	2	2	2	2	2	2	2	2	2	2
Surgeon 1	Mon	1	3	1	3	1	3	1	3	1	3	1	3
Type 1	Tue	2	3	2	3	2	3	2	3	2	3	2	3
Dept. TS	Wed	1	3	1	3	1	3	1	3	1	3	1	3
	Thu	4	4	4	4	4	4	4	4	4	4	4	4
	Fri	1	3	1	3	1	3	1	3	1	3	1	3
Surgeon 1	Mon	2	N	2	N	2	N	2	N	2	N	2	N
Type 1	Tue	1	4	1	4	1	4	1	4	1	4	1	4
Dept. TS	Wed	1	4	1	4	1	4	1	4	1	4	1	4
	Thu	2	N	2	N	2	N	2	N	2	N	2	N
	Fri	2	4	2	4	2	4	2	4	2	4	2	4
Surgeon 1	Mon	3	2	3	2	3	2	3	2	3	2	3	2
Type 2	Tue	4	3	4	3	4	3	4	3	4	3	4	3
Dept. TS	Wed	5	3	5	3	5	3	5	3	5	3	5	3
S6	Thu	3	3	3	3	3	3	3	3	3	3	3	3
	Fri	3	3	3	3	3	3	3	3	3	3	3	3
Surgeon 1	Mon	2	2	2	2	2	2	2	2	2	2	N	N
Type 2	Tue	3	3	3	3	3	3	3	3	3	3	N	N
Dept. THS	Wed	1	2	1	2	1	2	1	2	1	2	N	N
	Thu	4	4	4	4	4	4	4	4	4	4	N	N
	Fri	2	3	2	3	2	3	2	3	2	3	N	N
Surgeon 1	Mon	3	5	3	5	3	5	3	5	3	5	N	N
Type 2	Tue	2	3	2	3	2	3	2	3	2	3	N	N
Dept. THS	Wed	3	3	3	3	3	3	3	3	3	3	N	N
	Thu	3	4	3	4	3	4	3	4	3	4	N	N
	Fri	3	4	3	4	3	4	3	4	3	4	N	N

Table 20: Arrangement of the OR blocks.

