



## Supply Chain Analytics in Healthcare

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**DTU Management**  
Department of Technology, Management and Economics

# Supply Chain Analytics in Healthcare

Gaspard Hosteins



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## Summary

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Hospitals and the healthcare system play an indispensable role in society by providing critical care to patients, often in unpredictable and challenging conditions. Despite their vital function, many hospitals still rely on traditional, non-data-oriented practices in their supply chain management. This thesis delves into the potential of implementing data-driven Operations Management and Operations Research (OM/OR) techniques to enhance hospital supply chains. This thesis comprises three articles, each addressing real-life use cases that highlight specific challenges presented by the hospital context and propose OM/OR approaches to tackle them.

The first article focuses on optimising bed flow management within a hospital, addressing the complexities of matching an unpredictable patient demand with limited bed resources, primarily reliant on human decision-making. We introduce a model that incorporates the impact of demand variability on the workforce, emphasising the efficiency gained by considering this human factor. This approach helps mitigate the risk of bed shortages and enhances the overall supply chain.

The second article centres on the sterilisation process of surgical tools, presenting a comprehensive model of the entire cycle, including a dedicated model of the surgical demand. We demonstrate the necessity of such a holistic approach in accurately identifying weaknesses within the cycle and devising effective solutions.

The third paper explores the allocation of departments within a hospital under construction. It illustrates how proactive planning for resource flexibility can harness benefits in terms of resource utilisation while addressing the challenges posed by increased transportation flows.

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This thesis demonstrates how data-driven OM/OR methods can significantly improve hospital supply chains. However, it also highlights various challenges associated with the hospital context, including issues related to data quality, data availability, or the complexities of managing highly variable demand.

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## Resumé (Summary in Danish)

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Hospitaler og sundhedsvæsenet spiller en uundværlig rolle i samfundet ved at yde kritisk pleje til patienter, ofte under uforudsigelige og udfordrende forhold. På trods af deres vitale funktion er mange hospitaler stadig afhængige af traditionel, ikke-dataorienteret praksis i deres forsyningskædestyring. Denne afhandling dykker ned i potentialet om at implementere datadreven Operations Management and Operations Research (OM/OR) teknikker til at forbedre hospitalsforsyningskæder. Denne afhandling består af tre artikler, der hver omhandler brugscases i det virkelige liv, der fremhæver specifikke udfordringer fra hospitalskonteksten og foreslår OM/OR-tilgange til at tackle dem.

Den første artikel fokuserer på at optimere sengeflowstyringen på et hospital, idet den adresserer kompleksiteten ved at matche en uforudsigelig patientefterspørgsel med begrænsede sengeressourcer, primært afhængig af menneskelig beslutningstagning. Vi introducerer en model, der inkorporerer virkningen af efterspørgselsvariabilitet på arbejdsstyrken, og understreger effektiviteten opnået ved at tage højde for denne menneskelige faktor. Denne tilgang hjælper med at mindske risikoen for sengemangel og forbedrer den overordnede forsyningskæde.

Den anden artikel er centreret om steriliseringsprocessen af kirurgiske værktøjer, og præsenterer en omfattende model af hele cyklussen, inklusiv en dedikeret model af det kirurgiske behov. Vi demonstrerer nødvendigheden af en sådan holistisk tilgang til nøjagtigt at identificere svagheder i cyklussen og udtænke effektive løsninger.

Den tredje artikel undersøger fordelingen af afdelinger inden for et hospital under opførelse. Det illustrerer, hvordan proaktiv planlægning for ressource-

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fleksibilitet kan udnytte fordele i form af ressourceudnyttelse, samtidig med at de udfordringer, som øgede transportstrømme udgør.

Denne afhandling demonstrerer, hvordan datadrevne OM/OR-metoder markant kan forbedre hospitalernes forsyningskæder. Det fremhæver dog også forskellige udfordringer forbundet med hospitalskonteksten, herunder spørgsmål relateret til datakvalitet, datatilgængelighed eller kompleksiteten ved at håndtere højt varierende efterspørgsel.

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## Preface

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This thesis was carried out at the Division of Management Science at DTU Management, Technical University of Denmark, in partial fulfilment of the thesis requirements for the degree of Ph.D. in Engineering.

The project has been conducted between December 2019 and September 2023 under the supervision of Professor Allan Larsen, Associate Professor Dario Pacino, Christian Sørup (Decision Scientist, Rigshospitalet) and Daniel Sepulveda Estay (Senior Advisor in Supply Chain and Operational Digitalization, Rigshopitalet). The PhD studies also included a research visit to the Center for Healthcare Operations Improvement and Research (CHOIR) at the University of Twente in Enschede, The Netherlands, hosted by Professor Erwin Hans, between April and July 2022.

The PhD project has been supported by Rigshospitalet and DTU Management.

This thesis consists of an introduction and three academic papers that are currently under review or submitted to international peer-reviewed journals. The three paper-based chapters are co-authored, and they are each self-contained in terms of notation and with separate bibliographies.

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## Acknowledgements

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First and foremost, I would like to express my profound gratitude to my dedicated supervisors, Allan Larsen, Dario Pacino, Christian Sørup, and Daniel Sepulveda Estay, who have been unwavering guides throughout this nearly four-year journey. Their collective support and expertise have been invaluable, and I am deeply appreciative of the incredible experience they have provided. I extend my heartfelt thanks to Allan Larsen and Dario Pacino for entrusting me with the opportunity to pursue this PhD. Allan Larsen's unwavering support, guidance, and insightful discussions have enriched my understanding of management aspects and introduced me to the world of mathematical simulations. Dario Pacino's assistance, encouragement, constant availability, and high technical exigence have been instrumental in completing this project successfully, allowing me to extract the best possible outcomes. I am grateful to Christian Sørup for his invaluable assistance in navigating the hospital environment, facilitating access to resources and data, and offering continuous support. His critical perspective has significantly enhanced the quality and precision of my work. I would also like to acknowledge the contributions of Daniel Sepulveda Estay, who joined the project later, providing invaluable feedback and a fresh perspective.

I am deeply thankful to Erwin Hans for hosting me at the Center for Healthcare Operations Improvement and Research (CHOIR) at the University of Twente, where I had the privilege to engage with passionate researchers in Healthcare Operations. His extensive knowledge and enthusiasm for new projects were truly inspiring. I am also deeply thankful to Hayo Bos, for being an incredible and extremely smart collaborator and Greanne Leeftink for guiding us through our project. I extend my gratitude to all the IEBIS/BMS Group for their warm welcome. Special thanks go to the running group, including Fabian Ackermann, Rogier Harmelink, and Yifey Yu, for making my stay both

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highly enjoyable and quite sportive.

I extend my heartfelt appreciation to my colleagues in the Management Department. I am grateful to David Pisinger for his invitation to pursue a Ph.D. following my Master's thesis and for his infectious enthusiasm. I also want to thank my office mates, including Alastair, Amandine, Baptiste, Bernardo, Sotiria, and Martina, for their unwavering support and for creating a positive and enjoyable atmosphere even during challenging times

I would like to thank both Rigshospitalet and DTU Management for supporting this PhD project.

I'm thankful to my roommates for their support, positivity, and contributions that made this journey more enjoyable, Alvaro 'Gary', Jan, Mark and Telem for your incredible subtlety and Auriane, and Martina for your kindness and cheerfulness.

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A huge thank you to Julia for supporting, encouraging me and accompanying me throughout this journey. Thank you for everything, for listening and helping me through the ups and downs of this journey, for being the best cooking and eating companion, and for your patience and your kindness, I would not have finished it without you.

Last but not least, I would like to express my heartfelt gratitude to my family for their unwavering support despite the geographical distance and for warmly welcoming me back each time. I want to dedicate this to my grandfather, Claude, who passed away in January. He always displayed a keen fascination and interest in my academic and exotic journey and always encouraged me to go further.

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## Acronyms

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<b>APM</b> Average Patient Misplacement	<b>JIT</b> Just-In-Time
<b>CAP</b> Corridor Allocation Problem	<b>KPI</b> Key Performance Indicator
<b>CI</b> Confidence Interval	<b>LOS</b> Length of Stay
<b>CPFR</b> Collaborative Planning Forecasting and Replenishment	<b>MRP</b> Material Requirements Planning
<b>CSS</b> Central Sterilisation Service	<b>MSS</b> Master Surgical Schedule
<b>DES</b> Discrete Event Simulation	<b>NHN</b> Nyt Hospital Nordsjælland
<b>DRLP</b> Double-Row Layout Problem	<b>OM</b> Operations Management
<b>ED</b> Emergency Department	<b>OR</b> Operating Room
<b>ERP</b> Enterprise Resource Planning	<b>OR</b> Operations Research
<b>FF</b> Floating Facilities	<b>OT</b> Operation Theatre
<b>FIFO</b> First In First Out	<b>PACU</b> Post Anaesthesia Care Unit
<b>FLP</b> Facility Layout Problem	<b>QAP</b> Quadratic Assignment Problem
<b>GTA</b> Graph Theoretic Approach	<b>RMD</b> Reusable Medical Device
<b>HAI</b> Hospital-Acquired Infections	<b>SCM</b> Supply Chain Management
<b>HIT</b> Hospital Information Technology	<b>SDG</b> Sustainable Development Goal
<b>HLP</b> Hospital Layout Problem	<b>SLP</b> Strategic Layout Planning
<b>HOM</b> Hospital Operations Management (OM)/Operations Research (OR)	<b>SME</b> Subject Matter Expert
<b>ICU</b> Intensive Care Unit	<b>UN</b> United Nations
<b>IT</b> Information Technology	<b>WHO</b> World Health Organisation

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# 1 | Introduction

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In 2015, the United Nations (UN) adopted a common sustainability agenda (UN General Assembly, 2015), aiming to enhance peace, people, planet, and prosperity within the 2030 horizon. This agenda outlined 17 Sustainable Development Goal (SDG), including the SDG 3 that focuses on "ensuring healthy lives and promoting well-being for all at all ages" (UN General Assembly, 2015). One of the specific targets within this goal is SDG target 3.8, which emphasises the need for "Universal Health Coverage" (UN General Assembly, 2015).

The achievement of Universal Health Coverage points to the need for establishing an efficient and accessible healthcare system for everyone. As highlighted by the World Health Organisation (WHO) (World Health Organisation, 2020), hospitals play a vital role in attaining this coverage. They serve as an essential element within the healthcare network, ensuring the continuous availability of services for acute and complex conditions (Green, 2004).

Hospitals are instrumental in providing healthcare services to individuals, acting as essential hubs for care coordination and integration. Moreover, hospitals serve as educational institutions for healthcare professionals and critical bases for clinical research. Their role is fundamental in modern public healthcare systems, as defined by Acheson (1988), who describes public health as "the art and science of preventing disease, prolonging life, and promoting health through the organised efforts of society".

The COVID-19 pandemic highlighted the heavy reliance of modern healthcare systems on hospitals with hospitals being the first response point. The pandemic has exposed significant vulnerabilities in hospital supply chains, with 90% of hospitals reporting challenges in the procurement of supplies through-

out the pandemic as highlighted Goldschmidt and Stasko (2022). Bhaskar et al. (2020) analyses that several components such as low initial stock, difficulties for the suppliers to deliver and rigid supply circuits, could not cope with the sudden surge of demand for healthcare.

McKone-Sweet et al. (2005); Toba et al. (2008) and Moons et al. (2019) highlight that logistics and supply account for more than 30% of hospitals' total expenditures, which can even reach up to 45%. This substantial proportion is exacerbated by the rising healthcare costs attributed to an ageing population and advanced treatments, as predicted by Knowledge Centre on Migration and Demography (2022). The need to optimise and reduce costs while addressing waste, as identified by OECD (2017), poses a dual challenge for hospital managers and staff. They must strive to enhance cost-efficiency and affordability without compromising the quality of care (Hall, 2012b; Van Oostveen et al., 2014).

The pressure to maintain or improve quality of care while cutting costs is compounded by the limited resources of healthcare systems, as emphasised by Green (2004); Sinha and Kohnke (2009) and Litvak and Bisognano (2011). However, this pursuit of cost-efficiency may have inadvertently compromised the resilience of hospitals' supply chains, making them less prepared to respond to crises such as the COVID-19 pandemic (Harland et al., 2021). Additionally, Toba et al. (2008) notes a critical distinction between healthcare supply chains and more conventional industries, highlighting that stock-outs in healthcare have far more severe consequences than simply financial losses. Given the critical importance of hospital supply chains, it is essential to address and enhance their resilience and efficiency.

Kunwar and Srivastava (2019) explains that since its establishment in 1948 after World War II, the WHO has emphasised the use of research to improve healthcare systems. The WHO recognises the value of Operations Management (OM) and Operations Research (OR) in enhancing effectiveness, efficiency, and improving healthcare availability (World Health Organisation, 2008). In line with societal trends, hospitals are increasingly adopting information systems, resulting in the availability of extensive data on patient care and operational performance (Ferranti et al., 2010; Green, 2004). Data plays a significant role in the healthcare industry, enabling more accurate monitoring of products, procedures, and resource usage.

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The World Health Organization (2019) highlights the importance of digitalisation and data-driven techniques in achieving "Universal Health Coverage" (SDG 3.8), while Sharon Ross and Venkatesh (2016) demonstrates their potential in improving care quality and patient satisfaction. The growing prevalence of data offers excellent opportunities for improvement through data-driven supply chain approaches, ultimately ensuring the provision of high-quality care.

In light of the increasing demand for healthcare services, rising costs, and the need for hospitals to adapt, Bartenschlager et al. (2023) has presented a framework aimed at guiding the evolution of healthcare institutions into what can be referred to as the "Hospital of the Future." This framework draws inspiration from the digitally enabled advancements witnessed across various industries, particularly the emergence of more smart integrated facilities, and aims to foster a similar transition within hospitals. It underscores the pivotal role of central data-driven management for enhancing resource utilisation and ensuring efficient collaboration and coordination throughout the hospital supply chain. Additionally, it emphasises the broader adoption and integration of Information Technology (IT) to facilitate the monitoring, modelling, and optimising hospital processes.

Nevertheless, Bartenschlager et al. (2023) points out that while the transformation towards smart factories has significantly enhanced operational performance in other industrial contexts, the unique nature of service-oriented hospitals, with their core mission of providing care to human patients, poses multiple challenges requiring careful consideration when envisioning and constructing the "Hospital of the Future".

In alignment with these considerations, this thesis aims to explore how hospitals can leverage the increasing availability of operational data to build new data-driven approaches to enhance hospitals' supply chains. Employing data-driven methodologies, encompassing Business Intelligence techniques such as data analysis, visualisation, and statistics, in conjunction with OM/OR approaches, including simulation, optimisation, and forecasting, this thesis investigates the development of tailored methods that account for the specific hospital context and could actively contribute to improving hospital operational performance while ensuring hospital ability to deliver of high-quality care.

## **1.1 An Introduction to Hospital Supply Chains and Operations**

In his historical work, Risse (1999) presents an extensive account of the evolution of medical institutions, tracing their roots to the ancient god-healing temples in civilisations such as Egypt, Greece, Rome, and India. These early religious, medical groupings served as the precursors to what we now recognise as hospitals.

Risse (1999) further elucidates that the genesis of hospitals can be traced back to the medieval period. During this era, hospitals emerged as centres that amalgamated religion-based medicine with the first therapeutical and spiritual treatments and early surgical practices. Additionally, these early hospitals offered a haven for travellers seeking rest and recuperation.

In the 16<sup>th</sup> and 17<sup>th</sup> centuries, hospitals transitioned from a religious-based to a more scientific one with trained nurses and surgeons. They assumed the role of practical teaching centres, playing a pivotal role in medical advancements. The development of care and the subsequent rise of medical specialties propelled hospitals into hubs of medical innovation. The modern hospital, as we recognise it today, took shape in the late 19<sup>th</sup> century, primarily in European cities such as Paris and Vienna (Lesky and Williams, 1976; Weiner and Sauter, 2003). This period witnessed the advent of specialised departments within hospitals, fostering the specialisation of medical disciplines and ensuring the delivery of high-quality care.

Modern hospitals have evolved into pivotal hubs within healthcare systems, as emphasised by Garrick et al. (2019). They encompass diverse responsibilities ranging from delivering acute patient care to pioneering medical advancements and shaping the next generation of medical practitioners, as outlined by Green (2004) and World Health Organisation (2020). Given this multifaceted role, hospitals are integral to healthcare supply chains, underscoring the critical importance of efficient supply chain management to ensure their optimal performance and fulfilment of their overarching mission.

### **1.1.1 Supply Chain Management (SCM) in Public Hospitals**

Mentzer et al. (2001), observes that numerous definitions of supply chain exist and aggregates them into a comprehensive definition. The supply chain is defined as "a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer." Subsequently, the term SCM refers to the organisation and management of the resources and processes within this supply chain, intending to connect its various entities to deliver superior value to the customer (Christopher, 2005).

While this definition aligns well with conventional industrial contexts such as manufacturing, it necessitates refinement to accommodate the specificities of healthcare systems, particularly in the context of public-sector hospitals. Within these healthcare settings, the concepts of "value" and "customers" take on different dimensions, and the definition should be adapted accordingly. As highlighted by Landry and Philippe (2004), the primary mission of hospitals is to provide high-quality care to all incoming patients, in alignment with UN SDG 3.8. In this context, the patients themselves can be regarded as the equivalent of Mentzer et al. (2001)'s "customers." This perspective is further reinforced by de Vries and Huijsman (2011), who defines the goal of healthcare SCM and hospital SCM by extension as "enhancing clinical outcomes while controlling costs." It is important to note that, unlike many conventional industry settings, public hospitals do not pursue profit as an objective; instead, financial aspects in healthcare SCM are often considered as constraints. The clinical output serves then as the "value" pursued in SCM in the public healthcare setups.

As highlighted by de Vries and Huijsman (2011), healthcare SCM encompasses the comprehensive management of "the information, supplies, and finances involved in the acquisition and movement of goods and services from the supplier to the end user." In the context of hospitals, this entails the management of various resources crucial to the patient's journey throughout the hospital. This may refer to pharmaceutical goods and devices for patients similar to a classical manufacturing goods supply chain. It also extends to medical equipment that is reused among patients and medical professionals, representing just one step of the patient's journey, and ultimately, hospital SCM encom-

passes the entire patient journey itself, which has a significant impact on the clinical outcomes, which is the ultimate objective of hospital SCM.

de Vries (2011) notes that hospital SCM is a convergence point for various stakeholders with diverse objectives: profit-oriented suppliers, hospital management and purchasing units tasked with resource management, medical professionals who guide patients through their care journey and assess their needs and the resources and procedures involved, the patients themselves, and insurance companies and lawmakers on a higher level. This multitude of perspectives and objectives makes hospital SCM a complex and dynamic field that requires effective coordination and collaboration among these diverse stakeholders to achieve the best clinical outcomes and fulfil hospitals' goals.

### **1.1.2 Complexity and Evolution of Hospital Supply Chain Networks**

Drawing inspiration from the 19<sup>th</sup> century Paris and Vienna hospitals, modern hospitals maintain the clinic-based structure to improve their capacity to administer personalised, intricate, and advanced treatments to patients. When looking from a classical SCM material logistics point of view, the different medical clinics of the hospitals tend to act as silos. These departments have their own material need and their end-storage close to the point of use. Most hospitals have central storage common to all points of use upstream. Some hospitals are grouped and have another shared storage ahead. Consequently, this configuration creates what Sherbrooke (1968) described as a multi-echelon network structure for the hospital's inventory, as outlined by Lapierre and Ruiz (2007), de Vries and Huijsman (2011), Volland et al. (2017) and Moons et al. (2019).

As the quality and complexity of care continue to advance, accompanied by growing resource requirements, Sharon Ross and Venkatesh (2016) point out that these supply chain network structures are becoming more and more complex and interconnected. Dai and Tayur (2021) highlights the evolution's reflection in the expansion of hospitals' ecosystems.

In the end, hospital logistics represents a large proportion of the hospital bud-

get; it accounts for more than 30% of the total expenditures (see Volland et al. (2017), Moons et al. (2019)). The material logistic observation can be extended to the entire supply chain and management of the hospital where the fragmentation, silo-oriented organisation combined with a lack of collaboration and communication is often pinpointed as a major defect of hospital operational performance (see Moons et al. (2019); Saha and Ray (2019); Sinha and Kohnke (2009); Toba et al. (2008). Healthcare ecosystems involve a wide spectrum of stakeholders. The increasing number of actors necessitates heightened collaboration and coordination to ensure the highest quality of care for patients.

In summary, as highlighted by Harper (2002), the "provision of healthcare services" stands as one of the "largest and most complex industries worldwide", underscoring the need for advanced data-driven models to ensure the quality and delivery of care to the patient and enhance operational efficiency.

### **1.1.3 The demand variability in hospital SCM**

At the core of hospital and healthcare SCM lies the patient and their journey through the healthcare system. Patients are not just the instigators of healthcare demand; they also constitute the ultimate recipients of care, deciding clinical outcomes, which is the ultimate objective of healthcare SCM. However, patients are inherently variable and hard to predict.

Patients' arrival patterns exhibit variations across seasons, months, weeks, days of the week, and even hourly intervals (Hall, 2012a; Ordu et al., 2019). These patterns are susceptible to external influences such as sports events, weather conditions, or unprecedented peak events that can alter both the volume and characteristics of patient arrivals. Each patient is a unique individual, characterised by distinct medical conditions requiring tailored treatments, their own medical background and natural characteristics. Their responses to similar treatments can vary significantly, resulting in disparate Length of Stay (LOS) and resource requirements (Hall, 2012b).

Soyiri and Reidpath (2013) dates the earliest forms of health forecasting back to Hippocrates in ancient Greece but notes that despite these ancient origins, developing a modern framework for health forecasting remains an ongoing

challenge. Health forecasting encompasses a wide spectrum of predictive tasks, including predicting arrival patterns, modelling LOS, and anticipating peak events. While modelling frameworks such as the one proposed by Ordu et al. (2019) for patient arrivals in various medical departments exist, it is crucial to recognise that there is no universally applicable model. Accurate forecasting necessitates a highly tailored approach based on extensive operational data. Different models may be required for different medical specialities and time horizons to establish a hospital-wide perspective on patient arrivals. While understanding patient arrival patterns holds the potential for optimising scheduling as shown by Gartner and Kolisch (2014) and serves as a preliminary step toward demand for care modelling and forecasting, it is widely acknowledged among researchers that due to the inherent patient variabilities, achieving accurate and actionable resource forecasting remains an exceedingly challenging problem (see Haijema et al. (2007), Little and Coughlan (2008), Cruz and Marques (2013), Volland et al. (2017)).

Traditional industrial approaches typically employ cost penalty-based methods to strike a balance between operational costs and service levels (Guerrero et al., 2013). However, within the context of a hospital, failing to meet patient needs can have far more severe consequences for patient care than a mere loss of revenue (Moons et al., 2019). Consequently, hospitals, particularly those within public healthcare systems, require an organisational structure prioritising service and patient-centred care over profit-driven objectives.

Hospitals are confronted with the constraint of finite resources to accommodate highly variable and unpredictable demands. This challenge was strongly highlighted during the COVID-19 pandemic. Health expenditure keeps on rising faster than hospital budgets. The growing demand for healthcare, driven by an ageing population with increasing expectations of high-quality care, places additional strain on hospital resources (Van Oostveen et al., 2014). Hospitals house diverse costly and limited resources, including healthcare professionals, rooms, equipment, supplies, implantable devices, organs, and instruments (Hall, 2012b). In this context, effective capacity planning and resource management are crucial to prevent costs from skyrocketing in the cost-service level trade-off.