		OR1		OR2		OR3		OR4		OR5		OR6	
Surgeon	Day	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2
Instance 1	Mon	TS-1	TS-3	GS-2	TS-3	TS-2	GS-4	GS-2	THS-1	TS-2	TS-1	TS-3	TS-3
	Tue	GS-1	TS-1	GS-2	TS-3	TS-2	GS-4	GS-3	TS-3	TS-2	GS-3	GS-1	GS-1
	Wed	GS-1	THS-1	TS-2	TS-2	GS-3	TS-1	THS-2	GS-2	THS-1	GS-3	GS-2	TS-2
	Thu	GS-3	TS-3	TS-3	GS-4	GS-1	THS-2	THS-2	GS-2	GS-1	GS-3	GS-2	GS-4
	Fri	TS-1	THS-2	TS-1	TS-3	TS-1	GS-4	TS-1	GS-4	GS-1	TS-3	GS-2	GS-3
Instance 2	Mon	GS-4	TS-3	TS-1	TS-3	TS-1	GS-4	TS-1	THS-1	TS-3	TS-1	TS-2	GS-2
	Tue	GS-1	TS-3	TS-2	GS-1	GS-1	TS-3	GS-1	GS-3	GS-1	GS-2	TS-2	TS-3
	Wed	GS-3	GS-3	TS-1	GS-1	GS-2	GS-3	GS-3	TS-2	TS-2	GS-1	GS-1	GS-3
	Thu	GS-3	THS-2	TS-3	GS-2	GS-3	GS-2	TS-3	GS-4	THS-2	THS-1	TS-2	TS-1
	Fri	TS-1	GS-2	TS-3	TS-3	TS-1	GS-4	THS-2	GS-2	TS-1	THS-2	GS-4	TS-3
Instance 3	Mon	TS-2	GS-2	TS-2	THS-1	GS-2	TS-3	TS-3	GS-4	TS-1	GS-4	TS-3	TS-3
	Tue	TS-2	TS-3	THS-1	TS-3	GS-3	GS-2	GS-1	TS-1	GS-3	TS-2	GS-1	GS-2
	Wed	GS-2	GS-2	THS-1	GS-4	THS-1	TS-3	TS-2	THS-2	GS-1	GS-3	TS-2	GS-2
	Thu	TS-3	GS-4	GS-4	THS-2	GS-1	GS-1	TS-1	GS-3	TS-2	GS-1	GS-1	GS-3
	Fri	GS-4	THS-2	TS-1	GS-4	GS-2	GS-2	TS-1	TS-3	TS-1	TS-2	TS-1	GS-3
Instance 4	Mon	TS-3	GS-4	THS-1	GS-2	TS-1	GS-4	GS-2	TS-1	TS-1	GS-3	TS-1	TS-3
	Tue	GS-2	THS-2	TS-2	GS-3	THS-2	TS-1	TS-2	TS-2	TS-2	THS-1	TS-2	GS-4
	Wed	THS-1	GS-1	GS-2	TS-3	GS-3	GS-2	TS-2	TS-1	THS-2	GS-1	GS-2	TS-3
	Thu	GS-2	TS-3	GS-3	GS-2	TS-2	GS-4	TS-3	GS-1	GS-1	GS-4	GS-2	GS-3
	Fri	GS-1	TS-3	THS-2	GS-2	GS-4	TS-3	THS-1	THS-1	TS-2	GS-4	TS-3	GS-3
Instance 5	Mon	TS-2	GS-4	TS-3	TS-3	TS-1	TS-3	GS-2	TS-3	TS-1	TS-3	TS-2	GS-2
	Tue	THS-2	TS-3	TS-1	TS-1	GS-3	TS-3	TS-1	THS-2	TS-3	TS-1	GS-1	TS-2
	Wed	THS-1	THS-2	GS-3	GS-1	TS-1	TS-1	GS-1	GS-3	THS-2	TS-3	TS-1	TS-3
	Thu	GS-2	GS-1	GS-1	GS-2	GS-4	GS-3	TS-2	GS-3	TS-3	GS-2	GS-3	GS-1
	Fri	TS-1	GS-4	TS-2	GS-3	GS-3	GS-2	THS-2	THS-2	GS-4	TS-3	GS-1	GS-3

A.2 Selected outputs of the System Dynamics model

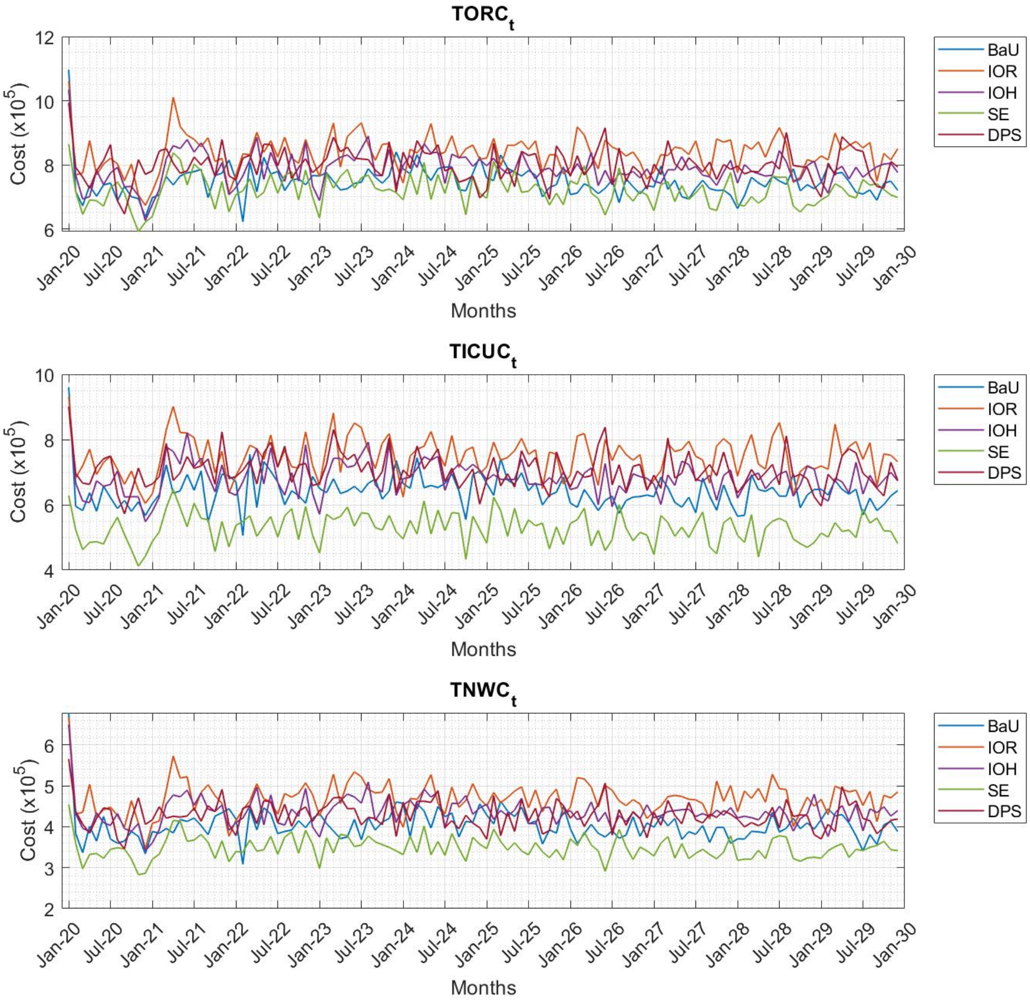


Figure 20: Behavior of $TORC_t$, $TICUC_t$ and $TNWC_t$ under different scenarios from Jan 2020 to Jan 2030.