### **1.1.4 Hospitals: Human-Centric Environments**

In contrast to the industrial sector, which has embraced digitalisation and increasingly evolved towards automation and heavy reliance on IT systems, hospitals have traditionally operated with a significant human presence (Moons et al., 2019; Toba et al., 2008; Volland et al., 2017). Patients and healthcare professionals constitute core human actors within the hospital supply chain, and many other critical processes within the hospital rely on human operations. For instance, lab technicians and medical professionals prepare equipment, establish treatments, and perform procedures and tests, while operators manage tasks such as sterilising tools and cleaning beds. This substantial human involvement in hospital operations has various implications for the supply chain.

Firstly, in contrast to data-driven models and decisions, humans cannot consistently make optimal choices and can be influenced by biases. Knox Lovell et al. (2009) and Hall (2012b) point out that personal preferences can influence medical decisions. Patients often prefer doctors they are familiar with, and healthcare professionals tend to use products and tools they are accustomed to. Additionally, individual preferences and time constraints can impact scheduling performance, as surgeons may prefer to schedule complex surgeries at the beginning of their workday, for example. Notably, Toba et al. (2008) highlights that in some US hospitals, physician-preferenced items can account for up to 40% of total medical spending, illustrating the substantial impact of these preferences.

Hospitals have evolved to pursue excellence in medical care, with the medical departments serving as centres of excellence. Consequently, many organisational decisions are made within these departments (Bartenschlager et al., 2023). However, these decisions are often made by medical professionals rather than experienced management professionals with advanced analytics backgrounds (Hall, 2012b). Preferences, habits, and workload can introduce biases into these decisions (Delasay et al., 2019). Research by Hopp et al. (2007) and Becker-Peth and Thonemann (2019), in the news-vendor model, have demonstrated that worker behaviour regarding risk plays a significant role in ordering practices and quantities. In the high-pressure healthcare environment, where maintaining service levels and avoiding potential consequences

of stockouts and delays is crucial, medical professionals making management decisions may exhibit risk-averse behaviour. This inclination could lead to solutions that appear safer but are sub-optimal. When combined with preferences, such behaviour can foster a culture of creating surpluses to handle demand variability, resulting in increased costs, waste, and inefficiency across all hospital specialities (Hall, 2012b; Landry and Philippe, 2004; Moons et al., 2019; Volland et al., 2017).

Human-operated processes lack the predictability and schedulability of automated, IT-based processes commonly found in the industrial sector. Humans are susceptible to making mistakes and do not maintain a constant, predictable work pace, as noted by Parkinson and Osborn (1957). However, humans possess the ability to make complex decisions independently. Therefore, it is possible to incorporate discretionary decision-making within processes performed by operators. Hopp et al. (2007) and Ibanez et al. (2018) explain that such decision-making provides organisational buffers for workers and enables them to prioritise tasks, potentially reducing cycle times and improving service levels. In the hospital sector, these discretionary decisions can help workers adjust their pace or choose alternative workarounds to ensure service levels.

Furthermore, discretionary decisions can facilitate incorporating complex operations, such as quality checks within the sterilisation process or batching of medical tests, leading to improved operational performance. Ultimately, while heavy reliance on human-based operations in hospitals presents challenges, it also offers flexibility that can be advantageous in dealing with the unpredictable nature of healthcare demand.

### **1.1.5 Adoption and Integration of Industry Supply Chain Standards in Hospitals**

As emphasised by Landry and Philippe (2004), the integration of supply chains and the adoption of IT have become standard practices in various industries such as manufacturing or retail, for example, since the 1980s. Subsequently, substantial research efforts and the implementation of diverse SCM standards, including lean methodologies, 5S principles, and various inven-

tory management practices, have evolved within these industries. Industry norms have progressively shifted towards data-driven approaches, employing management tools such as Enterprise Resource Planning (ERP), Material Requirements Planning (MRP), and Collaborative Planning Forecasting and Replenishment (CPFR) to coordinate production. These holistic strategies aim to increase operational efficiency, enhance productivity, reduce costs, and elevate both profitability and service quality (Volland et al., 2017).

However, the healthcare sector has lagged in embracing this innovative transformation (Volland et al., 2017). Toba et al. (2008) outlines several factors explaining this healthcare delay, encompassing outdated healthcare IT systems and infrastructure, insufficient executive involvement, an absence of process improvement culture, and numerous human-organised ad-hoc procedures that could benefit from data-driven approaches. Collectively, these factors create a gap between the healthcare sector and industry standards, resulting in sub-optimal operational performance and escalated costs.

In recent years, the healthcare sector has progressively adopted digitalisation trends. Hospital IT has experienced exponential growth since the 2000s, yielding large volumes of clinical and operational data. This digitalisation trend draws an interesting path towards the development and adoption of data-driven methodologies and industry-standard SCM practices. While the proliferation of healthcare and hospital IT raises concerns such as addressing privacy concerns, ensuring data quality, developing data standards, establishing effective data communication, and securing skilled personnel, it also presents substantial opportunities to reduce waste and redundancies, enhance resource utilisation, and foster collaboration across the healthcare supply chain. Ultimately, these enhancements would contribute to improved hospital SCM and better clinical outcomes (Ferranti et al., 2010; Green, 2004; Ward et al., 2014; Xie et al., 2021).

The transferability of standard industrial approaches to the healthcare sector has been a longstanding topic in Hospital OM/OR (HOM). As highlighted by Volland et al. (2017), while most researchers acknowledge the significant challenges in implementing these practices in healthcare, the prevailing consensus in publications is that adopting industry-standard SCM principles could substantially enhance healthcare supply chains. Notably, Volland et al. (2017) and de Souza (2009) have shown that lean principles and the chase to di-

minish surpluses and eliminate non-value activities would drive healthcare towards heightened operational efficiency and curtail costs, aligning with Bartenschlager et al. (2023) recommendation for the "Hospital of the Future". However, Volland et al. (2017) notes that these principles, along with contemporary SCM methodologies, necessitate a more holistic approach, which may clash with the prevalent silo mentality in healthcare settings, impeding the transition towards an integrated approach.

Hospital IT can play a pivotal role in facilitating this transition towards more holistic SCM approaches. Primarily, Hospital IT enables the development of analytics and data-based monitoring. Landry and Philippe (2004), explains that historically, hospitals struggle with performance measurement, but the expansion of hospital IT presents a significant opportunity to address this challenge, opening opportunities for more data-driven approaches in hospital SCM (Moons et al., 2019; Volland et al., 2017). While hospital SCM may still lag behind industry standards like retail and Walmart's CPFR approach, hospital IT is paving the way to bridge this gap (Moons et al., 2019).

The expansion of hospital IT holds substantial promise for enhancing hospital care from a clinical standpoint, subsequently contributing to high-quality care and improving clinical outcomes. Hospital IT provides enhanced visibility into patients' medical records, simplifies data sharing, identifies medical trends among various patient crowds, and facilitates medical advancements through advanced analytical approaches (Bartenschlager et al., 2023; Ferranti et al., 2010; Ward et al., 2014). This impact on clinical care ultimately extends to positively influencing hospital supply chains.

Nonetheless, the exponential data growth in hospital IT poses technical and IT infrastructure challenges. As noted by Caban and Gotz (2015), it also necessitates the development of efficient analytical techniques to prevent data overload, which could lead to misinterpretations, incorrect diagnoses, and missed warning signs. Developing efficient and high-quality analytics approaches in healthcare is both a significant opportunity and an imperative to enhance hospitals and healthcare delivery. Ultimately, this ensures hospitals can provide high-quality care to their patients.

## 1.2 Hospital OM/OR

The transformation of hospitals, evolving from religious temples and rest-houses to the complex, clinic-centred network institutions we have today, as described by Risse (1999), can be interpreted as first OM advancements. Parallely, the roots of OR can be traced back to World War II when military organisations began employing mathematically based decision-making (Taha, 2007). Afterwards OR found its application and various domains, including healthcare. Bailey (1952) proposed an early review of healthcare OR development in the early 1950s. Subsequently, the field of HOM<sup>1</sup> experienced continuous growth and exerted a significant influence on hospital operations, particularly after the 1980s, as highlighted by Gupta (2022).

### 1.2.1 Overview of HOM Research Landscape

Today, HOM stands as a vast and extensively researched field, as evidenced by the extensive literature, comprising over 10,000 papers published between 1982 and 2011, as documented by Dobrzykowski et al. (2014). For a comprehensive insight into the multifaceted research domains within HOM, Dai and Tayur (2021) and Gupta (2022) offer detailed introductions, while literature reviews by Rais and Viana (2011), Hulshof et al. (2012), Dobrzykowski et al. (2014), or Abe et al. (2016a,b,c) delineate the diverse trends within this expansive field. Additionally, Hulshof et al. (2011) have introduced ORchestra, a reference database tailored for HOM, facilitating comprehensive research exploration.

The expansive scope of healthcare and hospital SCM, encompassing numerous intricate tasks and processes, has translated into a substantial body of research in the field of HOM with a high variety of approaches, methods and problems (Carter et al., 2012; Hulshof et al., 2012). Dai and Tayur (2021) presented a comprehensive "tool-trust" analysis of the HOM literature. This analysis categorised approaches by their topic - the trusts - and the methods employed - the tools. The identified tools encompass classical OR techniques

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<sup>1</sup>Traditionally, the acronym HOM stands for Healthcare Operations Management. However, in the context of this thesis centred on the hospital SCM, we will use HOM to refer to Hospital Operations Management and Operations Research.

such as Markov Decision Processes, Deterministic and Stochastic Programming, Robust Optimisation, Queuing Theory, and Simulation. In addition, the toolbox includes disciplines like Econometrics, Game Theory, and Data Science. Notably, the analysis highlights the prominent roles played by Queuing Theory and Simulation methodologies in HOM.

This prevalence can be attributed to their ability to capture the intricacies of human-centred hospital processes and effectively address the inherent stochasticity in hospital demand (Brailsford et al., 2009). The thousands of simulation-based papers within HOM retrieved by Brailsford et al. (2009) corroborate the widespread adoption of these methods found by Dai and Tayur (2021) and highlight their efficiency.

Furthermore, Dai and Tayur (2021) reports that a substantial proportion of HOM research, up to 68%, has focused on the design of care delivery (24%), the Emergency Department (ED) (17%), stress and workload management and their impact on worker and work (10%), inpatient care (9%), and ambulatory care (8%). This aligns with the findings of Hulshof et al. (2012) and underscores the emphasis on downstream processes closely linked to patients and the task of delivering care by the medical profession within the expansive scope of hospital SCM.

Landry and Philippe (2004) describes the fundamental mission of hospitals as to provide care to patients, with a particular emphasis on acute care. This emphasis on clinical care processes, especially in areas such as EDs and Operation Theatres (OTs), can explain the extensive managerial and research focus in these domains and consequently, the abundant literature on these specific areas.

### **1.2.2 From Care-Delivery-Focus to Holistic Hospital SCM**

OTs hold a preeminent position within hospitals due to their significant financial impact, accounting for nearly 70% of patient admissions (Guerrero et al., 2013). This prominence is reflected in the extensive body of literature dedicated to optimising OT operations. However, it is important to recognise that surgery represents just one phase in a patient's journey through the hospi-

tal, as emphasised by He et al. (2019), and only a sub-section in the connected ecosystem of hospital supply chains. Hospitals operate as connected networks, facilitating the flow of patients, equipment, healthcare professionals, and information across various units.

The decisions made within the OT have consequences throughout the hospital, affecting upstream departments such as the ED and patient admissions, as well as downstream units such as the Intensive Care Units (ICUs), Post Anaesthesia Care Units (PACUs), and nursing wards. Consequently, in recent years, there has been a growing focus in HOM in connected departments and on the operational decisions' ripple effects on other hospital units. These comprehensive analytical approaches are described as "integral capacity management" by Schneider et al. (2020), as they are derived from a holistic vision of the hospital and its resources.

This care delivery-centric perspective also accounts for the limited attention directed towards support processes and activities that occur upstream in the hospital, such as material logistics and the sharing of equipment and resources between departments. Volland et al. (2017) echoes this observation, highlighting that support processes have received less consideration in healthcare contexts compared to other industrial sectors, despite holding substantial potential for improvement. These support processes play a crucial role in ensuring that resources are made available to meet the demands of care delivery, making them indispensable components of an efficient hospital supply chain Hall (2012b).

While material management and some aspects of scheduling are currently organised within individual departments, contemporary studies, such as those by Meijboom et al. (2011) and Volland et al. (2017), advocate for a more holistic and integrated approach to supply chain organisation. This approach suggests a shift from the traditional top-down organisational model, where medical departments dictate demand and organisation, to a bottom-up structure. The pursuit of a more holistic vision in hospital SCM echoes the supply chain standards and methodologies that have been applied in traditional industries since the 1980s, such as lean management, effective coordination, and collaboration among interconnected components.

Holistic approaches in hospital SCM rely on two critical elements: high-quality

data for actionable HOM projects and a robust IT infrastructure to facilitate coordination and collaboration among different sub-entities within the hospital supply chains (Landry and Philippe, 2004; Moons et al., 2019; Toba et al., 2008). The expansion and adoption of Hospital Information Technology (HIT) are thus imperative prerequisites for enhancing the efficiency of hospital supply chains.

### **1.2.3 The Potential of Holistic Approaches**

In the context of large highly interconnected healthcare supply networks, a holistic perspective offers dual advantages, to increase operational performance, contribute to hospital SCM, and ultimately enhance clinical outcomes.

While a departmental and singular operational focus, also characterised as a top-down or demand-centric approach by Meijboom et al. (2011), tends to concentrate solely on its internal processes, a holistic vision extends its purview to encompass the intricate interdependencies between neighbouring departments and processes. Sinha and Kohnke (2009) attributes a considerable share of healthcare systems' inefficiencies to the disregard of these intricate dependencies. The paradigm of "Integral Capacity Management," as introduced by Schneider et al. (2020), aims at considering the entire ecosystem of the process considered systematically incorporating these interdependencies. The inclusion of such dependencies yields models that closely mirror real-world complexities, thus yielding more pragmatic outcomes and heightened performance for both the processes under scrutiny and their interconnected counterparts. As underscored by Schneider et al. (2020), this "Integral Capacity Management" paradigm, with its goal of capturing dependencies between connected entities within the hospital, aligns with the patient journey that traverses multiple departments, treatments and processes through the hospital. This alignment resonates with Meijboom et al. (2011)'s patient-centric approach to hospital SCM.

From a bottom-up perspective, wherein the integral hospital vision perceives its supply chain and resources as an indivisible entity, facilitates the concept of resource sharing and pooling. This holistic outlook provides an aggregate perspective on both available resources and the existing demand. The pooling

principle, explained by Cattani and Schmidt (2005), enables more effective resource allocation to meet demand requirements. The aggregation effectively reduces variability, a crucial element given the highly fluctuating demand for care in hospitals. This, in turn, offers significant potential for hospital capacity planning, diminishing the necessity for surplus resources to mitigate demand uncertainty (Utley and Worthington, 2012). The advantages of resource pooling in hospital SCM are numerous, encompassing cost reduction, reduced waiting times, and heightened safety, as underscored by Lega and DePietro (2005), Meijboom et al. (2011), and Vanberkel et al. (2012). While some hospital capacity planning approaches have embraced the impact of pooling, as exemplified by Ma and Demeulemeester (2013) in bed capacity planning spanning a 6-month to 1-year horizon, Volland et al. (2017) points out the limited presence of quantitative holistic supply approaches in the literature, despite their substantial potential.

Historically, traditional hospital practices have leaned towards maintaining surplus capacity as a strategy to manage demand variability (Moons et al., 2019). This approach extends to the management of inventories, equipment, and healthcare professionals, often distributed across various medical departments. However, this decentralised surplus management proves costly and results in significant storage wastage. While hospitals offer the perfect setup to benefit from resource pooling, Cattani and Schmidt (2005) cautions that its implementation is not a guarantee for improved operational performance. Rather, it relies on the flexibility of resources and processes involved. Based on that observation, Vanberkel et al. (2012) has proposed a methodology to determine whether hospital clinics should be pooled or not, and access the benefits that come from this pooling.

For resource pooling to be effective, hospitals should aim to increase their flexibility. Kuntz et al. (2015) demonstrated the impact of flexibility in reducing mortality rates within the hospital context, highlighting the superiority of small additional flexible capacities over rigid, robust capacity increases, as they achieve better outcomes while utilising fewer resources. According to Vos et al. (2007), flexibility can be enhanced through resource standardisation and/or versatility, allowing resources to perform various tasks effectively. This pursuit of flexibility and resource pooling runs counter to the historical development of hospitals, which has tended towards increasing specialisation, ultimately leading to modern siloed structures.

### **1.3 An illustrative example: Hospital Drug Inventory Management in Rigshospitalet**

This section leverages a real-world case study of drug inventory management at Rigshospitalet to provide a concrete illustration of the potential benefits derived from advanced analytics and HOM techniques. Rigshospitalet, the largest public hospital in Denmark, in the heart of Copenhagen, has a capacity of 1200 beds, 12,000 employees, and an annual intake of 360,000 admitted patients. Rigshospitalet has 50 different medical departments and is centralising numerous specialised medicine in Denmark. Our case study focuses on the drug replenishment processes within the newly built North Wing, which has been operational since 2020. This wing comprises 12 departments with a combined capacity of 209 beds, encompassing surgical units equipped with 33 OTs and their associated ICUs. The data used for this analysis correspond to the entire year 2020 operations.

Hospital inventory management in the context of public healthcare institutions gives a pertinent illustration to highlight the differences that set healthcare apart from conventional industrial settings while revealing the potential of adopting established industry supply chain procedures and data-driven methodologies. Hospital inventory management holds the essential role of ensuring resource availability downstream, thereby enabling the hospital to fulfil its primary role of delivering care, as articulated by Landry and Philippe (2004). Public hospitals, operating with a service-oriented mission rather than a profit-driven one, bear the added weight of the severe consequences that stockouts can exert on patient care (Moons et al., 2019).

Concurrently, material logistics constitute a substantial portion of the hospital budget, representing more than 30% of total expenditures, as pointed out by Volland et al. (2017) and Moons et al. (2019). This cost continues to escalate, influenced by factors such as an ageing population, increased healthcare demands, and the rising costs associated with the development of research and advances of specialised medical items (Knowledge Centre on Migration and Demography, 2022).

Denmark adopts what Sinha and Kohnke (2009) calls a ‘socialised’ healthcare system, characterised by extensive public financing, ensuring affordability and

accessibility for all citizens, aligning with the UN SDG 3.8. Data from the pre-COVID-19 era reveals that, in 2019, the Danish government allocated 194 billion DKK to healthcare, constituting 16.9% of total expenditure, with a staggering 52.2% (101 billion DKK) directed towards financing public hospitals (Statistics Denmark, 2019). Notably, as highlighted in figure 1.1, a substantial portion, 9.2 billion DKK, was allocated to hospital drug expenditures, equivalent to 0.8% of the entire government budget. Furthermore, Figure 1.2 demonstrates a consistent upward trajectory, as exemplified by the 80.4% increase witnessed during the 2007-2018 period. Drugs only account for a part of the total hospital material logistics.

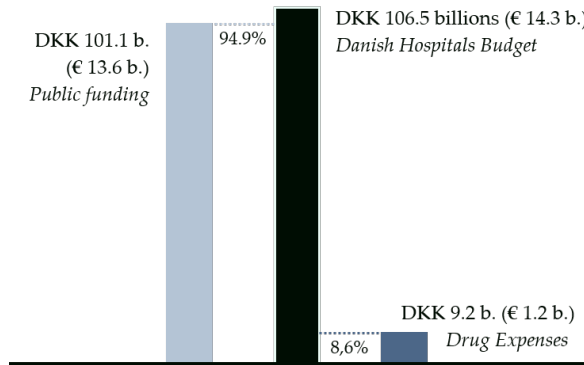


Figure 1.1: Danish Hospital Economy and Weight of the Drugs (source: Statistics Denmark (2019))

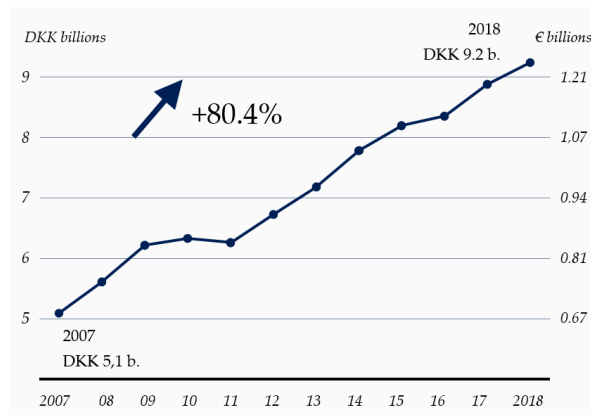


Figure 1.2: Evolution of Drug Expenses (source: Danske Regioner (2022))

The convergence of hospital inventory management's critical importance for

healthcare delivery and its substantial cost within a constrained hospital budget underscores the imperative for the development of efficient resource management. This environment gives both a fertile ground and a need for advanced analytics techniques alongside data-driven approaches, as advocated by Volland et al. (2017).

### **1.3.1 Mapping Rigshospitalet Supply Chain**

Figure 1.3 illustrates the logistics supply chain for drugs and other medical products at Rigshospitalet. Drugs and medical supplies are handled by two different units but follow a similar flow throughout the hospital. Starting downstream, from the patient side, these items are stored in numerous decentralised rooms and closets distributed across medical departments, ensuring proximity for easy access by medical professionals and nurses. The central services units, namely the pharmacy for drugs and the Service Centre for other medical supplies, manage the replenishment of these decentralised storage areas. These central units also oversee product arrivals at the central warehouse, serving as the hospital's initial point of receipt.

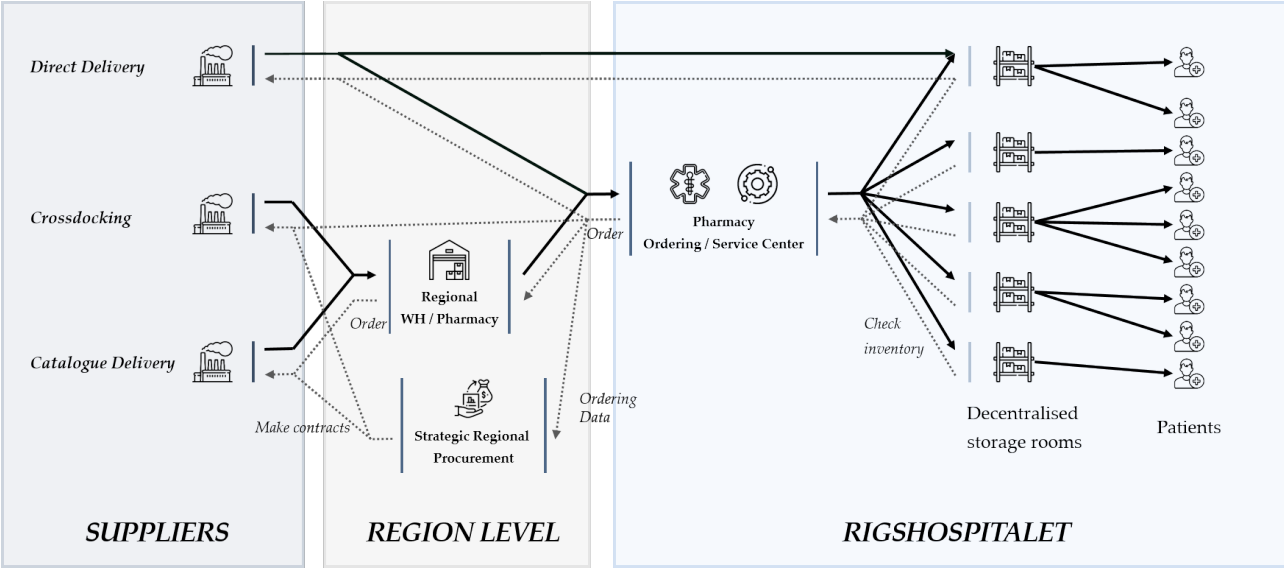


Figure 1.3: Scheme of Rigshospitalet material logistic and supply chain

Upstream, a regional pharmacy and regional warehouse for non-drugs medical supplies coordinate the initial consolidation of goods for the Greater Copenhagen Region hospitals. The arrival of drugs and medical supplies to the decentralised storage rooms is contingent upon their specificity and commonality. Commonly used items are catalogued, with the regional warehouse/pharmacy ensuring continuous availability for next-day hospital delivery. More specialised products may be ordered directly from suppliers but are routed through the regional hub, where they are cross-docked with the other catalogue daily deliveries. Lastly, exceptional specific items can be directly ordered from suppliers by medical departments, bypassing the regional hub and the hospital's central service unit. This delivery type concerns the punctual order of a small fraction of highly specific products.