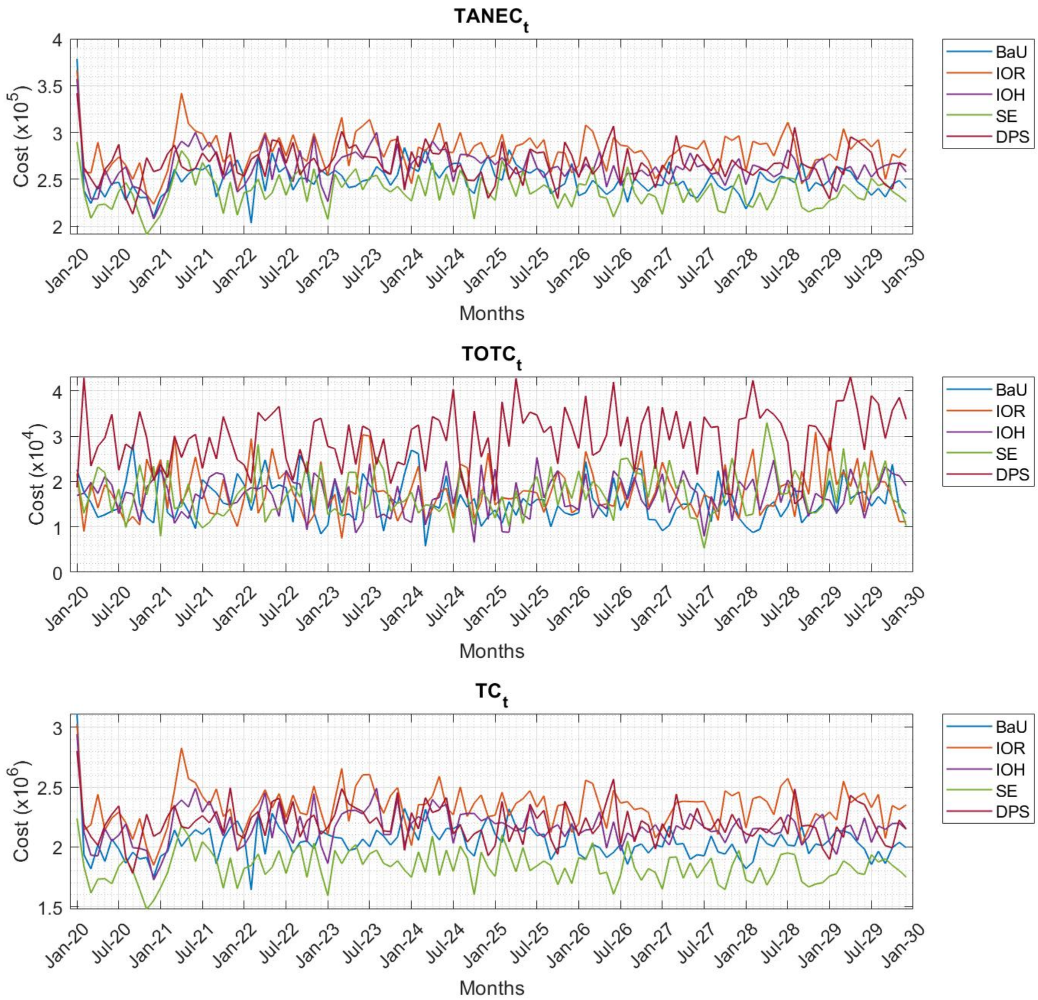


Figure 21: Behavior of $TANEC_t$, $TOTC_t$ and TC_t under different scenarios from Jan 2020 to Jan 2030.