This structure supplier, regional hub, central hospital arrival, decentralised storage corresponds to the multi-echelon structure of Sherbrooke (1968) that is highly common across hospitals (de Vries, 2011; Lapierre and Ruiz, 2007; Moons et al., 2019; Volland et al., 2017).

### **1.3.2 Automated Non-Digital Inventory Management at Point of Use**

In terms of information flow, the replenishment process is initiated downstream within the medical rooms. When ensuring replenishment in these rooms, the hospital pharmacy or service centre evaluates the requirements and places orders accordingly, encompassing catalogue orders, direct deliveries, and cross-docking. On an annual basis, a strategic regional procurement unit engages in supplier contracts for catalogue deliveries and a portion of the cross-docking items based on last year's order logs. These negotiations encompass price and volume considerations, ensuring the availability of these items in the regional hubs.

This pull-based inventory management, initiated by the decentralised medical rooms, aligns with the silo-ed organisational structure of hospitals described by Toba et al. (2008) and Moons et al. (2019). It entails the replenishment process being managed within each individual medical department, with limited collaboration fostered between departments.

Rigshospitalet employs the Two-Bin Kanban system to manage its inventories at the point of use. This system originates from World War II British army spare part inventory management and was further developed as Kanban in Toyota manufacturing setups and lean management theory as pointed out by Ohno and Bodek (2019). The two-Bin Kanban system has been adapted for hospital and healthcare use since the 1980s and is now widely adopted (Landry and Beaulieu, 2010). The concept involves using two bins for each inventory item: an "active" bin from which medical professionals retrieve items and a "safety" bin. When the active bin is empty, the safety bin becomes active, and a new bin is ordered to maintain a continuous supply.

The Two-Bin inventory system offers distinct advantages: It is a visual inventory management method with organised storage, aligning with lean theory principles that aim to minimise non-value-added tasks. Furthermore, its standardised approach for all items simplifies usability for medical professionals (Landry and Beaulieu, 2010; Landry and Philippe, 2004; Ohno and Bodek, 2019). Its simplicity and evident safety stock make the Two-Bin system extremely robust and trustworthy, which is essential for medical professionals and reduces the likelihood of them creating their own out-of-system safety stock.

However, it is important to note that the Two-Bin Kanban system functions without the need for data. Once the bin dimensions are set, it acts as a continuous review policy, eliminating the need for stock measurements. While this approach, as highlighted by Landry and Beaulieu (2010), reduces the risk of incorrect counting or overstocking due to risk-averse behaviour among medical professionals, it also results in surplus and safety stocks that must be managed in multiple medical rooms. The lack of data also limits opportunities for pooling and resource sharing between departments.

The absence of data-driven inventory management in the decentralised medical rooms leads to a significant data disconnection within Rigshospitalet's supply chain. Upstream, ordering data are recorded by the hospital's general pharmacy or service centre in the hospital's ERP system, while downstream, the data are registered by medical professionals in patient records. However, there are more medical rooms than medical departments, and some rooms may be shared by multiple departments, making it unclear which specific medical department should be attributed to an order. Furthermore, patients

may receive treatment from different departments, complicating the attribution of prescriptions to a specific department.

Furthermore, the inventory orders consist of bins and packaged, grouped items, from which individual products are dispensed to patients by medical professionals. The Rigshospitalet drug catalogue for 2020 includes a total of 51,926 references. However, it employs what Meijboom et al. (2011) describe as a demand-driven approach, where each item corresponds to a single active substance identified by its ATC code (see WHOCC (2022)), a specific dose, one method of administration, a single supplier, and a particular package size. For instance, the drug Paracetamol (ATC N02BE01) is represented in the catalogue by 152 references, including 98 variations of oral 500mg Paracetamol, among which 23 are tablets.

To streamline the data monitoring and facilitate a more comprehensive understanding of the inventory process, adopting a patient-oriented approach, as suggested by Meijboom et al. (2011), would reduce the catalogue to 9,095 items using the ATC code, dose, and administration method as a primary key. This simplification would significantly enhance the ability to monitor inventory processes effectively.

Moreover, despite using barcodes for product scanning before leaving the room, the immense quantity of items and the high-pressure working environment often lead to errors during the scanning process. Consequently, achieving a clear and precise data representation of Rigshospitalet's inventory processes remains an exceedingly complex challenge.

Figure 1.4, constructed using 2020 data retrieved from the hospital's ERP system, illustrates this impossibility by highlighting the significant discrepancy between the volume of items ordered and the volume consumed (i.e., administered to patients) in the departments of the North Wing. Notably, the Anaesthesiology department gives a striking example of this data disconnection. Due to its transversal role in the care of various types of patients, the Anaesthesiology department generates a high number of prescriptions but a relatively low number of orders since the products originate from all the medical rooms and are rarely directly associated with the Anaesthesiology department.

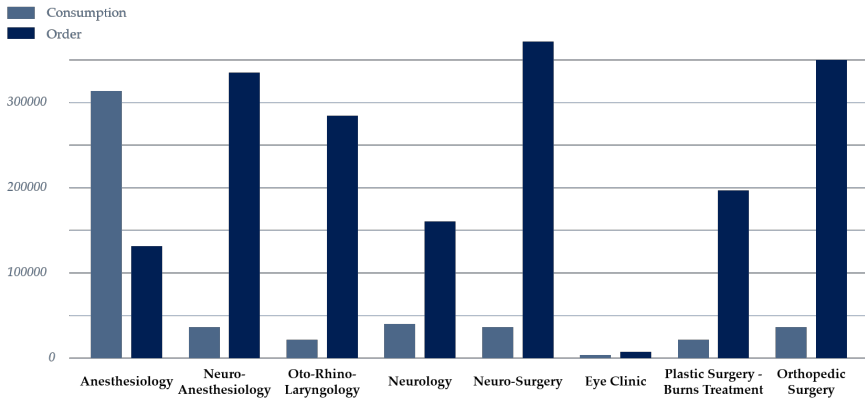


Figure 1.4: Comparison between the volume of drugs consumed and ordered by departments (in number of items)

### 1.3.3 Different strategies for improvement

As highlighted by Volland et al. (2017) and Moons et al. (2019), numerous researchers have proposed more advanced point-of-use replenishment policies, drawing inspiration from standard industry practices. Notable contributions include the work of Little and Coughlan (2008), who optimised service levels while considering spatial storage constraints, and Bijvank and Vis (2012), who proposed models for both maximising service levels with fixed capacity and minimising required capacity given a fixed service level. Guerrero et al. (2013) focused on minimising on-hand inventory costs to ensure a specified service level, while other researchers explored periodic or continuous systems, as seen in the studies by Rossetti et al. (2012) and Kelle et al. (2012).

These approaches all rely on having reasonably accurate data representations of the inventory ecosystem, including inventory levels, demand patterns, and lead times. However, the current two-bin Kanban system used at Rigshospitalet does not inherently support such data accuracy. To address this limitation, Landry and Beaulieu (2010) and Rosales et al. (2015) have proposed enhancements to the two-bin system, including the implementation of RFID marking for items. While this would require a significant initial investment in setup, it has the potential to transform the system into a more data-driven approach. This, in turn, could lead to improved inventory policies, increased service levels, and reduced waste and costs.

Implementing a point-of-use inventory system necessitates establishing safety stock levels at each point of use. Although they could be optimised at the individual level, these safety stock levels must be aggregated across the entire hospital to have a comprehensive understanding of surplus inventory, on-hand quantities, and associated costs. By enhancing the data quality of inventory management at the point of use, a more holistic approach becomes possible, allowing for the design of centralised safety levels and safety stock. This approach can leverage the pooling effect, as recommended by Cattani and Schmidt (2005), to achieve improved resource utilisation and cost reduction.

Figure 1.5 provides a histogram depicting the number of different drugs used by various departments within the hospital. For this analysis, drugs are defined according to a patient-oriented view, which groups them by ATC code, administration method, and dose. In the North Wing of Rigshospitalet, 1069 different drugs are employed, with 905 of them (84.6%) utilised by more than one department. This presents an opportunity for a more holistic approach, where centralised safety management can harness the benefits of demand pooling across multiple departments, ultimately leading to more efficient inventory management.

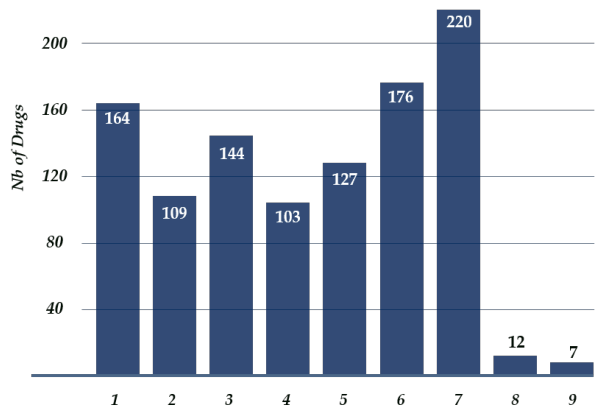


Figure 1.5: Distribution of drugs by the number of using departments

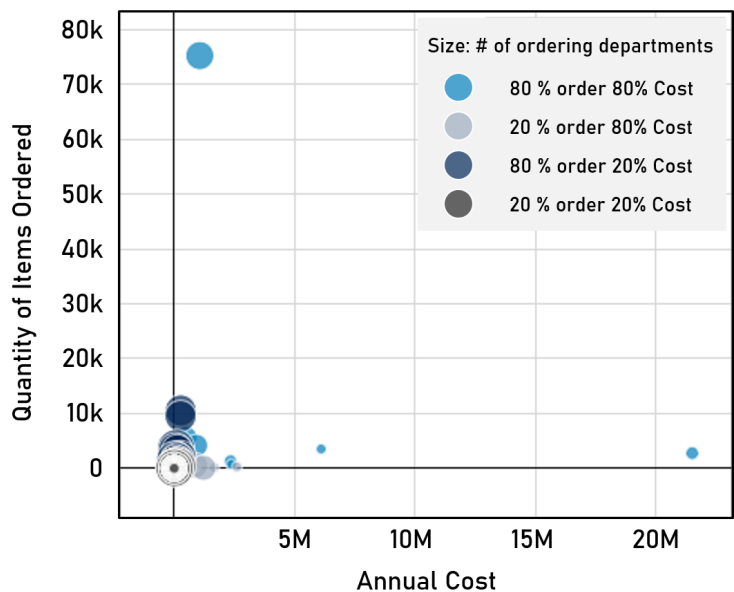
Rigshospitalet does not have a centralised inventory point that could fulfil the role of grouping items holistically. Rigshospitalet organisational structure is often referred to as "stockless". It is commonly employed in Just-In-Time (JIT) inventory systems, which aim to minimise on-hand inventory and prioritise small, downstream deliveries close to the point of demand. Rivard-Royer et al.

(2002) analysed these approaches and concluded that they could be effective for certain products, particularly those with consistent demand and lower variability. However, they may not be efficient for other products that could benefit from sharing a buffer to address large variations in demand.

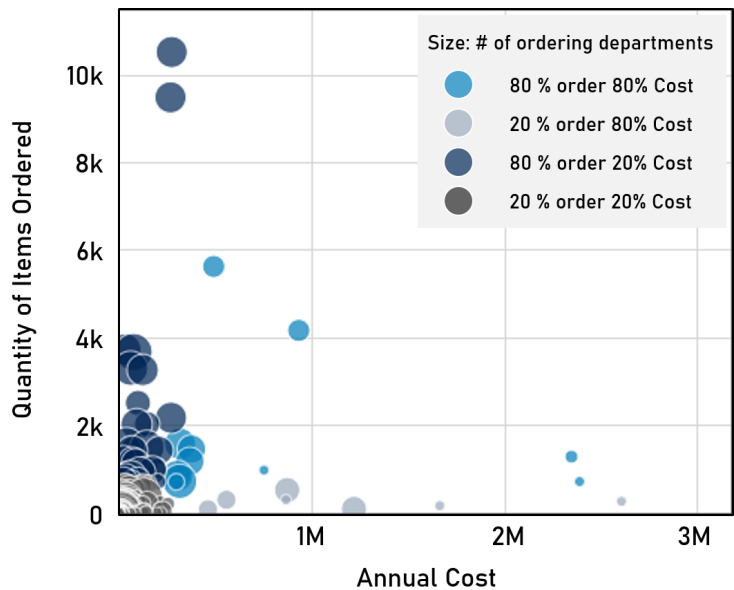
Physical hospital inventory can potentially provide the pooling effect and serve as a shared buffer between departments. Various replenishment policies have been proposed for such departments, as exemplified by Dellaert and Van De Poel (1996) and Vila-Parrish et al. (2012). Danas et al. (2002) highlighted that with clear data monitoring of the different inventory points at point-of-use locations, it becomes possible to envision a virtual inventory system. This virtual inventory system would digitally monitor drug inventory levels in all storage locations throughout the hospital while maintaining a digital safety stock to ensure inventory availability.

As Rivard-Royer et al. (2002) pointed out, not all items react the same way to inventory management policies. Two-bin Systems are efficient in managing small, highly volatile inventory, which corresponds to the reality of medical rooms. However, viewed from a holistic point of view, it exhibits numerous redundancy that could be removed. Figure 1.6 is a scatter plot of the drugs according to their total cost in the x-axis and volume in the y-axis. The color corresponds to an 80-20 analysis derived from the Pareto Principle (Sanders, 1987). The Pareto Principle started from the observation that 80% of the wealth was concentrated in 20% of the population. Following this, our 80/20 analysis aims to identify the cause of 80% of the cost and of the volume of items ordered. Figure 1.6 shows that Pareto's observation stands in this inventory setup with 80% of the cost being concentrated in a small number of items (light grey and light blue). Similarly, a small number of products generate 80% of the orders (light blue and dark blue). More specifically, 37% of the items ordered are saline water bags, with more than 200 bags ordered every day in the North Wing and 31% of the cost is generated by a single highly specific product. When zoomed in Figure 1.6b, it appears that the drugs highly ordered (dark blue), expensive (light grey) or both (light blue) only represent a small fraction of the drugs used in the hospital.

Table 1.1 depicts the drug distribution based on the 80-20 analysis, revealing noteworthy insights. In terms of cost, the top 80% of the most expensive drugs correspond to the drugs accounting for an annual expenditure exceed-



(a) Correlation between Drug Cost and Usage Volume



(b) Focus on Drugs with Fewer than 10,000 Items Ordered and Total Cost under 3M DKK

Figure 1.6: 80-20 Analysis of the drugs used in Rigshospitalet North Wing

Table 1.1: Distribution of drugs used in Rigshospitalet's North Wing in the 80-20 cost and volume analysis.

	20% Cheapest	80% Most Expensive
80% Most Ordered	33 Drugs (Dark Blue)	13 Drugs (Light Blue)
20% Less Ordered	1009 Drugs (Dark Gray)	10 Drugs (Light Gray)

ing 250,000 DKK, while the 80% most frequently ordered drugs each total more than 700 items per year. Strikingly, a mere 56 drugs (5.2%) are responsible for over 80% of both the drug flow and the total cost, underscoring significant disparities in drug profiles. Notably, the concentration of drugs in this scenario surpasses the conventional Pareto's 80-20 rule.

However, the inventory system at Rigshospitalet uses a standardised approach for all drugs. Tailoring specific inventory policies for these high-impact drugs can yield substantial cost savings and operational enhancements with minimal adjustments. Scholars such as Volland et al. (2017), Saha and Ray (2019), and Moons et al. (2019) have explored the concept of inventory classification, emphasising the need to incorporate an additional dimension of criticality into the analysis, as highly critical items could require more conservative safety stock sizing approaches. Furthermore, Gupta et al. (2007) and Al-Qatawneh and Hafeez (2011) have expanded upon cost analysis through ABC analysis and introduced a VED analysis, categorising drugs as Vital, Essential, or Desirable following doctor's input. Combining these classifications results in the creation of new inventory classes, for which Gupta et al. (2007) and Al-Qatawneh and Hafeez (2011) advocate tailored inventory practices.

## 1.4 Thesis Outline

This thesis is the result of a collaboration with Rigshospitalet, driven by the primary objective of investigating how academic OM and OR techniques can address real-world challenges within hospital supply chains. In pursuit of this goal, the thesis has been structured around tangible use cases presented by Rigshospitalet and other healthcare institutions. These use cases illuminate distinct facets of hospital operations and HOM, providing valuable insights into how data-driven OM/OR techniques can potentially enhance their effec-

tiveness and how such approaches should be adapted.

#### **1.4.1 Research Objectives:**

Our analysis primarily focuses on the context of public hospitals, with a specific emphasis on the support operations that occur upstream of the ultimate delivery of patient care within the broader hospital supply chain. This particular aspect, as emphasized by Dai and Tayur (2021), has historically garnered less attention within the existing literature when compared to the more prominent focus on acute and direct patient care delivery processes. While HIT has yet to fully align with conventional industrial standards, its growing adoption presents significant opportunities for the implementation of data-driven approaches and pioneering data-centric strategies within the sector of public healthcare. Consequently, the central research question guiding this thesis can be articulated as follows:

##### ***Main Research Question:***

How can data-driven OM/OR techniques be applied to enhance hospital supply chain management, considering the unique characteristics of hospital operations?

As outlined in Sections 1.1 and 1.2, numerous challenges arise within the context of public healthcare operations. These challenges encompass high levels of human dependency within hospital processes, the traditional silo-oriented organisation of hospital operations, and the interconnectivity of all entities within the healthcare supply chain. To comprehensively address these challenges, the primary research question can be further divided into several subquestions.

##### ***Sub-Research Question 1:***

How can the heavy reliance on human-based operation in hospital processes be accounted for when designing and implementing OM/OR techniques, and what are the implications for improving the efficiency and allocation of hospital resources?

**Sub-Research Question 2:**

How can traversal hospital support processes benefit from integrated, holistic, data-driven approaches to optimise resource availability and utilisation while mitigating costs?

**Sub-Research Question 3:**

How can flexibility be effectively and proactively incorporated when designing a hospital supply chain process to benefit from the pooling principle and have the drawback of the traditionally siloed and department-centric nature of HOM?

**1.4.2 Thesis Outline and Contributions**

The remainder of this thesis comprises three scientific papers, each presenting an OM/OR data-driven approach applied to real-life cases provided by hospitals. These papers contribute to answering the research questions and offer insights into various facets of .

**Chapter 2: A data-driven decision support tool to improve hospital bed cleaning logistics using discrete event simulation considering operators' behaviour**

In Chapter 2, we delve into hospital bed cycle management, with a specific focus on optimising bed cleaning procedures to ensure a consistent supply of sterile beds. The continuous availability of sterile beds is paramount for preventing Hospital-Acquired Infections (HAI) and upholding patient accommodation quality and care standards. Much like several other hospital processes, the bed cleaning process is heavily reliant on human-performed tasks and decisions. Hospital bed demand is highly unpredictable, encompassing scheduled and unscheduled admissions across departments and specialities. This chapter presents a real-life case study that combines the human-centred processes, high demand variability and the management of a critical and finite resource - hospital beds - which are common aspects throughout . This use-case addresses the sub-research questions 1 and 2.

In this study, we introduce a Discrete Event Simulation (DES) model for the hospital bed cleaning unit and propose a novel "tension level indicator" that effectively captures the specificities of staff behaviour in response to demand and stock fluctuations. This indicator serves a dual function, acting as both a measure of perceived workload by the staff and an integral component within the DES model, modelling discretionary decision-making of the operators.

Our proposed DES model serves as a tool to assess the bed cleaning unit's ability to consistently provide sterile beds in response to fluctuating demand while evaluating the influence of operator behaviour on process performance. Using this model, along with the tension level indicator, we have developed a novel schedule for the operators that effectively mitigates the risk of stockouts and reduces the workload-induced pressures on the operators.

The work of **Chapter 2** has been disseminated as follows:

- A journal paper co-authored with Allan Larsen, Dario Pacino and Christian Michel Sørup submitted for a third review to *Operations Research for Health Care*
- A presentation by Gaspard Hosteins at ORAHS 2020, the 46th Annual Meeting of the EURO Working Group on Operational Research Applied to Health Services which was supposed to be held at the University of Vienna, Austria in July 2020 but was moved online due to the Covid-19 pandemic and the resulting restrictions
- A presentation by Gaspard Hosteins at INFORMS Healthcare Conference 2021, which was supposed to be held at the Indianapolis in July 2021 but was moved online due to the Covid-19 pandemic and the resulting restrictions
- A seminar presentation by Gaspard Hosteins held in April 2020 at the Technical University of Denmark in Kgs. Lyngby, Denmark.

## **Chapter 3: Improving Hospital Sterilisation Processes: a Comprehensive Simulation Model of the Integrated Reusable Medical Devices Cycle**

In **Chapter 3**, we investigate the flow of Reusable Medical Device (RMD)

within a Dutch hospital. Similar to the focus on beds in Chapter 2, RMD represent a finite resource operating within a closed-loop system in the hospital. These devices undergo sterilisation in a dedicated Central Sterilisation Service (CSS) department to prevent HAI before being used in various surgical procedures and outpatient clinics, followed by another round of sterilisation. This use-case interconnecting multiple departments, including OTs, diverse outpatient clinics and the sterilisation centre, addresses sub-research question 2 within the context of Hospital SCM.

We have developed a comprehensive DES model that encompasses the entire RMD cycle, including medical procedures and the CSS. Our approach includes a novel surgery generation procedure to have a holistic model of the RMD cycle. This innovative integral approach to RMD management enables the consideration of the impact of surgeries and surgical schedules on RMDs sterilisation and sterile inventory. This, in turn, affects the hospital's ability to perform surgical procedures, aligning with the Integral Capacity Planning paradigm in healthcare.

Moreover, our approach considers the RMDs as a resource of our model, facilitating the integration of both CSS operations optimisation and RMDs base stock dimensioning. This holistic strategy evaluates the RMD cycle's performance, taking into consideration RMDs availability and the ability to conduct procedures with the appropriate equipment, ultimately ensuring the highest possible standard of care and clinical outcomes. Our comprehensive analysis uncovered a fundamental issue in our case study: an imbalance in RMDs base stock, a factor that would have remained unnoticed through a sole CSS-focused performance analysis. This highlights the significance of our approach, which recognises and addresses the intricate connections among hospital supply chain entities, such as the CSS and surgical procedures

To address this, we propose a Base Stock heuristic, which effectively reduces RMD unavailability-induced clinic disruptions by 66.1% while simultaneously reducing the total RMDs stock by 7.9%. This contributes to enhanced quality of care, cost reduction, and waste reduction.