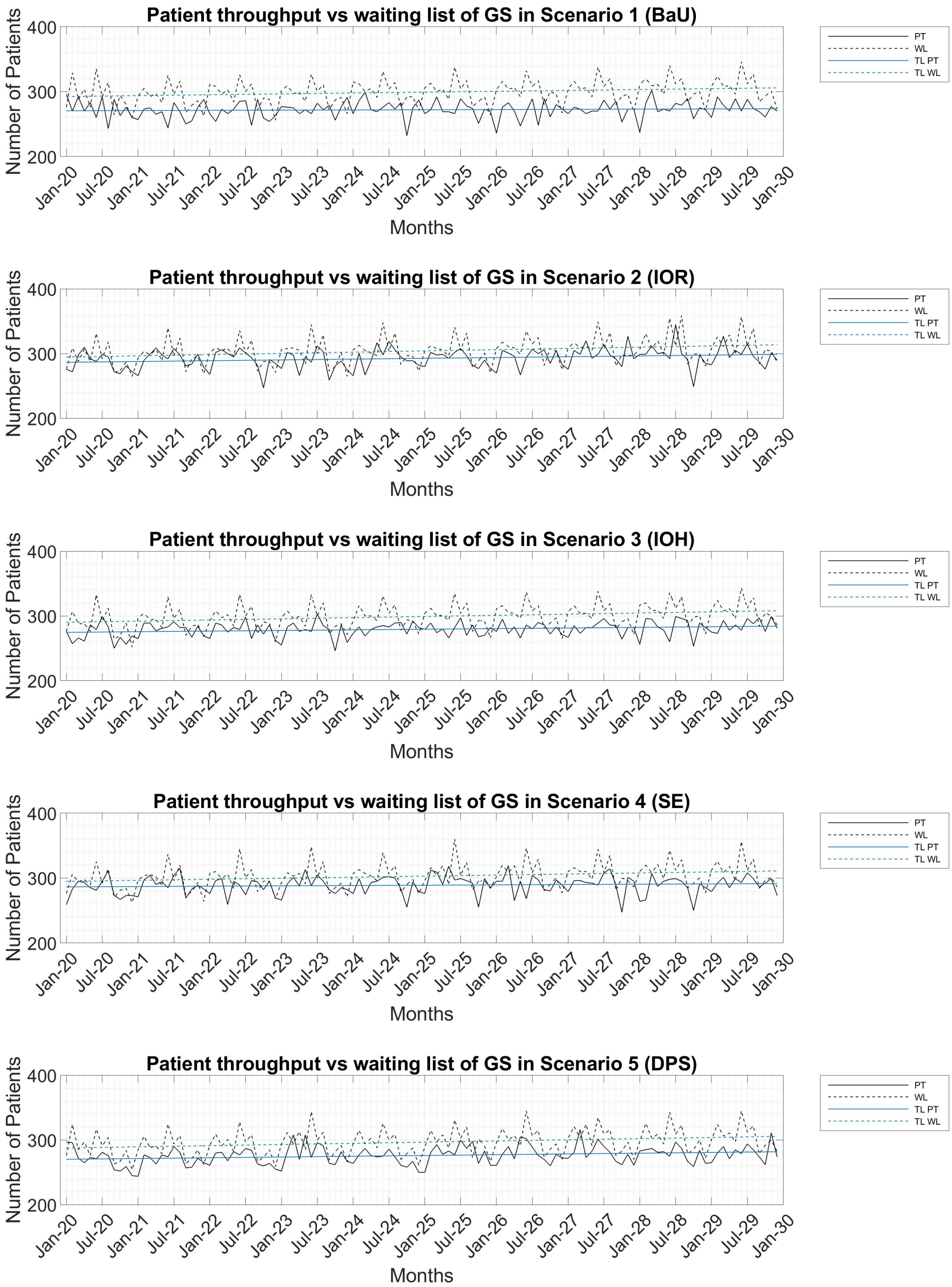


Figure 22: Behavior of patient throughput and waiting list of ward GS. "TL PT" and "TL WL" are fitted trend-lines to total patient throughput and waiting list, respectively.

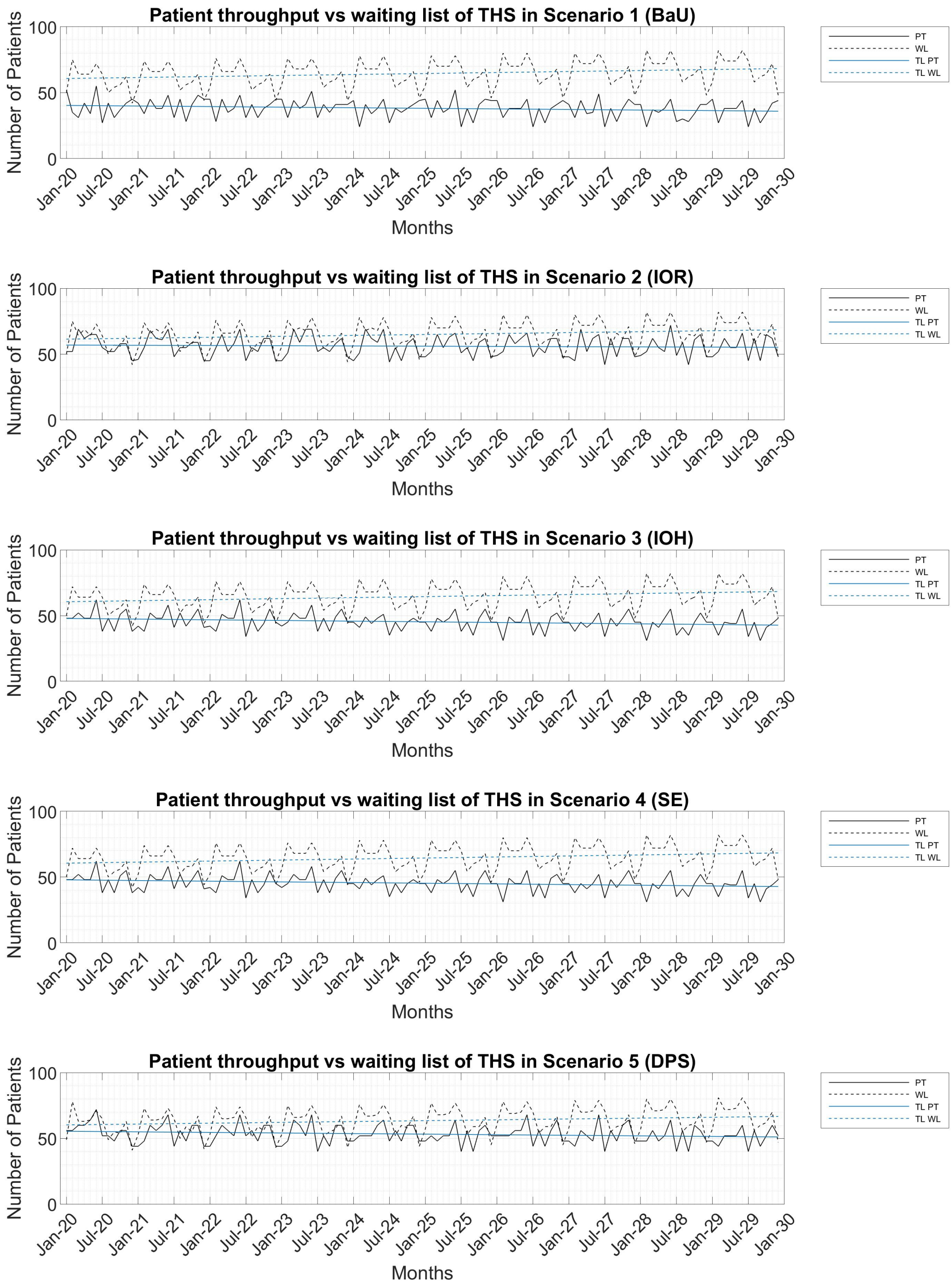


Figure 23: Behavior of patient throughput and waiting list of ward THS. “TL PT” and “TL WL” are fitted trend-lines to total patient throughput and waiting list, respectively.