The work of **Chapter 3** has been disseminated as follows:

- A journal paper co-authored with Hayo Bos and Gréanne Leeftink under

review at *OR Spectrum*

- A seminar presentation by Gaspard Hosteins held in April 2023 at the *Technical University of Denmark* in Kgs. Lyngby, Denmark
- A seminar presentation by Hayo Bos held in November 2022 at the *Diakonessenhuis Utrecht* in Utrecht, The Netherlands
- A seminar presentation by Hayo Bos held in February 2023 at the *University of Twente* in Enschede, The Netherlands

#### **Chapter 4: Optimising Department Allocation in Hospital Layouts: A Simulation Metaheuristic Approach**

In **Chapter 4**, we introduce an adaptation of the Hospital Layout Problem (HLP) within the context of a hospital under construction north of Copenhagen. The primary objective of the HLP is to strategically position medical activities within the hospital's architectural layout. Differing from the conventional HLP approach, our unique problem focuses on nursing units, reducing the emphasis on interdepartmental flows.

In the design of this hospital, the architectural team and management have opted for standardised patient rooms that can accommodate all types of patient types. While this adaptability offers substantial opportunities for resource pooling and improved room utilisation, it also presents challenges, including potential increased staff and material movements as well as avoidable flow crossings due to the mixed allocation of rooms to patients.

The objective of our novel HLP is to propose a department positioning strategy that minimises patient mixing and misallocation, thereby capitalising on the benefits of room flexibility and resource pooling. We employ a graph-based representation of the hospital layout, wherein medical departments are primarily determined by their central locations. Upon patient arrival, individuals are allocated as close as possible to their respective department centres. This patient allocation method effectively recreates conventionally separated departments within a flexible framework.

Our methodology includes a simulation that performs patient allocation, ac-

counting for patient arrival variations and LOS uncertainties. We evaluate the quality of the allocation based on the connectivity of the generated departments and its ability to prevent mixing patients from different departments. To achieve efficient layouts, we introduce a novel simulation-metaheuristic approach that employs TABU Search to determine department centres and employ simulation to assess their performance.

This novel approach empowers proactive hospital layout design, harnessing the full potential of resource flexibility and leveraging the pooling effect to enhance operational efficiency. This quest for flexibility is at the core of sub-research question 3

The work of **Chapter 4** has been disseminated as follows:

- A journal paper co-authored with Allan Larsen, Dario Pacino, Lisbeth Steinmann and Emilie Schröder submitted to *Healthcare Management Science*
- A workshop presentation by Emilie Schröder at the *Department of Digitalisation and Analytics* of the *Nordsjællands Hospital* in July 2022 in Hillerød, Denmark

### **Other work: Hospital Drug Inventory Management in Rigshospitalet**

**Section 1.3** present an overview of hospital drug inventory management, emphasising the challenges in maintaining data continuity and the prevailing conservative approach. This use case not only highlights the non-data-oriented nature of drug inventory management but also underscores the potential for resource pooling and more customised inventory strategies. Current practices follow a uniform rule, resulting in surpluses, avoidable costs, and wastage, our work highlighted the large potential that enhanced HIT could have to develop data-driven methods and increase drug availability while reducing cost and waste. In the end, this use-case highlights some of the challenges that OM/OR techniques have to face to efficiently enhance , and serve as a foundation for the three sub-research questions.

The work of **Section 1.3** has been disseminated as follows:

- A presentation by Gaspard Hosteins at *EURO 2022, the 32nd European Conference on Operations Research* in July 2022 at the *Aalto University* in Espoo, Finland
- A presentation by Gaspard Hosteins at *ORAHS 2022* in July 2022, the *48th annual meeting of the EURO Working Group on Operational Research Applied to Health Services* at the *University of Bergamo* in Italy
- A workshop presentation by Gaspard Hosteins at *Rigshospitalet* in December 2022 in Copenhagen, Denmark

## 1.5 Concluding Remarks and Future Work

As highlighted by Volland et al. (2017), the healthcare industry and would greatly benefit from the adoption of data-oriented OM/OR approaches to enhance operational efficiency and fulfil its crucial role of delivering care to patients. However, it's essential to acknowledge that healthcare operations have distinct characteristics that necessitate the development of tailored and efficient OM/OR approaches.

Chapter 2 focuses on hospital bed flow, a use-case exemplifying the inherent demand variability in hospital processes. Beds are a crucial and limited resource shared across all hospital departments. Human operators are responsible for cleaning beds and ensuring their availability throughout the hospital. The chapter demonstrates that optimising bed flow in a data-driven manner must consider the operators' influence on the flow and their response to demand pressures, addressing sub-research question 1.

Within the cleaning area, human operators perform various tasks, such as separating mattresses from frames, checking frame maintenance, and resetting beds after cleaning. Workload significantly impacts operators' performance, with higher workloads leading to faster work, and potential corners being cut. We propose introducing a tension level indicator that measures workload-induced stress, serving as both an operator's stress measure and a component within the simulation model of the bed flow to replicate operators' pace vari-

ations and corner-cutting tendencies. This tension level indicator provides an example answer to the sub-research question 1.

The model yields two significant outcomes: a new operator schedule that mitigates the risk of bed stockouts and reduces overall tension levels, subsequently minimising stress and corner-cutting practices. Since its implementation no stockout occurred, demonstrating the efficiency of the tension level indicator as a response to sub-research question 1. Secondly, it reveals that the current bed fleet is oversized, indicating potential cost-saving opportunities, thereby demonstrating the effectiveness of the comprehensive approach for managing transversal resources and addressing sub-research question 2.

Notably, while our method addresses the human aspect of the process and mitigates disadvantages by reducing the need for corner-cutting, it does not eliminate this possibility. In rare unanticipated peak situations, the corner-cutting approach provides a buffer for operators to adapt and respond to demand. Planning for this human buffer, making it the exception rather than the norm, could offer significant potential for efficiency and cost reduction, providing a promising avenue for future research. This strategic planning of human buffers aligns with the core focus of sub-research question 3, which centres on the planning and use of flexibility.

Chapter 3 focuses on the sterilisation process, specifically focusing on managing the flow of RMDs within the hospital. Similar to the bed flow discussed in Chapter 2, RMDs are essential but limited resources that follow a closed-loop supply chain, traversing numerous hospital departments. The demand for RMDs is complex, influenced not only by patient arrivals but also by surgical procedure requirements and surgeon preferences, leading to interdependencies among different RMDs types.

Unlike previous studies that focused solely on the sterilisation departments, our approach encompasses a surgery generation procedure that reproduces the complex demand for RMDs, accounts for the finite nature of the RMD stock and measures the sterilisation flow performance using its impact, downstream, on the surgical procedures. This comprehensive approach enables us to acknowledge the relations between the different involved departments and consequently to capture accurately the real nature of the RMD flow. Thus, Chapter 3 propose a tangible example response to sub-research question 2.

This comprehensive approach permits us to identify RMD base stock levels as the main disruption cause, which a sterilisation service optimisation approach focusing on operational efficiency and makespan reduction would not have revealed.

On top of this descriptive and diagnostic level of analytics (Delen and Ram, 2018), the proposed comprehensive model was used to create a novel heuristic for setting RMD base stock, resulting in potential cost savings and risk of stockout mitigation. The model was also used to assess the impact of increased demand and hospital expansion reaching the predictive level of analytics and enabling data-driven decision-support.

However, the simulation-based model does not provide prescriptive outputs and would require to be coupled with optimisation methods to reach the prescriptive level of analytics and provide a more complete answer to sub-research question 2. While some prescriptive integral approaches exist within specific fields such as in the OT and ED scheduling (Demeulemeester et al., 2013; Samudra et al., 2016), future research on material resources could hold substantial potential, particularly on inventory management as highlighted by the use-case presented in Section 1.3.

The prescriptive aspect of the use of OM/OR methods within is at the heart of the sub-research question 3 and of the department allocation problem presented in Chapter 4. Unlike the transversal resources discussed in Chapters 2 and 3, respectively beds and RMDs, which are moved throughout the hospital, the rooms central to the allocation problem depicted in Chapter 4 are shared resources that are fixed in the hospital. These rooms accommodate patients, serving as the source and destination for various materials, equipment, healthcare professionals, and visitor flows. While flexibility offers the potential to enhance resource utilisation when applied to hospital rooms, it can also lead to increased traffic, longer transportation routes, flows intermingling and, therefore, operational inefficiencies. Chapter 4 seizes the unique opportunity presented by a hospital under construction to propose a layout design approach that mitigates the challenges of full flexibility.

Our approach combines simulation to evaluate layout performance and a metaheuristic to identify efficient layouts. Rather than directly assigning rooms to departments, as in traditional siloed HOM approaches, our method posi-

tions department centres at a strategic level and allocates patients as close as possible to their respective centres on the operational level. This approach aims to replicate separate ward-like patient allocation, mitigating the disadvantages of a fully flexible setup while preserving the flexibility needed to accommodate patients who do not fit this ideal ward arrangement. The proposed approach significantly reduces patient misplacement and the resulting avoidable traffic flows, serving as an efficient example response to sub-research question 3.

The chapter highlights the downside of flexibility, introducing variability and uncertainty into processes, which may conflict with routine, robust, and well-optimised operations, particularly in patient, medical professionals and material flows. A significant portion of HOM literature focuses on optimising these flows, with a specific emphasis on patient flows. Additionally, traditional HLP literature aims to minimise transportation flows. Chapter 4 highlights the existence of a trade-off between flexibility and resource utilisation, such as rooms, and the optimisation of the processes relying on these resources. Analysing this trade-off offers a promising avenue for future research and to enhance . As observed in Chapters 2 and 3, a holistic analysis of processes and the involved resources across the hospital is essential to achieve efficient and actionable results, underscoring the need to address sub-research question 2 effectively.

Chapters 2, 3, and 4 are founded on three distinct hospital use cases, each offering valuable insights into addressing the main research question. Despite the differences between these cases, two common aspects emerge, providing answers to our primary research question.

Firstly, the diversity in hospital processes and contexts is evident, even though they share fundamental functions. Factors such as hospital layouts, operator behaviour, medical departments, patients, and organisational culture introduce variations into these processes that would make them different from one hospital to another. The approaches presented in this thesis were meticulously tailored to these specific contexts, aiming to produce effective and actionable outcomes. This quest to closely mirror the realities of each process, including their unique demands, resource constraints, and operator behaviours, represents a crucial element in developing efficient data-driven HOM methods for enhancing , providing a first answer item to our main research question.

The second key aspect involves the necessity of having holistic approaches. As advocated by Schneider et al. (2020), Integral Capacity Management emphasises global approaches to resource and process optimisation, encompassing the entire ecosystem of the process under examination. For data-driven OM/OR approaches to be efficient and actionable, they should be designed with a transversal, process-oriented perspective, moving beyond hospitals' traditionally siloed and management culture. This transversal approach contributes another dimension to addressing our primary research question, helping mitigate the narrow-focused vision of hospital management. It enables data-backed decision-making, providing a more comprehensive and factual understanding of the broader hospital processes landscape.

The complexity of addressing our main research question is complicated by the wide variety of hospital contexts and the necessity to tailor data-driven methods to each one. While this thesis has highlighted several challenges and proposed methods to tackle them, such as the human behavioural aspect in Chapter 2, the transversality of resources in Chapter 3, or the pursuit of flexibility in Chapter 4, many dimensions remain to explore within the field of HOM.

As demonstrated throughout this thesis, hospitals are intricate entities composed of numerous interconnected sub-entities. The rhythm of hospital processes is dictated by patient arrivals and procedures. While a significant portion of these arrivals remains highly variable and unpredictable, a portion is scheduled and thus eligible to be planned. While scheduling patients for elective procedures, especially in OTs, is already a critical topic within the literature, extending this approach throughout the entire hospital with better coordination of interconnected sub-departments could help smooth demand and reduce the potential impact of demand peaks. Improved control over demand would lead to better resource utilisation and enhanced operational efficiency. One example of such a demand-smoothing approach could be applied to inventory management by accurately forecasting the "schedulable" portion of demand, reducing the need for safety stock, which would only be necessary for the remaining unpredictable demand.

Another challenge arising from the proposed answers to our main research question is how to combine them effectively. The holistic perspective implies modelling more and more processes together, while the need for tailored ap-

proaches points toward the complexity and granularity required when modelling subprocesses. This could result in exceedingly large and complex models, as exemplified by the multi-echelon inventory management in hospitals, which would be computationally demanding and require substantial amounts of reliable data. These two aspects present numerous challenges for future research within the field of HOM.

## Bibliography

- Abe, T. K., Beamon, B. M., Storch, R. L., and Agus, J. (2016a). Operations research applications in hospital operations: Part i. *Iie Transactions on Healthcare Systems Engineering*, 6(1):42–54.
- Abe, T. K., Beamon, B. M., Storch, R. L., and Agus, J. (2016b). Operations research applications in hospital operations: Part ii. *Iie Transactions on Healthcare Systems Engineering*, 6(2):96–109.
- Abe, T. K., Beamon, B. M., Storch, R. L., and Agus, J. (2016c). Operations research applications in hospital operations: Part iii. *Iie Transactions on Healthcare Systems Engineering*, 6(3):175–191.
- Acheson, D. (1988). Public health in england. the report of the committee of inquiry into the future development of the public health function.
- Al-Qatawneh, L. and Hafeez, K. (2011). Healthcare logistics cost optimization using a multi-criteria inventory classification. In *International Conference on Industrial Engineering and Operations Management*, Kuala Lumpur.
- Bailey, N. T. J. (1952). Operational research in medicine. *Operational Research Quarterly (1950-1952)*, 3(2):24.
- Bartenschlager, C. C., Heider, S., Schiele, J., Kunz, J., and Brunner, J. O. (2023). Designing the hospital of the future: A framework to guide digital innovation. *Digital Medicine: Bringing Digital Solutions To Medical Practice*, pages 185–200.
- Becker-Peth, M. and Thonemann, U. W. (2019). Behavioral inventory decisions: The newsvendor and other inventory settings. *Handbook of Behavioral Operations*, pages 393–432.
- Bhaskar, S., Tan, J., Bogers, M. L., Minssen, T., Badaruddin, H., Israeli-Korn, S., and Chesbrough, H. (2020). At the epicenter of covid-19 the tragic failure of the global supply chain for medical supplies. *Frontiers in Public Health*, 8:562882.
- Bijvank, M. and Vis, I. F. (2012). Inventory control for point-of-use locations in hospitals. *Journal of the Operational Research Society*, 63(4):497–510.
- Brailsford, S. C., Harper, P. R., and Patel, B. (2009). An analysis of the academic

- literature on simulation and modelling in health care. *Journal of Simulation*, 3(3):130–140.
- Caban, J. J. and Gotz, D. (2015). Visual analytics in healthcare - opportunities and research challenges. *Journal of the American Medical Informatics Association*, 22(2):260–262.
- Carter, M., Hans, E. W., and Kolisch, R. (2012). Health care operations management. *Or Spectrum*, 34(2):315–317.
- Cattani, K. and Schmidt, G. M. (2005). The pooling principle. *Informations on Education*, 5(2):17–24.
- Christopher, M. (2005). *Logistics and supply chain management: creating value-adding networks*. Financial Times/Prentice Hall.
- Cruz, C. O. and Marques, R. C. (2013). Flexible contracts to cope with uncertainty in public-private partnerships. *International Journal of Project Management*, 31(3):473–483.
- Dai, T. and Tayur, S. (2021). Healthcare operations management: A snapshot of emerging research. *Manufacturing and Service Operations Management*, 22(5):869–887.
- Danas, K., Ketikidis, P., and Roudsari, A. (2002). A virtual hospital pharmacy inventory: An approach to support unexpected demand. *Journal of Medical Marketing: Device, Diagnostic and Pharmaceutical Marketing*, 2(2):125–129.
- Danske Regioner (2022). Medicine. <https://www.regioner.dk/sundhed/medicin/>.
- de Souza, L. B. (2009). Trends and approaches in lean healthcare. *Leadership in Health Services*, 22(2):121–139.
- de Vries, J. (2011). The shaping of inventory systems in health services: A stakeholder analysis. *International Journal of Production Economics*, 133(1):60–69.
- de Vries, J. and Huijsman, R. (2011). Supply chain management in health services: An overview. *Supply Chain Management: an International Journal*, 16(3):159–165.
- Delasay, M., Ingolfsson, A., Kolfal, B., and Schultz, K. (2019). Load effect on service times. *European Journal of Operational Research*, 279(3):673–686.

- Delen, D. and Ram, S. (2018). Research challenges and opportunities in business analytics. *Journal of Business Analytics*, 1(1):2–12.
- Dellaert, N. and Van De Poel, E. V. (1996). Global inventory control in an academic hospital. *International Journal of Production Economics*, 46-47:277–284.
- Demeulemeester, E., Beliën, J., Cardoen, B., and Samudra, M. (2013). Operating room planning and scheduling. *International Series in Operations Research and Management Science*, 184:121–152.
- Dobrzykowski, D., Saboori Deilami, V., Hong, P., and Kim, S. C. (2014). A structured analysis of operations and supply chain management research in healthcare (1982-2011). *International Journal of Production Economics*, 147:514–530.
- Ferranti, J. M., Langman, M. K., Tanaka, D., McCall, J., and Ahmad, A. (2010). Bridging the gap: Leveraging business intelligence tools in support of patient safety and financial effectiveness. *Journal of the American Medical Informatics Association*, 17(2):136–143.
- Garrick, R., Sullivan, J. J., Doran, M., and Keenan, J. (2019). The role of the hospital in the healthcare system. *Modern Hospital: Patients Centered, Disease Based, Research Oriented, Technology Driven*, pages 47–60.
- Gartner, D. and Kolisch, R. (2014). Scheduling the hospital-wide flow of elective patients. *European Journal of Operational Research*, 233(3):689–699.
- Goldschmidt, K. and Stasko, K. (2022). The downstream effects of the covid-19 pandemic: The supply chain failure, a wicked problem. *Journal of Pediatric Nursing*, 65:29–32.
- Green, L. V. (2004). Capacity planning and management in hospitals. *Operations Research and Health Care*, pages 15–41.
- Guerrero, W. J., Yeung, T. G., and Guéret, C. (2013). Joint-optimization of inventory policies on a multi-product multi-echelon pharmaceutical system with batching and ordering constraints. *European Journal of Operational Research*, 231(1):98–108.
- Gupta, R., Gupta, K. K., Jain, B. R., and Garg, R. K. (2007). Abc and ved analysis in medical stores inventory control. *Medical Journal Armed Forces India*, 63(4):325–327.

- Gupta, S. D. (2022). Health management: An introduction. *Healthcare System Management: Methods and Techniques*, pages 1–17.
- Haijema, R., van der Wal, J., and van Dijk, N. M. (2007). Blood platelet production: Optimization by dynamic programming and simulation. *Computers and Operations Research*, 34(3):760–779.
- Hall, R. (2012a). Bed assignment and bed management. *International Series in Operations Research and Management Science*, 168:177–200.
- Hall, R. (2012b). Matching healthcare resources to patient needs. *International Series in Operations Research and Management Science*, 168:1–9.
- Harland, C. M., Knight, L., Patrucco, A. S., Lynch, J., Telgen, J., Peters, E., Tátrai, T., and Ferk, P. (2021). Practitioners’ learning about healthcare supply chain management in the covid-19 pandemic: a public procurement perspective. *International Journal of Operations and Production Management*, 41(13):178–189.
- Harper, P. R. (2002). A framework for operational modelling of hospital resources. *Health Care Management Science*, 5(3):165–173.
- He, L., Chalil Madathil, S., Oberoi, A., Servis, G., and Khasawneh, M. T. (2019). A systematic review of research design and modeling techniques in inpatient bed management. *Computers and Industrial Engineering*, 127:451–466.
- Hopp, W. J., Iravani, S. M., and Yuen, G. Y. (2007). Operations systems with discretionary task completion. *Management Science*, 53(1):61–77.
- Hulshof, P. J., Boucherie, R. J., van Essen, J. T., Hans, E. W., Hurink, J. L., Kortbeek, N., Litvak, N., Vanberkel, P. T., van der Veen, E., Veltman, B., Vliegen, I. M., and Zonderland, M. E. (2011). Orchestra: An online reference database of or/ms literature in health care. *Health Care Management Science*, 14(4):383–384.
- Hulshof, P. J., Kortbeek, N., Boucherie, R. J., Hans, E. W., and Bakker, P. J. (2012). Taxonomic classification of planning decisions in health care: a structured review of the state of the art in or/ms. *Health Systems*, 1(2):129–175.
- Ibanez, M. R., Clark, J. R., Huckman, R. S., and Staats, B. R. (2018). Discretionary task ordering: Queue management in radiological services. *Management Science*, 64(9):4389–4407.
- Kelle, P., Woosley, J., and Schneider, H. (2012). Pharmaceutical supply chain

specifics and inventory solutions for a hospital case. *Operations Research for Health Care*, 1(2-3):54–63.

Knowledge Centre on Migration and Demography (2022). Projected growth in demand for long-term care services represents a major challenge for ageing europe | knowledge for policy 2022. [https://knowledge4policy.ec.europa.eu/news/projected-growth-demand-long-term-care-services-represents-major-challenge-ageing-europe\\_en](https://knowledge4policy.ec.europa.eu/news/projected-growth-demand-long-term-care-services-represents-major-challenge-ageing-europe_en).

Knox Lovell, C. A., Rodríguez-Álvarez, A., and Wall, A. (2009). The effects of stochastic demand and expense preference behaviour on public hospital costs and excess capacity. *Health Economics*, 18(2):227–235.

Kuntz, L., Mennicken, R., and Scholtes, S. (2015). Stress on the ward: Evidence of safety tipping points in hospitals. *Management Science*, 61(4):754–771.

Kunwar, R. and Srivastava, V. (2019). Operational research in health-care settings. *Indian Journal of Community Medicine*, 44(4):295–298.

Landry, S. and Beaulieu, M. (2010). Achieving lean healthcare by combining the two-bin kanban replenishment system with rfid technology. *International Journal of Health Management and Information*, 1(1):85–98.

Landry, S. and Philippe, R. (2004). How logistics can service healthcare. *Supply Chain Forum: an International Journal*, 5(2):24–30.

Lapierre, S. D. and Ruiz, A. B. (2007). Scheduling logistic activities to improve hospital supply systems. *Computers and Operations Research*, 34(3):624–641.

Lega, F. and DePietro, C. (2005). Converging patterns in hospital organization: Beyond the professional bureaucracy. *Health Policy*, 74(3):261–281.

Lesky, E. and Williams, L. (1976). The vienna medical school of the 19th century. (*No Title*).

Little, J. and Coughlan, B. (2008). Optimal inventory policy within hospital space constraints. *Health Care Management Science*, 11(2):177–183.

Litvak, E. and Bisognano, M. (2011). Analysis & commentary: More patients, less payment: Increasing hospital efficiency in the aftermath of health reform. *Health Affairs*, 30(1):76–80.

Ma, G. and Demeulemeester, E. (2013). A multilevel integrative approach to

- hospital case mix and capacity planning. *Computers and Operations Research*, 40(9):2198–2207.
- McKone-Sweet, K. E., Hamilton, P., and Willis, S. B. (2005). The ailing health-care supply chain: A prescription for change. *Journal of Supply Chain Management*, 41(1):4–17.
- Meijboom, B., Schmidt-Bakx, S., and Westert, G. (2011). Supply chain management practices for improving patient-oriented care. *Supply Chain Management*, 16(3):166–175.
- Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., and Zacharia, Z. G. (2001). Defining supply chain management. *Journal of Business Logistics*, 22(2):1–25.
- Moons, K., Waeyenbergh, G., and Pintelon, L. (2019). Measuring the logistics performance of internal hospital supply chains a literature study. *Omega (united Kingdom)*, 82:205–217.
- OECD (2017). *Tackling Wasteful Spending on Health*.
- Ohno, T. and Bodek, N. (2019). *Toyota Production System: Beyond Large-Scale Production*. Taylor and Francis.
- Ordu, M., Demir, E., and Tofallis, C. (2019). A comprehensive modelling framework to forecast the demand for all hospital services. *International Journal of Health Planning and Management*, 34(2):e1257–e1271.
- Parkinson, C. N. and Osborn, R. C. (1957). *Parkinson’s law, and other studies in administration*, volume 24. Houghton Mifflin Boston.
- Rais, A. and Viana, A. (2011). Operations research in healthcare: A survey. *International Transactions in Operational Research*, 18(1):1–31.
- Risse, G. B. (1999). *Mending bodies, saving souls: a history of hospitals*. Oxford University Press.
- Rivard-Royer, H., Landry, S., and Beaulieu, M. (2002). Hybrid stockless: A case study. lessons for health-care supply chain integration. *International Journal of Operations and Production Management*, 22(4):412–424.
- Rosales, C. R., Magazine, M., and Rao, U. (2015). The 2bin system for controlling medical supplies at point-of-use. *European Journal of Operational Research*, 243(1):271–280.

- Rossetti, M. D., Buyurgan, N., and Pohl, E. (2012). Medical supply logistics. *International Series in Operations Research and Management Science*, 168:245–280.
- Saha, E. and Ray, P. K. (2019). Modelling and analysis of inventory management systems in healthcare: A review and reflections. *Computers and Industrial Engineering*, 137:106051.
- Samudra, M., Van Riet, C., Demeulemeester, E., Cardoen, B., Vansteenkiste, N., and Rademakers, F. E. (2016). Scheduling operating rooms: achievements, challenges and pitfalls. *Journal of Scheduling*, 19(5):493–525.
- Sanders, R. (1987). The pareto principle: its use and abuse. *Journal of Services Marketing*, 1(2):37–40.
- Schneider, T. A. J., Van Essen, T. J., Carlier, M., and Hans, E. W. (2020). Scheduling surgery groups considering multiple downstream resources. *European Journal of Operational Research*, 282(2):741–752.
- Sharon Ross, D. and Venkatesh, R. (2016). Role of hospital information systems in improving healthcare quality in hospitals. *Indian Journal of Science and Technology*, 9(26).
- Sherbrooke, C. C. (1968). Metric: A multi-echelon technique for recoverable item control. *Operations Research*, 16(1):122–141.
- Sinha, K. K. and Kohnke, E. J. (2009). Health care supply chain design: Toward linking the development and delivery of care globally. *Decision Sciences*, 40(2):197–212.
- Soyiri, I. N. and Reidpath, D. D. (2013). An overview of health forecasting. *Environmental Health and Preventive Medicine*, 18(1):1–9.
- Statistics Denmark (2019). Accounts and budgets of regions. <https://www.dst.dk/en/Statistik/emner/oekonomi/offentlig-oekonomi/regionernes-regnskab-og-budgetter>.
- Taha, H. A. (2007). *Operations research*. Pearson.
- Toba, S., Tomasini, M., and Yang, Y. H. (2008). Supply chain management in hospital: a case study. *California Journal of Operations Management*, 6(1):49–55.
- UN General Assembly (2015). Transforming our world: The 2030 agenda for sustainable development. <https://www.refworld.org/docid/57b6e3e44>.

- html. Resolution adopted by the General Assembly on 21 October 2015, A/RES/70/1.
- Utley, M. and Worthington, D. (2012). Capacity planning. *International Series in Operations Research and Management Science*, 168:11–30.
- Van Oostveen, C. J., Ubbink, D. T., Huis In Het Veld, J. G., Bakker, P. J., and Vermeulen, H. (2014). Factors and models associated with the amount of hospital care services as demanded by hospitalized patients: A systematic review. *Plos One*, 9(5):e98102.
- Vanberkel, P. T., Boucherie, R. J., Hans, E. W., Hurink, J. L., and Litvak, N. (2012). Efficiency evaluation for pooling resources in health care. *Or Spectrum*, 34(2):371–390.
- Vila-Parrish, A. R., Ivy, J. S., King, R. E., and Abel, S. R. (2012). Patient-based pharmaceutical inventory management: a two-stage inventory and production model for perishable products with markovian demand. *Health Systems*, 1(1):69–83.
- Volland, J., Fügener, A., Schoenfelder, J., and Brunner, J. O. (2017). Material logistics in hospitals: A literature review. *Omega (united Kingdom)*, 69:82–101.
- Vos, L., Groothuis, S., and Van Merode, G. G. (2007). Evaluating hospital design from an operations management perspective. *Health Care Management Science*, 10(4):357–364.
- Ward, M. J., Marsolo, K. A., and Froehle, C. M. (2014). Applications of business analytics in healthcare. *Business Horizons*, 57(5):571–582.
- Weiner, D. B. and Sauter, M. J. (2003). The city of paris and the rise of clinical medicine. *Osiris*, 18:23–42.
- WHOCC (2022). Atc structure and principle.
- World Health Organisation (2008). *The Third Ten Years of the World Health Organization, 1968-1977*. World Health Organization.
- World Health Organisation (2020). Hospitals. [https://www.who.int/health-topics/hospitals#tab=tab\\_1](https://www.who.int/health-topics/hospitals#tab=tab_1).
- World Health Organization (2019). Who guideline: recommendations on digital interventions for health system strengthening. <https://www.who.int/publications/i/item/9789241550505>.

Xie, J., Zhuang, W., Ang, M., Chou, M. C., Luo, L., and Yao, D. D. (2021). Analytics for hospital resource planning - two case studies. *Production and Operations Management*, 30(6):1863–1885.

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## 2 | A data-driven decision support tool to improve hospital bed cleaning logistics using discrete event simulation considering operators' behaviour

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**Abstract** Beds are a critical resource for hospitals, requiring effective management to ensure the quality of care for patients. Beds operate in a closed-loop circuit and must be thoroughly cleaned between patients' arrivals to prevent infections. Hospitals must implement efficient logistics systems to collect, transport, store, and clean unclean beds from discharged patients. These systems must be robust and efficient to meet the varying bed supply needs, given the available resources such as beds, staff and machines. This study aims to develop a decision support tool to optimise bed cleaning logistics and ensure the availability of sterile beds for incoming patients at all times. The study is based on the bed flow and cleaning organisation of a Danish public hospital. A discrete event simulation model (DES) of the back-end bed flow has been developed. The paper also presents a tension level indicator to reflect the behaviour of cleaning staff when facing variations in demand and bed stock. Using the organisational set-up (staff schedules, policies, and bed fleet size), the DES model: 1) evaluates the ability to provide sterile beds in a reasonable time, 2) measures the stress on cleaning staff, and 3) visualises resource usage. This study illustrates how to incorporate the staff's perceived workload and resulting behaviour into a DES model to capture the behavioural aspect of staff's decision-making.

**Keywords:** *Bed Logistics, Simulation, Behavioural modelling, Analytics*

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## 2.1 Introduction

The efficient management of healthcare systems is a requirement to ensure a high level of service. Professionals and health-providing organisations, such as hospitals, strive to optimise their tasks efficiency and resource utilisation to meet this demand (see Hulshof et al. (2012)). Often, these process management tasks are handled directly by health professionals rather than individuals with advanced analytical backgrounds (see Hall (2012b)). Hence, operations research (OR) and operations management (OM) techniques can provide opportunities for improvement. Jacobs and Chase (2014) defines OM in healthcare as "the design, management, and improvement of systems that create and deliver healthcare services". Optimising resource usage in hospitals has been a recurring theme with growing importance in OM and OR in healthcare (see Hulshof et al. (2012), Cevik Onar et al. (2018)).

The demand for hospital care is evolving in the European Union and the OECD countries. Hospital admissions have slightly increased during the last decade (see OECD (2021)). At the same time, hospitalisations have changed with the evolution of techniques and the development of home care. The average length of stay of a patient has decreased, and at the same time, to optimise costs, the number of beds per capita also diminished (see OECD (2021); OECD and European Union (2020)). This evolution results in higher resource usage, increased bed turnover and intensified pressure on bed logistic supply chains. The COVID-19 outbreak has highlighted the importance of hospital beds and the challenges healthcare systems face (see OECD and European Union (2020)).

Beds are indeed one of the essential resources that follow an in-patient throughout their entire stay in the hospital. Beds are a transverse resource, common to all departments, with strict hygiene requirements and protocols. The bed fleet and all the bed-related processes are directly linked to the capacity of a hospital to treat patients. Patient arrivals and their length of stay constitute the demand for beds. However, the patients' arrival and characteristics are variable and uncertain. To ensure hygiene standards, beds must go through cleaning processes before being stored appropriately and later reused. Improving or devising efficient bed flows and related procedures is a challenging but critical task for a hospital.

The consequences of delays and stockouts of beds can be extremely detrimental to patient care, imposing a significant dependency on bed-cleaning operators to meet the fluctuating demand. The hospital bed fleet is finite, and the storage space for sterile is limited. The cleaning equipment and the staff to operate it are bounded. These constraints make ensuring the sterile bed supply of hospitals more complex and can increase the stress level on the operators when demand exceeds supply. The requirement to meet the demand in a stressful environment influences the operators' decision process and the overall bed flow. Such a decision process must be considered when attempting to understand, model, and improve the bed flow of a hospital.

Simulation modelling, specifically discrete event simulation (DES), is a practical and widely used technique to model hospital processes with stochastic behaviour and numerous interlinked sub-processes, such as bed management. However, the operators' behavioural aspect of the bed flow is difficult to measure and integrate into such a simulation approach. No quantitative data is available to highlight how operators react to changes in demand and the experienced stress on the system in which they are embedded. This study aims to build a simulation model to understand and improve the bed flow of a hospital, taking into account the stressful nature of the work and the impact it has on the operators involved in the bed flow. The proposed approach aims to improve the bed cleaning operations and the technical part of the bed logistic supply chain using a DES model that incorporates the operators' decision process and behaviour. Working jointly with a public hospital in Denmark, we develop a system tension level indicator that measures the pressure on the bed cleaning system. This indicator is used to anticipate the corresponding behaviour of the staff and adapt the DES model accordingly. The model allows for scenario testing of proposed organisational interventions before practical implementation.

The rest of the paper is organised as follows. Section 2.2 presents a literature review introducing bed management and behavioural modelling. Section 2.3 presents a use case from a Danish public hospital and the scope of the problem. Section 2.4 describes the methods and techniques used in the proposed approach. The simulation implementation and set-up are detailed in Section 2.5. The results of the study are presented and discussed in Section 2.6. Section 2.7 concludes this paper and suggests avenues for further research.

## 2.2 Literature Review

Bed management is the sub-field of healthcare operations (OM and OR) dedicated to efficiently using bed resources. The first bed management studies are from the 1950s with Bailey (1954) where queuing models are used to allocate beds to patients.

Beds accommodate patients throughout their stay and need to be cleaned between patients. Hall (2012a) decompose the full bed-cycle in ten steps. Two parts of the cycle can be distinguished. The front-end or in-patient part of the cycle starts with the bed's allocation to the patient and continues until the discharge. The backend of the cycle corresponds to all the technical steps needed in-between use: cleaning, storing, and transporting. Performance evaluation in bed management is usually reflected in the bed occupancy rate (see Hall (2012a)). Other indicators related to bed management include: waiting time (see Bailey (1954)), cancellations, postponements or misplacement (see Hall (2012a), Hulshof et al. (2012)).

Bed management encompasses all the organisational problems encountered when managing bed resources, from strategic to operational planning (see Baru et al. (2015)). The healthcare management taxonomy of Hulshof et al. (2011) identifies capacity planning, bed reservation, and patient assignment as the main areas of research in bed management. The goal of capacity planning is to quantify the number of beds required to accommodate the incoming patients (see Hulshof et al. (2011)). Patient arrivals to hospitals are only partly scheduled, with the request for beds from the emergency department being stochastic, making capacity planning more complex. Sizing the entire bed fleet is the strategic level of capacity planning and the most studied one, with around 80 papers listed in Hulshof et al. (2012). Hulshof et al. (2012) identifies bed reallocation between departments and temporary fleet changes as tactical-level bed management tasks. At the operational level, Hall (2012a) lists bed and patient handling tasks such as bed-patient or room assignment.

The other large part of the bed management literature focuses on the in-patient part of the bed cycle and the assignment of beds to patients. He et al. (2019) identifies several patient characteristics that can influence bed allocations, such as gender, diagnosed disease, acuity level, or isolation re-

quirement. In most in-patient studies, bed fleet and associated staff (nurses, porters, or technicians) are considered constraints. Various simulations and queuing models have been proposed to evaluate the performance of different allocation policies (see He et al. (2019), Hulshof et al. (2012), Hall (2012a)). Reservation strategies with dedicated capacity either pre-or dynamically allocated have also been proposed (see He et al. (2019), Hulshof et al. (2012)). Simulation is a very common technique with literally thousands of papers within healthcare management as detailed in Brailsford et al. (2009), and is also the most used methodology within bed management (see Hulshof et al. (2012), Hall (2012a), Cevik Onar et al. (2018), He et al. (2019)). Simulation, particularly Discrete Event Simulation (DES), is well suited to model bed flows, with patient flow as a stochastic demand and numerous interlinked processes.

Most of the bed management approaches described in Hulshof et al. (2012), Hall (2012a), He et al. (2019), Cevik Onar et al. (2018) are based upon case studies jointly developed with application hospitals. All studies aim at improving the hospital bed flow but differ due to the difference in setup and management of the studied hospital. Bed cleaning can be managed internally in each department or in centralised, dedicated units. Regardless of the organisation, the goal of the bed logistics remains to meet patient demand in terms of volume, quality, and hygiene.

Several studies have been proposed about the in-patient part of the bed cycle; however, to the best of our knowledge, process optimisation of the backend of hospitals' bed flow has not yet been considered in the literature. The ability to clean and store beds to make them available to patients directly impacts the overall number of beds needed for the hospital and the capacity of the hospital to treat patients. Therefore the backend of the bed cycle should also be studied and improved.

Hospital processes are heavily human-based and are often influenced by the discretionary decisions of a human operator. The behaviour of the operators could then influence the decisions and thus change the outcome of the processes. Several econometrics studies highlighted that stress and workload impact human operators and ultimately affect the system's performance. Kc and Terwiesch (2009), in a hospital context, and Shunko et al. (2018), in a bank, showed that an increased workload tends to decrease service time as operators would work faster to keep the rhythm. Parkinson and Osborn (1957) notes that

human operator will use their entire work time to perform the scheduled tasks. Hence, a lower workload will result in decreased work speed. Delasay et al. (2019) proposed a framework to identify the mechanisms impacting operators' behaviour and their impact on the system. To the best of our knowledge, these operator behaviour mechanisms have rarely been considered when modelling healthcare processes. We can cite Delasay et al. (2016) and Azriel et al. (2019) who incorporated social loafing in queuing and markovian processes. Brailsford et al. (2012) proposed a breast screening model encompassing a human component and the patient's behaviour. It showed that the patients' behaviour impacted the process outcomes and suggested how to incorporate this when modelling.

Behavioural mechanisms might be of greater importance to model accurately processes that encompass discretionary decisions left to the operators. These discretionary decisions can be used to adapt the throughput and service times. Ibanez et al. (2018) showed how discretionary task ordering could reduce cycle time, and Hopp et al. (2007) explains that discretionary task completion turns quality into a buffer and ultimately improve service level by reducing service time. However, Becker-Peth and Thonemann (2019) for the newsvendor model and Goodwin et al. (2019) on forecasting decisions showed that the behaviour of the operators influenced their decisions and, therefore, should be taken into consideration when modelling discretionary processes. Both approaches also highlight that the operators' attitude towards risk accentuates their decision bias.

In a hospital's resource-constrained and stressed environment, there is a need for more efficient management of the bed resource to ensure bed supply at any time, particularly on the backend processes of the bed flow. This paper aims to improve these backend processes through simulation. It is crucial to enhance the simulation model to quantitatively take into consideration operators' behaviour to capture the stressful environment of the hospital and its impact on the bed flow, as our approach tries to do.

## 2.3 Use Case and Problem Description

Glostrup Hospital (a part of Rigshospitalet) is a large public hospital west of Copenhagen with a capacity of 290 in-patient beds distributed across 20 different departments. A centralised bed cleaning facility in the basement supports the need for sterile beds for the approximately 40,000 patients the hospital admits each year.

The arrivals- and discharges of patients in the hospital set the demand and pace of sterile beds that the cleaning unit needs to manage. The patients' flow is only partially scheduled and highly uncertain, which shows the significant variations in the demand for beds that happen across weekdays (see Figure 2.1).

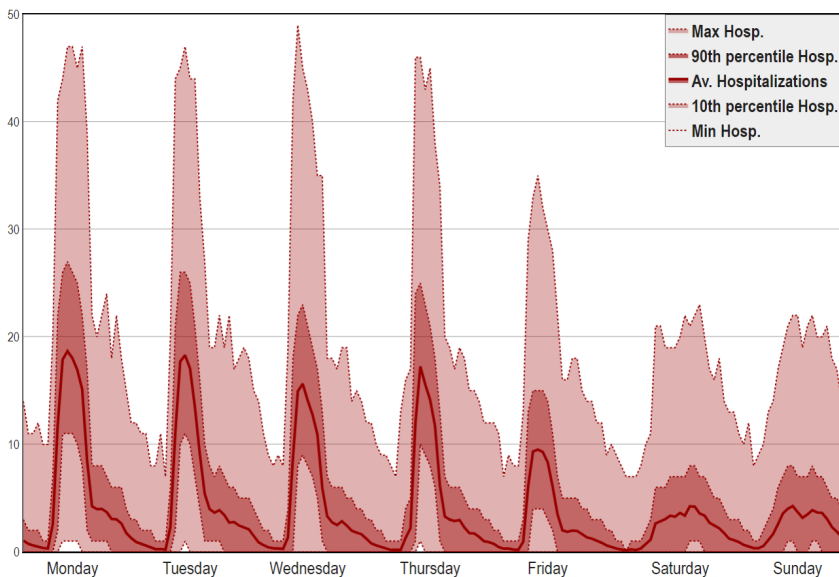


Figure 2.1: Weekly distribution of the patients' arrival in the period of March 2019 through February 2020 before the national lockdown in Denmark due to the COVID-19 pandemic.

Information about patient arrivals is not readily available to the centralised bed cleaning unit staff. Consequently, the operators can only estimate the actual bed demand by looking at the current stock levels and the pace at

which sterile beds are requested. Daily work planning is thus heavily dependent upon the operators' own experience. Consequences of delays and stockouts can be highly detrimental to patient care, making operators act with a risk-averse behaviour. The bed cleaning unit does not use predetermined safety levels of sterile beds and solely relies on the operators' estimation of the needed level of beds. Their risk-averse behaviour urges the operators to overstock and speed up the cleaning process to cope with any demand variation. This phenomenon is amplified by the lack of information downstream and the highly uncertain demand and makes the bed cleaning unit prone to overreaction (following the bullwhip effect Lee et al. (2004)).

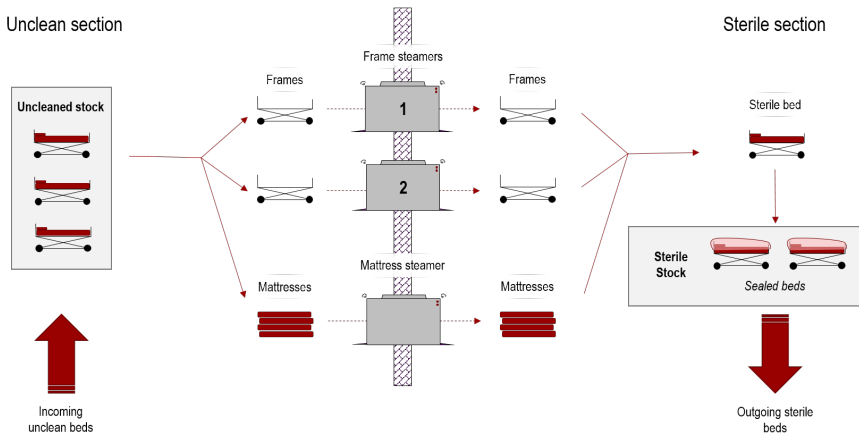


Figure 2.2: Conceptual model of the bed cleaning unit at Glostrup hospital

Figure 2.2 depicts the organisation of the bed cleaning unit at Glostrup Hospital. Two parts compose the work area: the "unclean" section, where beds are waiting to be cleaned, and the "sterile" section, storing beds before their use. When a bed is taken from the unclean stock, it is pre-cleaned by the staff (taking an average of two minutes) before being pushed through the steamers. There are two frame steamers and one steamer for mattresses and linen. As shown in Figure 2.2, those machines are sealed into a wall and act as a transfer lock between the unclean and the sterile sections. The frame-steamers are the bottleneck as only one frame can go through, whereas the steamer for mattresses can clean ten at a time. All the frame-steamers have a six minutes standard cleaning program. Sometimes, the operators might decide that a bed requires deep cleaning (e.g. in case the bed was previously occupied by a patient with an infectious disease), in which case a 15 minutes intense cleaning

program is applied. Once a frame is cleaned, a worker makes the beds using a sterile mattress and bedsheets, as depicted on the right-hand side of Figure 2.2. This operation takes two minutes on average. Another worker wraps plastic foil around the bed and stores it (which takes approximately 1'30). The unclean and sterile sections have a capacity of 90 and 164 beds, respectively, and the hospital currently has a total bed fleet of 413 beds.

From a managerial viewpoint, a waiting time exceeding 15 minutes upon request for a clean bed is deemed unacceptable. Hence, operators try to build stock to meet future demand. In very tense situations (low stock, demand peaks or machine breakdowns), frames can be "hotel cleaned", i.e. simply a manual cleaning performed by the staff. The frames are then pushed to the cleaning section through the steamers without launching any cleaning program. This corner-cutting process takes on average 2 minutes but has a lower sanitary quality and is only used in tense situations. Beds that require deep cleaning are never hotel cleaned. The decision to use a hotel cleaning is made by the operators and corresponds to their estimation of the pressure on the cleaning unit. This decision corresponds to the discretionary task completion described by Hopp et al. (2007). Cleaning quality acts as a buffer to ensure that the stock will be sufficient to meet the demand. The risk-averse nature of the operators influences their estimation of whether the stock is sufficient to meet the demand and pushes them to use this corner-cutting mechanism to compensate.

At the hospital, a dedicated team of 6 operators cleans the beds. They work from Monday through Friday, from 7 AM to 3 PM, with two breaks of 15 minutes and a lunch break of 30 minutes. Cleaning hours are extended on Fridays when three operators work the usual hours, and three operators start and finish 1h30 later in order to build stock before the weekend. This schedule is made according to operators' preferences and is not explicitly designed to meet the demand for beds.