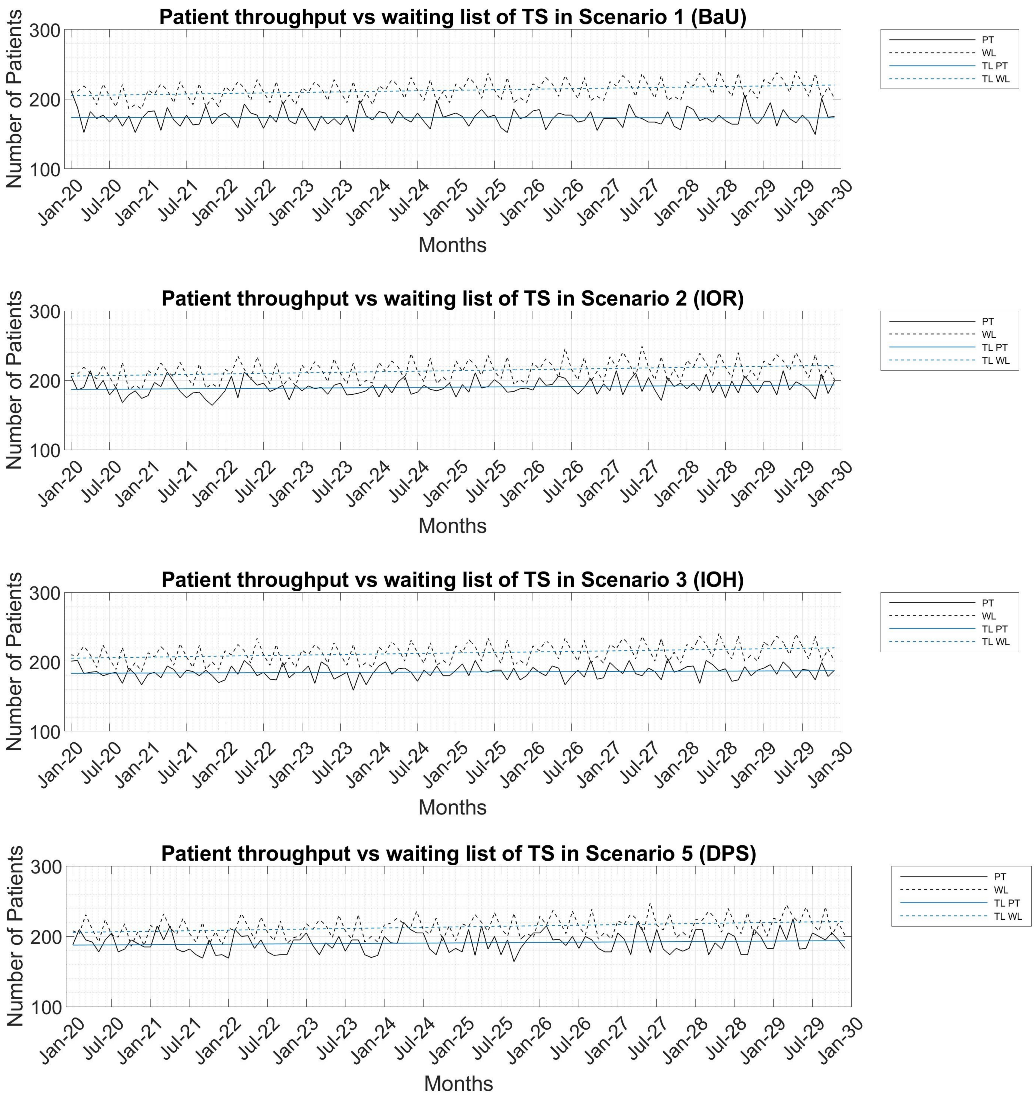


Figure 24: Behavior of patient throughput and waiting list of ward TS. “TL PT” and “TL WL” are fitted trend-lines to total patient throughput and waiting list, respectively.