This work setup allows for little system flexibility, defined as the system and the operator's ability to adapt and react to the evolving demand. The limited storage capacity of the sterile section reduces the capacity to have safety stock and anticipate peaks. When the capacity of the used section is exceeded, used beds have to be stored in other areas such as corridors or even the treating part of the hospital, which is not acceptable seen from a safety aspect. Furthermore,

the fixed work hours limits the number of bed that can be cleaned. These constraints make work planning more complex for the operators. Combined with the operators' risk-averse nature, those constraints amplify the risk of overreacting to demand variations, stressed situations, and falling into the bullwhip effect.

## **2.4 Material and Methods**

In order to study the bed flow of Glostrup Hospital and how it is affected by the behaviour of the staff under peak demand, a DES model was developed.

### **2.4.1 DES model of the use case**

The model considers three types of resources; the staff cleaning the beds, the porters, and the frame steaming machines. During interviews with the staff and visits to the facility, it has been established that the mattress steamer is not a bottleneck of the system and is, therefore, disregarded in the rest of the study. Bed operators operate on a fixed schedule set as an input to the model. Those schedules include the working hours as well as the number of operators at each hour. Porters are not considered a scarce resource. They transport the sterile beds to the patient and unclean beds to the cleaning section. Outside the bed staff's regular working hours, porters are responsible for cleaning beds if needed.

Figure 2.3 is a conceptual diagram of the entire bed flow at Glostrup Hospital and is the base of our simulation model. The light grey part on the left corresponds to the patient flow. Starting from the top left corner of Figure 2.3, patients arrive, get admitted, and are assigned a bed for their stay until discharge. A porter brings the unclean bed to the cleaning section, which starts the bed flow loop in dark grey in Figure 2.3. First, the unclean bed is stored in the dedicated area, then inspected by a worker and put into an available steamer. Another bed worker receives it at the steamer's exit, makes sure it is ready for use, and stores it in the sterile section where a porter will transport it to a new patient if needed.

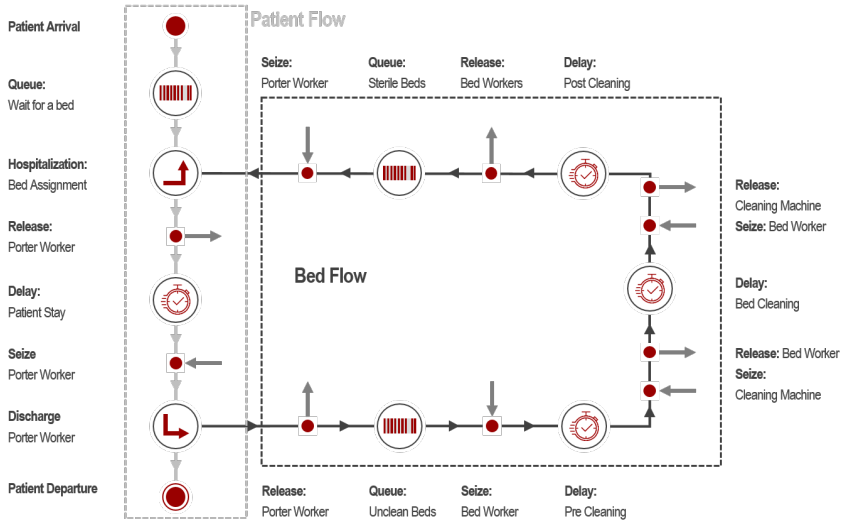


Figure 2.3: Conceptual diagram of the bed flow at Glostrup Hospital

The bed flow pace depends upon the patients' arrivals and discharges. The patients' arrival defines the demand. The schedule for the staff and the number of beds in the system are parameters to decide before running the model.

### 2.4.2 Input Data: Patient Arrival

The patient flow used as input for the DES model is based on two sources of data: patients' hospitalisation data and operational data. The patients' hospitalisation data is extracted from the hospital IT system and corresponds to one year of anonymised hospitalisation data on all the patients from March 2019 to February 2020 (before the national lockdown due to COVID-19). These contain 1,389,528 records corresponding to 38,381 different hospitalizations. Each row corresponds to selected events for hospitalised patients inside the hospital. These are admission, discharge and all movements between visited departments. The operators manually recorded the operational data, which contains the number of beds cleaned each day and the stock of unclean and sterile beds at shifts beginnings and ends. These operational data are mainly used as control data to verify and validate the models made with hospitalisation data.

The input for the model is the arrival rates and length of stay (LOS) from the patient flow. The patient flow tends to have variation in three different levels, which are: between hours, between days of the week, and between months (see Figure 2.4), all of which is in alignment with Hall (2012a). Weekdays tend to follow the same pattern with a peak during work hours and numbers similar to the weekends outside regular working hours. Thursday's peaks are slightly delayed as the mornings are usually reserved for department morning briefings. The 7 AM arrivals are staggered throughout the rest of the day. The provided data did not allow for considering monthly variation. The arrival rates and LOS have been computed for every hour of the week, modelling the hourly and daily variations.

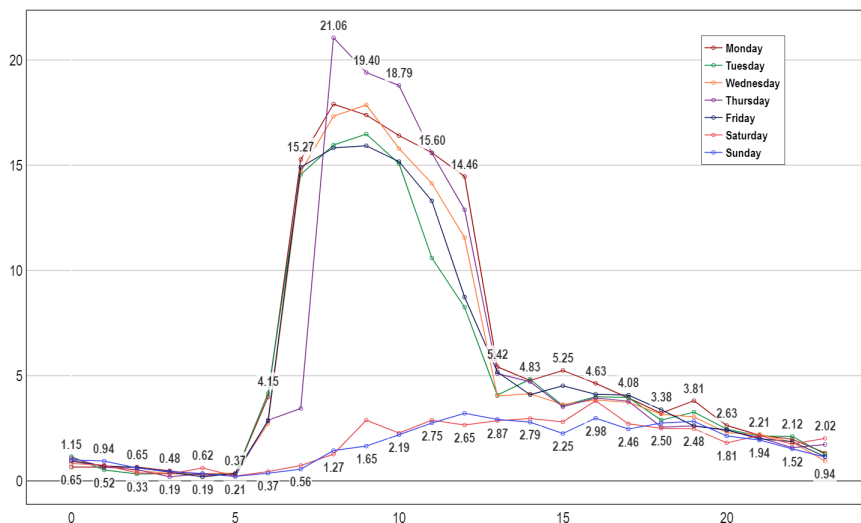


Figure 2.4: Average hospitalisation volume for each hour and each day of the week

The LOS of patients can fluctuate based on a patient's arrival hour- and week-day. Hence, LOS distributions are computed for every hour of the week. The LOS of patients staying overnight and patients not staying is calculated separately. The LOS of patients staying overnights is fitted in two parts: the number of nights they will stay on one side and their discharge hour on the other, whereas the LOS of patients not staying overnight is directly fitted. Those sub-distributions are then combined using the probability of a patient staying overnight.

Patients' arrival rates have been modelled as Poisson processes with different rates for every hour of the week. This approach complies with standard practice seen across the literature (see Holm et al. (2013), Andersen et al. (2017), Gimenez-Mallor et al. (2007), Hagen et al. (2013)).

In this study, we only consider the bed flow from the cleaning unit. Note that the departments do not always order and release a bed when a patient arrives or is discharged. Like the Emergency Department, departments with high throughput tend to build stock before busy periods and order/release beds in bulks that the IT system does not adequately handle. Such practices result in higher utilisation of sterile beds compared to the demand directly computed from the patient movement data. Thus, daily correcting factors have been used to match the demand with the average volume of sterile beds leaving the bed cleaning unit. These factors have been computed using operational data.

### **2.4.3 Tension Level**

Traditionally, DES models do not include discretionary decisions left to the agent and does not consider how operator behaviour changes their decisions. In our study, such a traditional DES modelling approach is not well suited to simulate how the operators adapt their work to the current situation, how operators choose to use hotel cleanings and the impact it has on the system. The proposed *tension level* indicator aims at tackling this issue. Brailsford et al. (2012) suggested using a quantitative measure of the human component to integrate into a DES model. Operators decide to use 'hotel beds' depending on the experienced stress in the bed cleaning unit. This corner-cutting choice allows them to adapt their throughput. We propose to model this phenomenon by estimating the throughput that operators believe to be required. The *tension level* indicator is then the ratio between the estimated and the average throughput. This relation between the experienced stress on the system and the throughput described by the operators corresponds to the ones studied by Kc and Terwiesch (2009), Shunko et al. (2018), Parkinson and Osborn (1957) and to the task reduction, workload smoothing, social speedup pressure or social loafing mechanisms detailed by Delasay et al. (2019).

The bed cleaning unit operates isolated from the other departments of the

hospital. Information on demand variations does not reach the bed cleaning unit. Hence, the only way the staff can estimate whether they will meet the demand is by visually inspecting both sterile and unclean bed stock levels and, by experience, adapt the perceived demand. The proposed tension level indicator aims at replicating this operators' evaluation process. The indicator combines the current demand and stock levels and computes the throughput necessary to meet the demand operators expect.

According to the operators, two main components constitute the workload and make the basis of their decision process:

- **The workload:** the production component; the number of beds that needs cleaning in order to meet the demand.
- **The backlog:** the number of beds ready to be cleaned. Maintaining a low unclean bed inventory is required to be able to receive new unclean beds and for those not to stay elsewhere in the hospital.

Kc and Terwiesch (2009) and Shunko et al. (2018) showed that load directly impacts service times, but the variation of the load also impacts operators' perception of the load and ultimately the service times. To model this phenomenon, we introduced *the busyness level*. The busyness level measures how busy the time period is compared to normal, computed as the ratio between the current and average demand.

The operators do not work overnight or on weekends. Moreover, in busy periods the demand for beds could be greater than the maximum production. To accommodate these situations, operators use sterile stock. Visits to the cleaning unit highlighted that several objectives and demands co-existed, corresponding to different time frames:

- **Shift Level:** Having a sufficient number of beds to satisfy the demand throughout the shift. This level is significant on Monday mornings when the demand peaks, but the stock is at its lowest.
- **Daily Level:** Having a sufficient number of beds for the demand for the day and enough stock for the night. Monday nights can sometimes be difficult if the stock on Monday morning is low and the demand remains

high the entire day. Then the stock at night could be an issue.

- **Future Level:** Having a sufficient number of beds for the following days. This level is important on Fridays when the operators prepare sterile beds for the entire weekend and the Monday mornings

At any time, the busyness level, the workload, and the backlog are evaluated on the three time-horizons. The maximum value for each of the objectives is kept. The corresponding component is then the predominant one at this precise time. The workload and the backlog are then compared together to determine whether the backlog is the main preoccupation. Then, the corresponding estimated throughput can be computed. The tension level corresponds to the ratio between the throughput operators estimate to be required and their baseline throughput, defined as the average throughput they usually have.

#### 2.4.3.1 Computation of the tension level

Consider  $D$  the demand for bed,  $A$  the arrival of unclean beds,  $C$  the sterile bed inventory level and  $U$  the unclean bed inventory level. For any of these quantities  $X$ ,  $X_\tau$  denote the value over time horizon  $\tau \in \{shift, day, future\}$ ,  $X_\tau(t)$  denote the value until instant  $t \in T$  from the start of the corresponding time horizon  $\tau \in \{shift, day, future\}$ , and  $\widehat{X}$  the expected value. The expected value is used as the operators' reference.

All of the quantities are computed over all the time horizons (shift, day and future) and then compared. To simplify the notations,  $\tau \in \{shift, day, future\}$  will be omitted:  $X_\tau \sim X$ .

The busyness level is based on the demand ratio  $r(t)$ : the ratio between the demand and arrival that operators expect which is approximated to the average one  $\widehat{D}(t) + \widehat{A}(t)$ ,  $\forall t \in T$  and the real one  $D(t) + A(t)$ ,  $\forall t \in T$ . This ratio is a simplified version of the "overtime" used by Kc and Terwiesch (2009). We used the average instead of a moving average over the last periods.

$$r(t) = \frac{D(t) + A(t)}{\widehat{D}(t) + \widehat{A}(t)}, \quad \forall t \in T \quad (2.1)$$

The operator's perception of the busyness level is also influenced by the past and how busy the last period was. To model this memory bias, the demand ratio is smoothed with a factor  $\alpha \in [0, 1]$ , to compute the busyness level  $\rho(t)$

$$\rho(t) = \alpha \cdot \rho(t-1) + [1 - \alpha] \cdot r(t), \quad \forall t \in T \quad (2.2)$$

where  $\rho(t-1)$  is the ratio computed at the end of the previous time horizon.

The operators' main priority is to ensure that the demand will be met. Hence they tend to overshoot and thus build safety stock. Moreover, the lack of downstream demand information makes the operators prone to the "overreaction phenomenon", especially in situations with high demand fluctuations. Wakker (2010) and Schmidt and Zank (2008) also describe similar overreaction phenomena and propose to use convex transformation such as exponential utility functions to model it. Similarly, a convexity coefficient  $\gamma \geq 1$  is used as a power to amplify the operators' reaction to the "busyness level" as shown in Equations 2.3 and 2.4.

The workload  $\omega(t)$  measures the amount of work to do during the time period considered. This corresponds to the estimated demand over the period (i.e. the product of the busyness and the demand) minus the current stock. The workload is computed as the pace needed to produce enough beds:

$$\omega(t) = \frac{\rho(t)^\gamma \cdot \widehat{D(t)} - C(t)}{\theta}, \quad \forall t \in T \quad (2.3)$$

with  $\theta$  being the duration of the considered time horizon.

The backlog  $\beta(t)$  is the unclean bed counterpart of the workload. It corresponds to the number of unclean beds that should be cleaned to reach a base level, allowing new unclean beds to be transported near the bed cleaning unit. The backlog is also bounded by the capacity  $K_C$  of the sterile stock. It is not possible to clean more beds than the sterile stock can receive:  $K_C - C(t)$ .

With  $B$  being the acceptable base level of unclean beds and  $U(t)$  the current

stock level of unclean beds.

$$\beta(t) = \text{Min} \left\{ K_C - C(t), \frac{\rho(t)^r \cdot \widehat{A(t)} + U(t) - B}{\theta} \right\}, \forall t \in T \quad (2.4)$$

The perceived throughput objective  $\phi(t)$  is then the maximum of the workload and the backlog:

$$\phi(t) = \text{Max} \{ \omega(t), \beta(t) \}, \forall t \in T \quad (2.5)$$

The tension level  $\Psi(t)$  is then the ratio between the perceived throughput objective and the baseline throughput  $\phi_0$ :

$$\Psi(t) = \frac{\phi(t)}{\phi_0}, \forall t \in T \quad (2.6)$$

The tension level can be plotted across the entire week firstly to understand the operators' concerns and, secondly, to identify how to adapt the work schedule to reduce tension. Figure 2.5 shows the decomposition of the estimated throughput. The estimated throughput is defined as the maximum of the backlog and workload across the three time horizons considered. Figure 2.5 displays all these components; first, the figure illustrates the workload (the ability of the sterile stock to match the demand) at the shift (yellow), daily (orange), and future (red) levels. Secondly, Figure 2.5 illustrates the backlog (the ability of the system to receive new, used beds to clean) at the shift (blue), daily (purple) and future (green) levels. Finally, the dotted line represents the maximum of these components and depicts the estimated throughput. The decomposition of the estimated throughput in Figure 2.5 shows that the backlog at the daily level is the predominant objective on Monday mornings. This translates to that the main concern for the operator on Monday mornings is to ensure that there will be sufficient space in the section holding the unclean beds to receive more used beds before the next day. The corresponding estimated throughput is around 28 (beds per hour), meaning that operators estimate that they have to work almost twice as fast as their baseline pace (15 beds per hour). Here the analysis of the entire week shows that the backlog's daily and future levels are the operators' main concerns.

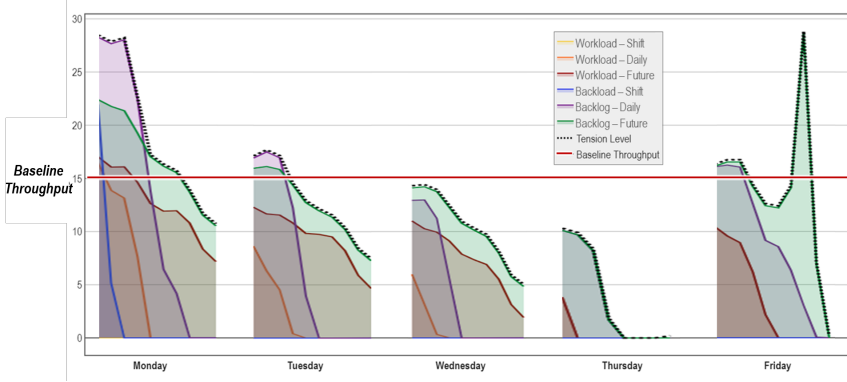


Figure 2.5: Decomposition of the estimated throughput into workload and backlog across the time horizons.

### 2.4.3.2 Use of the tension level

The primary goal of the tension level is to model the operators' discretionary decision of using a "hotel bed" cleaning or not. The tension level is directly correlated to the operators' estimated throughput. With the tension level indicator, it is now possible to compute the probability of a bed being hotel-cleaned. Let  $p(t)$  designate the ratio of beds being hotel cleaned. Given that, at reference pace, beds are cleaned using the two steamers' regular program lasting 6 minutes per bed, the following relation gives the ratio of hotel-cleaned beds needed to match the estimated throughput:

$$\begin{aligned} 6 \cdot \phi_0 &= (2 \cdot p(t) + 6 \cdot (1 - p(t))) \cdot \phi_t \\ p(t) &= 1.5 \cdot (1 - \phi_0 / \phi(t)) = 1.5 \cdot (1 - 1/\psi(t)), \quad \forall t \in T \end{aligned} \quad (2.7)$$

If the ratio is negative, no bed should be hotel cleaned. If the ratio is greater than one, all the beds should be hotel cleaned.

On the other hand, when the estimated throughput is lower than the reference one, operators tend -consciously or not- to slow down following Parkinson's law (see Parkinson and Osborn (1957)). From the estimated throughput, a 'slowdown' factor  $\sigma_t$ ,  $\forall t \in T$  can be computed. The time required to perform the tasks by the bed operators will then be multiplied by this factor represent-

ing the operators' adapted work pace.

$$\psi_t = \text{Min} \{1, \phi^{(t)}/\phi_0\} = \text{Min} \{1, \Psi_t\}, \forall t \in T \quad (2.8)$$

#### 2.4.4 System evaluation through measurement of key metrics

Several indicators have been used to measure the system's performance, including the computed tension level itself.

##### **Tension level indicator**

The tension level measures the pressure operators experience on the system. It is both an indicator of the quality of work as it is related to the probability of a bed being hotel cleaned and how difficult is the work for the operators. The lower the tension level, the more thorough the cleaning will be.

##### **Stockout probability**

The overall objective of the cleaning unit is to meet the demand for beds. When demand exceeds supply, stockouts occur. If the stockout occurs during the regular operator working hours, the patient is waiting for the bed to be cleaned. Outside regular working hours, other operators have to fill in to clean beds. The likeliness of a stockout is the indicator to measure the ability of the system to meet the demand.

##### **Bed waiting time**

From a patient-centric perspective, hospital management aims at delivering beds to patients in less than 15 minutes upon request. The distribution of the waiting time for a bed is the indicator used to measure the system service level performance.

##### **Bed fleet size: number of beds required to meet the demand**

The flow size corresponds to the number of beds the system needs to provide patients with beds within 15 minutes at all times. Using 15 minutes as a hard constraint, the flow size becomes an indicator of the system resource utilization.

## 2.5 Experimental Design

The proposed simulation-based approach has been developed, and continuously verified and validated, with the hospital management team and the bed operators.

The performance of the bed cleaning unit is closely tied to the bed flow situation within the hospital, including the availability of sterile beds, unclean beds inventory, the number of beds in use and patient arrivals. However, due to data constraints, it was not possible to obtain accurate initial conditions for the simulation. Therefore, the simulation runs were initiated with all beds being sterile and ready to use and no patients occupying the beds. To mitigate the potential bias introduced by this artificial starting condition, an initial warm-up period was established (see Subsection 2.5.1). This warm-up period is used to calibrate the tension level indicator, quantitatively validate the model, and determine the appropriate run length and number of replications.

### 2.5.1 Warm-up period

To determine the appropriate warm-up period for a simulation model, White (1997) and White et al. (2000) introduced MSER (Marginal Standard Error Rules) and MSER-m which are two heuristic approaches that find the best truncation point to eliminate the bias of initial conditions by reducing the marginal confidence interval around the truncated sample mean. Table 2.1 shows the results of the MSER-5 analysis of the proposed DES model with a run of ten replications over a 400-week period and a pool of 413 beds, corresponding to the hospital's current fleet. The MSER-5 analysis indicates that a 5-week warm-up period is sufficient for most indicators, but a 25-week warm-up period is optimal for the tension level indicator. As Table 2.1 illustrates, using a 25-week warm-up period does not significantly change the marginal 95% confidence interval width for all indicators compared to the optimal truncation point. Hence, a 25-week warm-up period is applied in all subsequent experiments.

Table 2.1: MSER-5 Analysis results

Indicator	Mean	Optimal			25 Weeks	
		Truncation	95% CI		95%CI	
Tension Level	1.27	25 weeks	$7.22 \cdot 10^{-3}$	0.57%	$7.22 \cdot 10^{-3}$	0.57%
Stockout Probability	$2.94 \cdot 10^{-4}$	5 weeks	$5.53 \cdot 10^{-5}$	18.79%	$5.70 \cdot 10^{-5}$	19.2%
Monday Stock	40.51	10 weeks	0.81	1.7%	0.82	1.74%
Tuesday Stock	68.99	5 weeks	1.04	1.22%	1.07	1.25%
Wednesday Stock	74.33	5 weeks	0.76	0.89%	0.78	0.92%
Thursday Stock	92.96	5 weeks	1.30	1.16%	1.33	1.19%
Friday Stock	123.84	5 weeks	0.75	0.55%	0.76	0.56%
Hotel Cleaning Proportion	0.29	5 weeks	$2.94 \cdot 10^{-3}$	1.02%	$3.02 \cdot 10^{-3}$	1.04%

### 2.5.2 Tension Level Calibration

The tension level is composed of three parameters: 1) the baseline throughput  $\phi_0$ , 2) the convexity  $\gamma$ , and 3) the exponential smoothing  $\alpha$ . The baseline throughput is the average number of beds that can be cleaned per hour under normal conditions. The baseline throughput was determined to be  $\phi_0 = 15$  beds per hour through on-site observations. The convexity must be greater than one and the smoothing value must be between zero and one. Various values for both parameters were tested ( $\gamma \in 1, 1.5, 2, \alpha \in 0.4, 0.6, 0.8$ ). The bed cleaning team has qualitatively validated that the tension level accurately reflects the system stress and that it leads to a realistic use of hotel beds.

The tension level significantly impacts the proportion of hotel-cleaned beds and it has been calibrated to match the average quantity of hotel-cleaned beds. For each pair of parameters ( $\alpha, \gamma$ ), we ran 100 replications of 12-week experiments with a 25-week warmup period and current 413-bed fleet size. We then compared the average proportions of hotel-cleaned beds for each pair with those observed within the manually recorded data from the operators over the 12-week period. Our operational data showed that 25.41% of beds were cleaned. We calculated a 95% confidence interval for the difference of means between simulation output and operational data, as shown in Table 2.2. The results indicate that the pair  $\gamma = 1.5$  and  $\alpha = 0.6$  offers the narrowest confidence interval centred around 0; thus, all future experiments and validation will be conducted using these values.

Table 2.2: Tension Level Calibration

$\alpha$	$\gamma$	Simulation Result		Difference of the Means	
		Mean	Std	95% <i>CI</i>	in % of mean
0.4	1.0	25.38	2.39	[-1.57, +2.20]	[-5.17%, +8.83%]
0.4	1.5	24.83	2.10	[-1.69, +1.52]	[-6.80%, +6.12%]
0.4	2.0	25.08	1.99	[-1.42, +1.73]	[-5.69%, +6.94%]
0.6	1.0	26.19	2.35	[-0.46, +2.99]	[-1.84%, +12.0%]
0.6	1.5	25.22	2.25	[-1.42, +1.58]	[-5.59%, +6.22%]
0.6	2.0	25.12	2.50	[-1.57, +1.97]	[-6.29%, +7.91%]
0.8	1.0	24.97	2.15	[-1.57, +1.68]	[-6.30%, +6.72%]
0.8	1.5	26.30	2.40	[-0.37, +3.13]	[-1.47%, +12.56%]
0.8	2.0	25.76	2.52	[-0.96, +2.64]	[-3.86%, +10.6%]

### 2.5.3 Model Validation

To quantitatively validate the accuracy of our model in representing the hospital's bed flow, we conducted a comparison between the average sterile bed stock in the morning generated by our simulation and the manually recorded data by the operators. Using the same simulation design as for the tension level calibration with 100-replication, 12-week experiment, Figure 2.6 displays the morning inventory levels from the simulation in grey, contrasted with the real manually recorded averages in red. A comprehensive comparison is presented in Table 2.3, where, as discussed in subsection 2.5.2, confidence intervals for means differences are computed for all weekdays. The results demonstrate the model's ability to accurately reproduce the morning stock from Monday to Thursday, with 0 falling within the centre of the means difference confidence intervals.

Table 2.3: Morning sterile inventory position - Means' Difference 95% confidence interval

Day	Real Mean	Simulation Result		Difference of the Means	
		Mean	Std	95% <i>CI</i>	in % of mean
Monday	39.33	40.50	4.53	[-2.14, +4.48]	[-5.43%, +11.4%]
Tuesday	66.92	68.99	4.98	[-1.67, +5.81]	[-2.49%, +8.69%]
Wednesday	77.92	74.33	6.92	[-7.85, +6.78]	[-10.08%, +0.87%]
Thursday	92.42	92.96	7.11	[-4.10, +5.19]	[-4.44%, +5.61%]
Friday	97.17	123.84	5.30	[+23.0, +30.4]	[+23.65%, +31.26%]

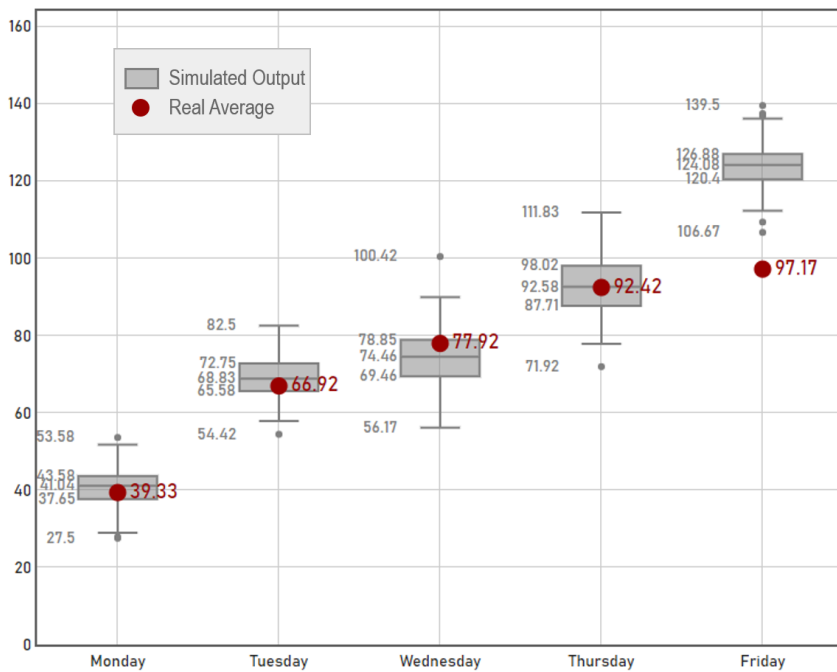


Figure 2.6: Comparison of the morning sterile inventory position from the simulation model (grey) and operational data (red).

However, a significant disparity exists between the simulation's Friday morning stock and the actual figures. The simulation tends to overestimate the Friday morning stock by 23 to 30 beds. Discussions with hospital management attribute this inconsistency to an increased demand for sterile beds from larger departments, such as the ED. This surge in demand is considered as over-ordering, driven by the perceived need to establish local safety buffer stocks mitigating the risk of stockouts. Consequently, the demand for beds no longer aligns with patient arrivals. This phenomenon is deemed undesirable by the management.

Unfortunately, no data is available to quantify this over-ordering phenomenon and the difference between bed demand and patient arrivals. We acknowledge that this Friday morning discrepancy hinders the quantitative accuracy of the model, especially given that stockouts tend to occur over the weekend or on Monday mornings. Ideally, obtaining a more precise measurement of the difference between actual demand and patient arrivals would enhance the model's accuracy. Given the inability to quantify this phenomenon and its undesirability, we have chosen to acknowledge its presence but not incorporate it into the simulation and to focus on mitigating stockouts, which are one of its causes.

Due to the limited operational data, the same 12 weeks of manually recorded data were used both for calibrating the tension level and validating the entire model. We acknowledge that this may lead to overfitting and provide an overly optimistic view of the model's validity. Ideally, with a larger dataset, calibration and validation could have been performed on separate datasets, mitigating that risk and providing a stronger validation.

#### **2.5.4 Estimation of the run length and number of replications**

The proposed simulation model requires a 25-week warm-up period. Robinson (2014) recommends to minimise the quantity of replications required, hence we employ a run length period of 104 weeks (2 years). A trial run with 100 replications and 104 weeks was conducted. The cumulative mean and the 95% confidence interval were computed for each indicator by gradually adding the replications. As illustrated in Figure 2.7 for the hotel cleaning propor-

tion example, the majority of convergence is achieved within the initial 25 replications. Table 2.4 presents the 95% confidence interval determined for all indicators, providing an estimation of their precision.

Table 2.4: Confidence interval after 25 replications

Indicator	Cumulative Mean	95% CI width	
Tension Level	1.21	$9.01 \cdot 10^{-3}$	0.74%
Stockout Probability	$2.92 \cdot 10^{-3}$	$6.22 \cdot 10^{-4}$	28.32%
Monday Stock	40.82	0,66	1.62%
Tuesday Stock	69.31	0,99	1.43%
Wednesday Stock	76,83	0,87	1.13%
Thursday Stock	93.11	0,86	0.92%
Friday Stock	122.89	0,44	0.36%
Hotel Cleanings	25,80%	$2.96 \cdot 10^{-3}$	1.15%

From Table 2.4, the confidence interval for the stockout probability is significantly wider than for the other indicators. This is because stockouts is an infrequent event. A single stockout can greatly impact the results of a replication, leading to a high level of variability. The current study estimates that more than 700 replications would be needed to reduce the 95% confidence interval for the stockout probability to 5%, (see Robinson (2014)). Despite the fact that the confidence interval for the stockout probability is notably wider, the number of replications was chosen to be 25, since it was found to be sufficiently accurate for all other indicators being considered in the study. The authors acknowledge that model replication precision can be deemed imprecise when it comes to the stockout probability, it is decided to be an acceptable trade-off given the high number of replications required to achieve a more narrow interval.

## 2.6 Computational results

The proposed simulation-based approach is composed of two stages. The first stage analyses the current situation using the suggested KPIs: stockout probability, tension level, and hotel cleaning probability. Using the learnings from the current situation, the second stage identifies adaptation levers and devises alternative scenarios.

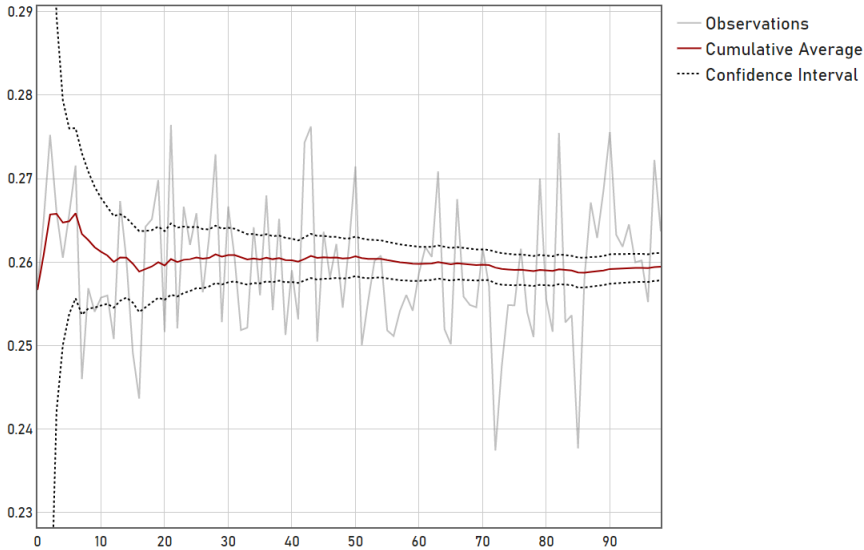


Figure 2.7: Hotel cleaning cumulative mean and confidence interval by number of replications

### 2.6.1 Performance Measurement and Implementation

Two experiments are conducted to measure all KPIs. The first experiment estimates the required number of beds by preventing stockouts. The second experiment measures the other KPIs using a fixed number of beds.

The first experiment begins with a minimal number of beds set to the hospital's capacity (290 beds). Beds are added to the system when patients arrive; no sterile beds are available within a 15-minute window. Although stockouts are infrequent, they occasionally occur on Monday mornings when demand is high. Additional beds can then be added to the system to measure the stockout magnitude, which is highly stochastic and dependent on patient arrival patterns. The final number of beds corresponds to the number needed to avoid stockouts. This experiment may not reflect real-world conditions, but it still gives a fair assessment of the necessary bed inventory. The hospital faces challenges with limited storage space and high costs associated with beds. Therefore, having the optimal number of beds to ensure smooth bed flow operations and minimize the risk of stockouts is a crucial goal for the

hospital.

In the second experiment, we set the number of beds to the average value determined from 25 replications of the first experiment, ensuring each scenario has an appropriate number of beds. This allows us to accurately compute the other KPIs using the same number of replications.

The DES simulation model and the tension level indicator of the current situation have been implemented using Anylogic (University Researcher version 8.7.2). The model was run on an Intel(R) Xeon(R) CPU X5660 5.80GHz processor with 16 GB of memory under Windows 10. The model run time for the full experiment with 25 weeks of warmup and 25 replications was 35 minutes.

### **2.6.2 First Stage: Analysis of the baseline scenario**

The simulation of the current situation highlighted the issues described by the bed operators when developing the model. The sterile stock on Monday mornings can be too low, leading to stockouts with a probability of 1.79% (90th percentile: 3.25%). Depending on the demand on Mondays, the sterile stock at the end of the operators' shift might not be sufficient, inducing stockouts Monday nights or Tuesday mornings. A complete overview of the KPIs from the baseline scenario can be seen in Table 2.6.

Figure 2.8a shows that patient arrivals often exceed the production of beds, particularly on Monday, Tuesday and Wednesday mornings. In 59.9% of the Morning hours (between 7 AM and 10 AM), more patients arrive than beds are cleaned. This imbalance indicates that the bed supply on Monday mornings frequently depends on the previous week's production and that a lack of safety cannot be compensated by production flexibility. On the other hand, the demand is lower in the afternoon than the production of sterile beds as shown in Figure 2.8b. Sterile stock to cover non-working periods (nights and weekends) is typically built in the afternoon. As a result, the sterile stock for peak demand must be built the working day before without knowing the exact demand. As seen in Figure 2.4, demand is highly variable and difficult to predict, resulting in significant fluctuations in sterile stock levels, see Table 2.5.

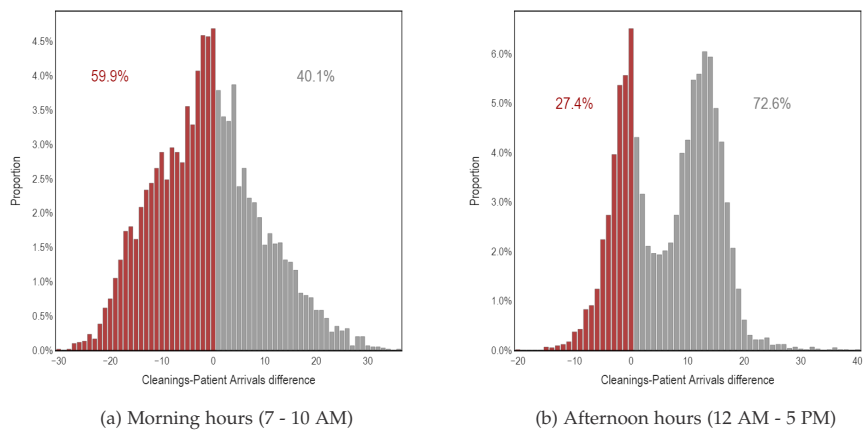


Figure 2.8: Distribution of the hourly difference between sterile beds production (cleanings) and patient arrivals

Table 2.5: Comparison between morning sterile inventory position and the number of hospitalisation

Day	Morning Stock (7AM)			Hospitalisation (Peak)		
	Min.	10%	Mean	Mean	90%	Max
Monday	0	27	40.43	19.41	25	47
Tuesday	0	39	67.89	18.75	23	47
Wednesday	0	49	73.97	16.24	19	48
Thursday	15	71	93.07	17.15	21	46
Friday	57	112	122.96	9.83	14	37

The system variability can also be seen in the number of beds required to avoid stockout, computed in the first experiment. Across the 25 replications, the number of beds needed fluctuates from 290 to 364, with a median of 323. The high values of the required bed fleet correspond to runs with stockouts of significant magnitude and the need for surplus capacity.

The relatively high demand on Monday mornings often results in operators resorting to hotel bed cleaning to keep up with demand. Over half of the beds are hotel cleaned on Mondays (57.25%). Operators use quality as a buffer for production, as described by Hopp et al. (2007). This need to clean beds faster can also be seen in the tension level, which is slightly above 1 on average and as high as 1.48 on Mondays.

The decomposition of the estimated throughput for the baseline scenario, shown in Figure 2.5, also identifies that the main tension points are on Monday mornings, when the sterile stock is low and the unclean one peaks, and on Fridays to leave the unit ready for the weekend. Figure 2.5 shows that, on Monday mornings, the main objective of the operators is to empty the unclean stock to receive new unclean beds before the end of the day. On Fridays, the operators want to leave the unclean section as empty as possible for the weekend. Extra hours on those days might help reduce the induced tension, whereas mid-weekdays are usually quiet.

### 2.6.3 Second Stage: Alternative scenarios

Different scenarios were proposed to improve the bed cleaning logistics using the analysis of the current situation. The goal of the proposed scenario is to add cleaning periods at strategic moments of the week to add production flexibility and adequate capacity.

- **EM** - Early Monday: One shift of 1 hour and 45 minutes with three operators added from 5 AM to 6:45 AM on Mondays
- **LM** - Late Monday: One shift of 1 hour and 45 minutes with three operators added from 3:15 PM to 5:00 PM on Mondays

- **LF** - Late Friday: One shift of 1 hour and 30 minutes with three operators added from 4:30 PM to 6:00 PM on Fridays
- **WE** - Weekend: One shift of 4 hours with three operators added from 10:00 AM to 2:00 PM on Saturdays
- **EMLF** - Early Monday Late Friday: A combination of the EM and LF scenarios. One shift of 1 hour and 45 minutes with three operators added from 5 AM to 6:45 AM on Mondays and another shift of 1 hour and 30 minutes with three operators added from 4:30 PM to 6:00 PM on Fridays
- **HP** - Intermediate scenario proposed by the hospital management team: One morning shift of 45 minutes with three operators added from 6 AM to 6:45 AM on Mondays and a late shift from 3:15 PM to 5:00 PM also added on Mondays alongside a short shift from 3 PM to 4 PM on Fridays.

The results of the different scenarios are presented in Table 2.6. For any given indicator, the average value observed in the 300 replications is given with the 10<sup>th</sup> and 90<sup>th</sup> percentile to compare the general behaviour and robustness of the system.

Table 2.6 shows that the WE scenario, adding 4 hours of work for three operators at the weekend, offers the greatest improvements. The stockout probability is reduced by a factor of six, the hotel cleaning probability by three, and the probability of a patient waiting for a bed for more than 15 minutes is less than 1/10 of the baseline scenario going, corresponding to less than one patient per year. On top of reducing the risk of a patient not getting a bed in time, the average tension level is reduced to 0.56, meaning that the operators estimate their average pace to be 8.4 beds per hour. Figure 2.9 compares the weekly-aggregated average tension level of the different scenarios. The lowest line, corresponding to the WE scenario, returns a tension level below one for Monday mornings and the first two hours of Tuesday. A low tension level is a sign of the added flexibility that operators have to face demand fluctuations. This flexibility gives stability to the system resulting in a reduced variance for all indicators as shown by the reduced 10<sup>th</sup> and 90<sup>th</sup> percentiles ranges in Table 2.6.

Table 2.6: Comparison of the main indicators for the different scenarios

	Cu.	EM	LM	LF	WE	EMLF	HP
<i>Bed Waiting Time</i>							
Av.	1'01 1'00	1'57 1'57	1'01 1'02 1'01	1'00 1'01 1'59	1'57 1'57 1'57	1'57 1'57 1'57	1'57 1'58 1'57
15 min + (Patients per year)	38.10 105.30 0.00	4.54 10.10 0.00	32.89 82.10 0.00	24.82 80.90 0.00	2.08 3.07 0.00	1.12 2.78 0.00	7.09 18.78 0.00
<i>Stockout Probability</i>							
Monday	1.79% 3.25 0.00	0.04% 0.00 0.00	1.48% 4.17 0.00	1.56% 2.72 0.00	0.04% 0.00 0.00	0.05% 0.00 0.00	0.47% 1.00 0.00
Tuesday	0.04% 0.00 0.00	0.28% 1.08 0.00	0.00% 0.00 0.00	0.08% 0.00 0.00	0.16% 0.92 0.00	0.20% 0.92 0.00	0.08% 0.00 0.00
Wednesday	0.00% 0.00 0.00	0.04% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.04% 0.00 0.00	0.04% 0.00 0.00	0.04% 0.00 0.00
Thursday	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00
Friday	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00
Saturday	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00
Sunday	0.04% 0.04 0.00	0.08% 0.00 0.00	0.00% 0.00 0.00	0.04% 0.00 0.00	0.00% 0.00 0.00	0.04% 0.00 0.00	0.12% 0.92 0.00
Av.	1.85% 3.67 0.00	0.36% 0.92 0.00	1.48% 4.17 0.00	1.60% 2.88 0.00	0.24% 0.92 0.00	0.29% 0.92 0.00	0.71% 2.05 0.00
<i>Average Tension Level</i>							
Monday	1.48 1.51 1.43	1.02 1.05 0.95	1.18 1.24 1.16	1.29 1.33 1.27	0.90 0.90 0.88	0.94 0.98 0.94	0.92 0.95 0.91
Tuesday	0.82 0.83 0.79	0.70 0.73 0.69	0.74 0.76 0.72	0.77 0.79 0.76	0.70 0.73 0.68	0.70 0.71 0.68	0.65 0.67 0.63
Wednesday	0.69 0.72 0.67	0.60 0.62 0.57	0.64 0.65 0.60	0.63 0.65 0.62	0.59 0.61 0.57	0.56 0.59 0.55	0.53 0.54 0.49
Thursday	0.88 0.90 0.84	0.80 0.82 0.77	0.83 0.85 0.80	0.76 0.79 0.75	0.61 0.62 0.58	0.72 0.76 0.70	0.77 0.78 0.75
Friday	1.15 1.20 1.08	0.61 0.63 0.55	1.15 1.22 1.08	1.27 1.35 1.20	0.35 0.38 0.32	0.57 0.59 0.51	0.91 0.97 0.83
Saturday	0.00 0.00 0.00	0.00 0.00 0.00	0.00 0.00 0.00	0.00 0.00 0.00	0.51 0.60 0.42	0.00 0.00 0.00	0.00 0.00 0.00
Sunday	0.00 0.00 0.00	0.00 0.00 0.00	0.00 0.00 0.00	0.00 0.00 0.00	0.00 0.00 0.00	0.00 0.00 0.00	0.00 0.00 0.00
Av.	1.01 1.03 0.88	0.75 0.82 0.67	0.91 1.05 0.83	0.94 1.09 0.87	0.61 0.68 0.57	0.70 0.81 0.66	0.76 0.88 0.71
<i>"Hotel Cleaning" proportion</i>							
Monday	57.25% 59.01 53.22	24.67% 26.12 23.01	34.96% 36.92 33.34	51.04% 53.72 49.80	21.95% 24.01 20.12	22.94% 24.54 21.25	14.52% 15.22 12.76
Tuesday	13.78% 14.54 11.76	8.56% 9.67 7.79	11.02% 11.92 9.45	12.23% 14.32 11.67	8.66% 9.87 7.57	7.99% 9.28 7.07	5.54% 6.95 4.46
Wednesday	5.22% 6.54 4.65	2.56% 3.56 1.99	4.27% 5.68 3.65	4.98% 6.06 3.88	2.72% 3.41 2.11	2.57% 3.32 1.81	1.87% 2.45 1.19
Thursday	14.34% 15.77 12.23	10.71% 12.05 9.45	13.79% 15.52 11.26	9.98% 11.36 8.45	1.88% 2.69 1.13	7.66% 9.32 6.45	9.28% 10.58 7.95
Friday	19.78% 21.60 16.89	7.56% 9.32 5.75	20.35% 23.01 18.75	11.12% 12.45 8.89	0.34% 0.88 0.00	4.17% 5.27 2.88	11.01% 13.04 9.27
Saturday	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	5.91% 8.33 4.22	0.00% 0.00 0.00	0.00% 0.00 0.00
Sunday	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00	0.00% 0.00 0.00
Av.	25.80% 30.04 22.89	12.32% 14.62 10.45	18.04% 21.22 16.56	20.28% 24.42 18.82	7.81% 9.27 6.81	10.45% 12.98 9.22	8.78% 11.28 7.52
<i>Required number of beds</i>							
	322 364 298	292 294 290	324 344 303	316 335 294	292 295 290	291 294 290	293 299 290

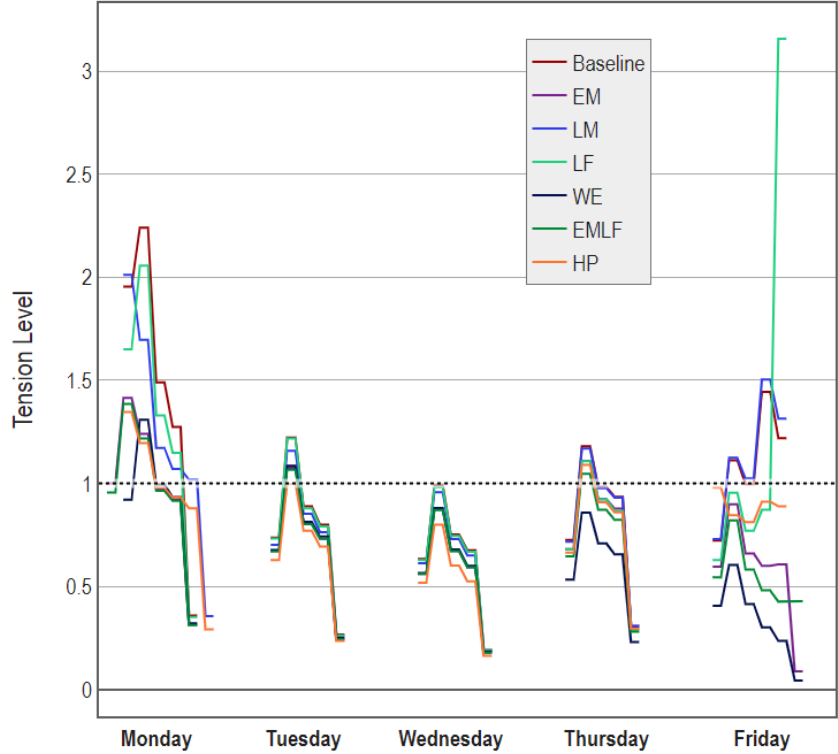


Figure 2.9: Comparison of the average Tension Level across the week for the different scenarios studied

The studied scenarios show that extra work hours building stock ahead of the Monday rush (EM, EMLF, and WE) are the most effective means to reduce both stockout risk and tension level throughout the week. The intermediate scenario proposed by the hospital performs better than the current situation but is less efficient than the EM, EMLF or WE scenarios. In the hybrid scenario, the small amount of added hours smoothen the Monday peak and stagger the risk and tension across the rest of the week. However, the change only provides little flexibility.