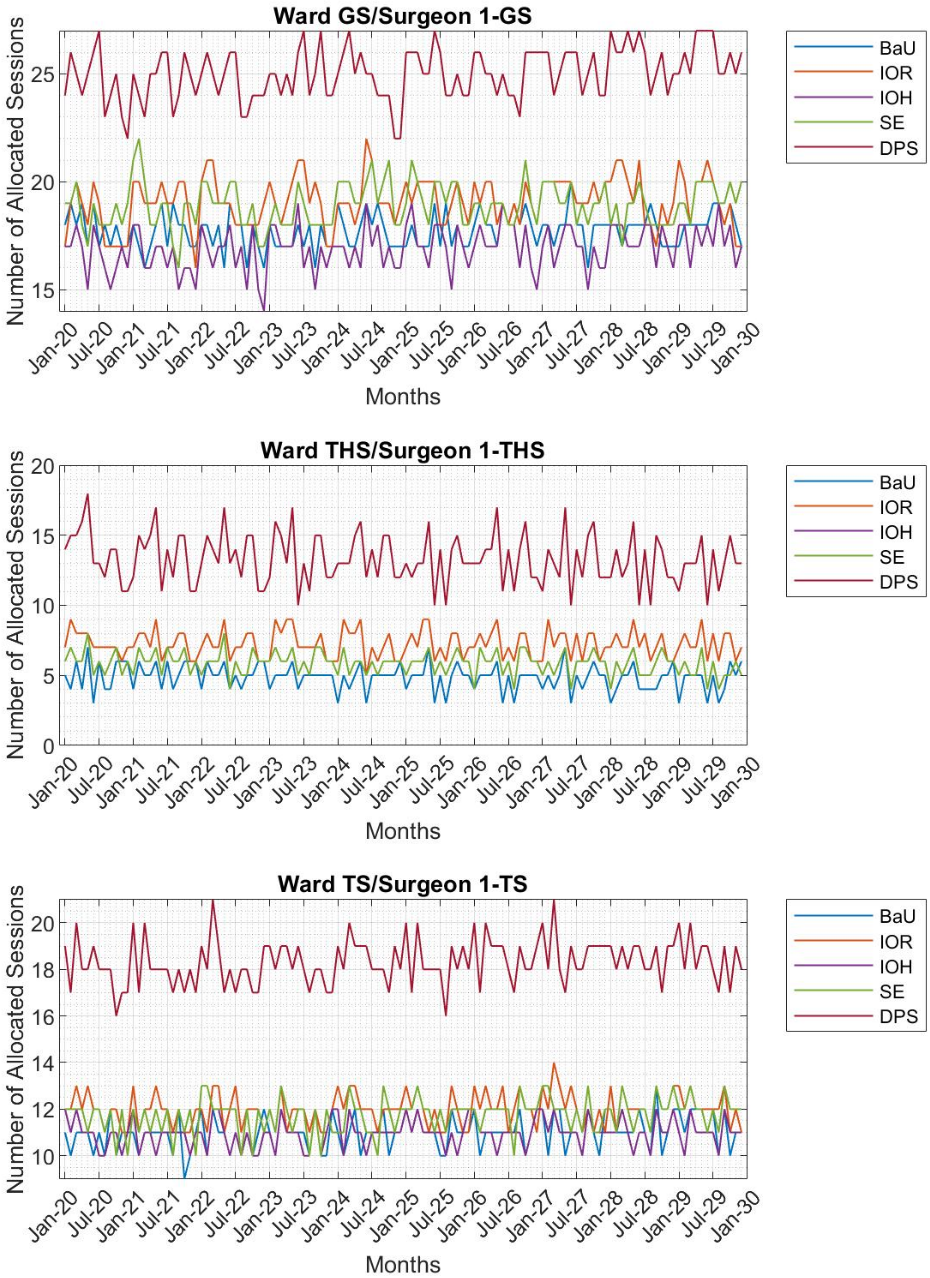


Figure 25: Allocated resources to surgeons 1-GS (upper), 1-THS (middle), and 1-TS (lower) from January 2020 to January 2030.

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