The Late Monday Late Friday scenario does not provide significant improvement. The impact of both scenarios on the Monday morning rush is limited, as shown in the tension level (Figure 2.9). The inventory level of clean beds on Friday night is as high as possible. Adding extra hours Friday night only delays the last moment the stock will be full before the weekend. However, the demand on Friday nights is relatively small (under 4 beds per hour). The extra stock built to face the Monday peak is thus limited.

## **2.7 Conclusions and further research**

Efficient bed logistics is a requirement for a well-performing hospital. We developed a DES model to improve the back-end of the hospital bed cycle to ensure a stable supply of beds. Hospitals are resource-constrained, stressful environments where human operators play a pivotal role in the back-end processes. To model how operators' behaviours impact the system, we developed a tension level indicator to measure the work-induced stress on the operators. This indicator is incorporated into the DES model to replicate the operators' decision process and have a decision support tool corresponding to the actual bed cleaning unit of the use case.

The proposed model highlighted the main shortcomings of the current organisational setup at the case hospital. The operators' work schedule limits the number of beds cleaned per week and reduces the system's surplus capacity and flexibility. The lack of anticipation of the demand peaks adds stress to the system, which, combined with the excessive bed fleet and flexibility deficiency, can lead to stockouts. The proposed tool allows testing different scenarios to

increase flexibility and improve resource usage. By reorganising the work schedule, we showed that it is possible to reduce the stockout risk by a factor of ten and reduce the bed fleet size by 10%. After completing this project, the hospital implemented an adapted work schedule following the proposed ideas. During the year and a half since implementing the new schedules, the hospital has not experienced any stockouts.

It is well-known that the workload impacts the stress, performance, and health of the operators (see Bakker et al. (2005), Delasay et al. (2019)). The proposed tension level indicator suggests a quantitative measure to gauge such stress. In addition to the direct learnings from measuring the stress experienced and the perceived working environment conditions, we believe that it is valuable to be able to incorporate quantitative measurements inside analytical studies to better understand and replicate human operators' behaviour. We believe that the indicator proposed in this paper is an efficient way of modelling the operators' bias and its impact on their discretionary decisions inside a DES model. This indicator-based approach could be used to design efficient DES models of systems where human-based decisions play an important role. Systems, in which employees can adapt the capacity to meet the demand (e.g. by opening additional production lines or counters), or decide to refuse or delay customers if they believe they will not be able to serve them on time, could use similar indicator-based approaches to model operators' decisions.

Hospitals are often built around their care departments that tend to act as independent silos. The information sharing between departments and the back-end support units, such as the bed cleaning unit, is often lacking and can be significantly improved. The bed logistics system would benefit from more information sharing and real-time information on the demand. Operators' decisions could then be based on actual figures and thus be more realistic. Further research on real-time demand data may provide a basis for more efficient and dynamic schedules for the operators leading to improved resource management and better monitoring of risks. Additionally, the bed ordering policies and practices often differ across departments and depend on the trust the operators have in the hospital bed logistics system. Further research on more integrated approaches to bed ordering could lead to more transparency and more reliability which may improve the flow of beds.

## Bibliography

- Andersen, A. R., Nielsen, B. F., and Reinhardt, L. B. (2017). Optimization of hospital ward resources with patient relocation using markov chain modeling. *European Journal of Operational Research*, 260(1):1152–1163.
- Azriel, D., Feigin, P. D., and Mandelbaum, A. (2019). Erlang-s: A data-based model of servers in queueing networks. *Management Science*, 65(10):4607–4635.
- Bailey, N. T. J. (1954). Queueing for medical care. *Journal of the Royal Statistical Society: Series C (applied Statistics)*, 3(3):137–145.
- Bakker, A. B., Demerouti, E., and Euwema, M. C. (2005). Job resources buffer the impact of job demands on burnout. *Journal of Occupational Health Psychology*, 10(2):170–180.
- Baru, R. A., Cudney, E. A., Guardiola, I. G., Warner, D. L., and Phillips, R. E. (2015). Systematic review of operations research and simulation methods for bed management. *Iie Annual Conference and Expo 2015*, pages 298–306.
- Becker-Peth, M. and Thonemann, U. W. (2019). Behavioral inventory decisions: The newsvendor and other inventory settings. *Handbook of Behavioral Operations*, pages 393–432.
- Brailsford, S. C., Harper, P. R., and Patel, B. (2009). An analysis of the academic literature on simulation and modelling in health care. *Journal of Simulation*, 3(3):130–140.
- Brailsford, S. C., Harper, P. R., and Sykes, J. (2012). Incorporating human behaviour in simulation models of screening for breast cancer. *European Journal of Operational Research*, 219(3):491–507.
- Cevik Onar, S., Oztaysi, B., and Kahraman, C. (2018). A comprehensive survey on healthcare management. *International Series in Operations Research and Management Science*, 262:23–51.
- Delasay, M., Ingolfsson, A., and Kolfal, B. (2016). Modeling load and overwork effects in queueing systems with adaptive service rates. *Operations Research*, 64(4):867–885.

- Delasay, M., Ingolfsson, A., Kolfal, B., and Schultz, K. (2019). Load effect on service times. *European Journal of Operational Research*, 279(3):673–686.
- Gimenez-Mallor, F., Blanco, R., and Azcarate, C. (2007). Combining linear programming and multiobjective evolutionary computation for solving a type of stochastic knapsack problem. *Evolutionary Multi-criterion Optimization. 4th International Conference, Emo 2007. Proceedings (lecture Notes in Computer Science Vol.4403)*, pages 531–45.
- Goodwin, P., Moritz, B., and Siemsen, E. (2019). Forecast decisions. *Handbook of Behavioral Operations*, pages 433–458.
- Hagen, M. S., Jopling, J. K., Buchman, T. G., and Lee, E. K. (2013). Priority queuing models for hospital intensive care units and impacts to severe case patients. *Annual Symposium Proceedings / Amia Symposium. Amia Symposium*, 2013:841–850.
- Hall, R. (2012a). Bed assignment and bed management. *International Series in Operations Research and Management Science*, 168:177–200.
- Hall, R. (2012b). Matching healthcare resources to patient needs. *International Series in Operations Research and Management Science*, 168:1–9.
- He, L., Chalil Madathil, S., Oberoi, A., Servis, G., and Khasawneh, M. T. (2019). A systematic review of research design and modeling techniques in inpatient bed management. *Computers and Industrial Engineering*, 127:451–466.
- Holm, L. B., Luras, H., and Dahl, F. A. (2013). Improving hospital bed utilisation through simulation and optimisation with application to a 40% increase in patient volume in a norwegian general hospital. *International Journal of Medical Informatics*, 82(2):80–89.
- Hopp, W. J., Iravani, S. M., and Yuen, G. Y. (2007). Operations systems with discretionary task completion. *Management Science*, 53(1):61–77.
- Hulshof, P. J., Boucherie, R. J., van Essen, J. T., Hans, E. W., Hurink, J. L., Kortbeek, N., Litvak, N., Vanberkel, P. T., van der Veen, E., Veltman, B., Vliegen, I. M., and Zonderland, M. E. (2011). Orchestra: An online reference database of or/ms literature in health care. *Health Care Management Science*, 14(4):383–384.
- Hulshof, P. J., Kortbeek, N., Boucherie, R. J., Hans, E. W., and Bakker, P. J. (2012). Taxonomic classification of planning decisions in health care: a structured review of the state of the art in or/ms. *Health Systems*, 1(2):129–175.

- Ibanez, M. R., Clark, J. R., Huckman, R. S., and Staats, B. R. (2018). Discretionary task ordering: Queue management in radiological services. *Management Science*, 64(9):4389–4407.
- Jacobs, F. R. and Chase, R. B. (2014). *Operations and supply chain management*. McGraw-Hill Education,.
- Kc, D. S. and Terwiesch, C. (2009). Impact of workload on service time and patient safety: An econometric analysis of hospital operations. *Management Science*, 55(9):1486–1498.
- Lee, H. L., Padmanabhan, V., and Whang, S. (2004). Information distortion in a supply chain: The bullwhip effect. *Management Science*, 50(12):1875–1886.
- OECD (2021). OECD Health Statistics 2021. [https://stats.oecd.org/Index.aspx?DatasetCode=HEALTH\\_STAT](https://stats.oecd.org/Index.aspx?DatasetCode=HEALTH_STAT).
- OECD and European Union (2020). Health at a glance: Europe 2020. <https://www.oecd-ilibrary.org/content/publication/82129230-en>.
- Parkinson, C. N. and Osborn, R. C. (1957). *Parkinson's law, and other studies in administration*, volume 24. Houghton Mifflin Boston.
- Robinson, S. (2014). *Simulation: The Practice of Model Development and Use, 2nd edition*. Bloomsbury Publishing.
- Schmidt, U. and Zank, H. (2008). Risk aversion in cumulative prospect theory. *Management Science*, 54(1):208–216.
- Shunko, M., Niederhoff, J., and Rosokha, Y. (2018). Humans are not machines: The behavioral impact of queueing design on service time. *Management Science*, 64(1):453–473.
- Wakker, P. P. (2010). *Prospect theory: For risk and ambiguity*. Cambridge university press.
- White, K. P. (1997). An effective truncation heuristic for bias reduction in simulation output. *Simulation*, 69(6):323–334.
- White, K. P., Cobb, M. J., and Spratt, S. C. (2000). A comparison of five steady-state truncation heuristics for simulation. *2000 Winter Simulation Conference Proceedings (cat. No.00ch37165)*, 1:755–60 vol.1.

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### 3 | Improving Hospital Sterilisation Processes: a Comprehensive Simulation Model of the Integrated Reusable Medical Devices Cycle

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**Abstract** Hospitals are under increasing pressure to provide a steady and sufficient supply of sterile medical devices to meet patient needs while minimising the risk of healthcare-associated infections. Inefficient sterilisation processes can disrupt surgeries and hospital operations, leading to direct and indirect costs. Our study proposes a comprehensive discrete-event simulation model that accounts for all aspects of a hospital's Reusable Medical Device (RMD) flow, including surgery and outpatient schedules and the Central Sterilisation Service (CSS). This approach, of going beyond hospital department barriers and incorporating all the involved resources, is crucial for achieving high service levels and cost efficiency, aligning with the integral capacity planning paradigm in healthcare. The model considers RMDs as a resource of the sterilisation system and incorporates base stock dimensioning to identify improvement areas not visible with a CSS-only perspective. The approach enables testing of various improvements and changes in demand to reflect potential changes in hospital surgical capacity. Applying the approach to a Dutch hospital we revealed an RMD base stock imbalance not identified by a CSS-only analysis and proposed a base-stock dimensioning heuristics reduced surgical and outpatient clinic disruptions by 66.1%, using 231 fewer trays, leading to a 7.9% reduction in the total RMD fleet. Our approach provides a valuable tool for optimising RMD flow, reducing disruptions, and minimising inventory costs.

**Keywords:** *Integral Planning, Hospital Sterilisation, Simulation, Healthcare Management, RMD Cycle, Base Stock Optimisation*

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### 3.1 Introduction

Hospitals face increasing pressure to manage rising numbers of patients and procedures (OECD, 2021; OECD and European Union, 2020). To meet this demand, hospitals must ensure a steady and sufficient supply of sterile medical devices, which can be either disposable or RMD requiring sterilisation between uses. Sterilisation can be centralised, outsourced, or pooled (Tlahig et al., 2013; World Health Organization, 2016), but regardless of the approach, it must maintain high quality and efficiency to ensure an adequate supply of devices for all procedures and prevent the spread of healthcare-associated infections which affect hundreds of millions of people every year (World Health Organization, 2016). Inefficient sterilisation processes may disrupt up to 12% of surgeries due to the lack of supply of surgical tools (Rupnik et al., 2019).

Surgery departments consume a significant portion of a hospital's budget, and asset-related costs such as the usage and sterilisation of RMDs contribute to this (Van De Klundert et al., 2008). As many countries seek to reduce healthcare expenditures, efficient resource usage is crucial. The sterilisation process of RMDs should ensure a high service level with optimal resource allocation for cost efficiency.

This paper aims at understanding and improving the RMD flow in a hospital to ensure the supply of sterile instruments. We are motivated by a case study of a medium-sized Dutch hospital. Facing future hospital expansions, the management requested a thorough evaluation of the current sterilisation activities, including an assessment whether or not the current sterilisation capacity is sufficient, and whether or not the current sterilisation facility could be organised more efficiently, without losing quality. To this end, we develop several indicators that both consider efficiency and quality of service.

The RMDs constitute a transversal resource for the hospital, and are used throughout the hospital in a closed-loop cycle from sterile storage to Operating Rooms (ORs) or outpatient clinics, to the sterilisation facility, and back to storage. To effectively manage this cycle, it is essential to analyse and model all components of the system, rather than solely focusing on the sterile storage area. This approach aligns with the Integral Capacity Management paradigm proposed by Schneider (2020), which emphasises the need for comprehensive

analysis of hospital resources.

Our study presents a comprehensive Discrete Event Simulation (DES) model of a hospital's RMD flow, which takes into account all the components of the RMD cycle, beyond the sole analysis of the CSS alone. Building on prior work such as Di Mascolo and Gouin (2013) and Rupnik et al. (2019), our model incorporates the surgical schedule and the demand for RMDs in the outpatient clinic. This allows us to evaluate the system's performance in terms of its impact on hospital activities, with the aim of minimising disruptions to surgical or clinical procedures. We also introduce a novel surgery generation procedure to replicate the surgical schedule, which heavily influences the inflow of RMDs to the sterilisation department (Dobson et al., 2015; Rupnik et al., 2019). To our knowledge, this is the first time such a procedure has been included in a DES model of the RMD cycle. Our comprehensive approach enables us to consider RMDs as a resource of the system and incorporate base stock dimensioning into our analysis, which has been studied previously but never integrated into an analysis of the RMD cycle of a hospital.

In what follows we review the existing literature in Section 3.2. In Section 3.3, we formulate the problem and present the application hospital. Our model-building approach is presented in Section 3.4, and the experimental results are discussed in Section 3.5. In Section 3.6, we summarise our findings, draw conclusions, and discuss potential future work.

## **3.2 Literature review**

Hospital sterilisation flow refers to the series of operations that are necessary to provide sterile surgical tools to operating theatres. Tools are categorised as single-use tools, such as needles or catheters, and multiple-use tools, such as surgical forceps, endoscopes, and stethoscopes. They arrive at the hospital either packaged or unpackaged, requiring pre-cleaning before use. The multiple-use tools are further divided into processing stock with all the tools required to support the hospital's regular activities, and replacement stock, which includes safety stock and stock to replace broken or worn-out tools from the processing stock as Fineman and Kapadia (1978) explains.

We focus on multiple-use tools, referred to as RMDs, which require sterilisation after use. The sterilisation process starts with rinsing and cleaning, which is often done by hand. Next, the RMDs are disinfected in specialised disinfection machines. The RMDs are then inspected for any potential damage or need for replacement before being sterilised in autoclaves. This step ensures that all remaining microorganisms are killed, ensuring the RMDs are safe for storage and use in the hospital (Di Mascolo and Gouin, 2013; Lin et al., 2008; Ozturk et al., 2010; Van De Klundert et al., 2008). This sterilisation process can be either in-housed in a CSS Di Mascolo and Gouin (2013); Lin et al. (2008), outsourced Diamant et al. (2018), or pooled between several hospitals in a network Di Mascolo and Gouin (2013); Tlahig et al. (2013).

The sterilisation department's goal is to supply the demand for sterile tools, determined by amongst others the surgical schedule. Surgery scheduling is one of the most studied fields of healthcare Operations Research. Cardoen et al. (2010), Demeulemeester et al. (2013), Samudra et al. (2016), and Zhu et al. (2019) provide extensive literature reviews on this topic. Demeulemeester et al. (2013) and Samudra et al. (2016) highlight that although numerous approaches to surgery scheduling have been proposed, only a limited share of them considered downstream integration of other hospital departments. Furthermore, the literature on upstream integration is even more scarce. Some approaches consider the nursing wards, the Intensive Care Unit (ICU), or the Post Anaesthesia Care Unit (PACU) when building the Master Surgical Schedule (MSS). E.g., Beliën and Demeulemeester (2007), Beliën et al. (2009), Fügener et al. (2014) and Schneider et al. (2020) use the bed occupancy of these departments in their objective function. Latorre-Núñez et al. (2016) include the ICU and PACU resources availability as a constraint for the MSS. Moosavi and Ebrahimnejad (2018, 2020) introduces bed wards capacity as a constraint to the MSS in both upstream and downstream departments. Calegari et al. (2020) includes upstream surgical resource availability, such as surgical RMDs and teams, but do not optimize the RMD flow, as the resources are assumed to be available at the start of the shift. To the best of our knowledge, the literature does not yet consider the impact of the sterilisation flow, through the availability of surgical tools, on the surgical schedule. However, Rupnik et al. (2019) showed that the insufficient supply of surgical tools could significantly disrupt the operating theatres' daily operations, e.g., through delays or cancellations of surgeries.

The literature on the sterilisation department in Operations Management (OM) and Operations Research (OR) is broadly classified into three categories: tray design, inventory management, and flow analysis/optimisation.

A large part of the literature dedicated to the sterilisation department focuses on the design of trays. The RMDs are often grouped in specialised trays, to improve the operational efficiency, system cost and quality of care Cardoen et al. (2015). These trays contain several tools and are the base unit of the sterilisation flow. The tools arrive in one tray and leave in the same tray. They might temporarily disintegrate to RMDs through the process for specific cleaning procedures (hollow tools, for example), but get reassembled in trays right after. Cardoen et al. (2015) proposed that the grouping of RMDs in trays could be formulated as an NP-hard set-covering problem, and various cost-optimisation-based packing strategies have been proposed Cardoen et al. (2015); Dobson et al. (2015); Reymondon et al. (2006, 2008). Moreover, Dobson et al. (2015) noted that the optimal setting of the trays depends on the surgical schedule. Reymondon et al. (2007) studied the delayed differentiation of trays. Generic trays are used but could be specialised for specific procedures during the sterilisation process; specialisation must happen after the disinfection but before the sterilisation, requiring a dedicated stock. These procedures, however, do not solve the stock dimensioning problem. Dobson et al. (2015) consider the total inventory for each instrument to be the maximum of the demand for this instrument across the period considered, preventing any stock-out, while in a similar fashion Cardoen et al. (2015); Reymondon et al. (2006, 2008) consider the instruments always available and solely focus on finding the optimal set covering to minimise cost.

In terms of inventory management, research has focused on optimising surgical tool stock levels to minimise purchasing and holding costs, such as in the work of Fineman and Kapadia (1978). Van De Klundert et al. (2008) optimised the arrival of sterile trays from an inventory management perspective. Using Markov chains, Diamant et al. (2018) developed an approach that calculates the service level for different instrument base stocks in an outsourced sterilisation setup, where RMDs are sent for sterilisation and become available again 2 days later. Other inventory approaches, such as those by Little and Coughlan (2008), Bijvank and Vis (2012), and Guerrero et al. (2013), considered service levels and hospital-specific constraints but are not specifically designed for RMDs and would need to be adapted to take into account the circular nature

of the RMD flow. To the best of our knowledge, no previous approach has considered the entire RMD cycle, specifically the sterilisation process, when determining the appropriate levels of instruments and/or tray base stocks.

A third stream of research in the field of sterilisation focuses on flow analysis and optimisation. Di Mascolo and Gouin (2013) and Lin et al. (2008) proposed simulation modelling approaches to reduce the sterilisation time, from tray arrival in the CSS to sterile storage. Rupnik et al. (2019) used simulation models to evaluate the system's ability to meet surgical demand in terms of tray availability and surgical schedule perturbations (delays and cancellations). Rupnik et al. (2019) used historical data from the busiest 3-month period of the hospital's surgery schedule as input. However, the models proposed by Lin et al. (2008) and Rupnik et al. (2019) only measured the CSS's performance given a historical surgical schedule. This means that adjustments are only found retrospectively, and a more generic model is needed to devise and validate improvements. Di Mascolo and Gouin (2013) modelled the number of surgeries and the number of trays used as Poisson processes, but due to a lack of data, the tray and surgery type could not be specified. This means that the proposed model could not use the surgical schedule to plan and optimise the sterilisation operation.

As up to 90% of surgeries are typically scheduled more than a day in advance Reymondon et al. (2007), and the entire sterilisation procedure takes around 4 hours, the surgery schedule can be used when planning the sterilisation flow to increase tray availability. Following this principle, Rossi et al. (2013) and Ozturk et al. (2010) modelled the sterilisation flow as a job scheduling problem reducing the makespan similarly to Di Mascolo and Gouin (2013). As the sterilisation flow is a closed loop where surgeries set the availability of trays to be cleaned and the demand for sterilised trays, cycle time improvements can benefit tray availability. However, this heavily depends on the nature of the demand and the specific trays needed. Rupnik et al. (2019) proposes to adjust the surgery schedule to reduce CSS bottlenecks, RMD stock-outs, and subsequently, surgery perturbations.

Our approach aims to build a generic simulation model for the sterilisation flow. By modelling the entire flow of RMDs, our approach allows for considering trays and RMDs as resources and optimising their base stock in the same way as one would optimise the number of machines or operators. Ad-

ditionally, by incorporating the surgical schedule into the model, we are able to prioritise tray cleaning and generate surgeries, taking into account the dependency between tray arrivals - a novel aspect not previously addressed in the literature. The proposed surgical generation process also allows for generating long runs and different replications, assessing the effect of demand stochasticity and, therefore, generating more accurate insights. Building on Rupnik et al. (2019), our goal is to improve the sterilisation process but in a more integrated and holistic manner, including the surgeries, and the inventory management to the analysis of the CSS

### **3.3 Problem formulation**

This research is conducted at the Diaconessenhuis, a medium-sized hospital in Utrecht, the Netherlands. This hospital has approximately 500 beds, and an in-house CSS. The motivation underlying this research is threefold. First, the operators of the CSS experience high working pressure at peak hours. Second, the hospital plans to increase the number of surgeries, resulting in a higher workload for the CSS. Third, the CSS management thinks that stock levels are not properly aligned with the usage of trays. In this section, we will conceptualise the RMD cycle in terms of layout and flow (Section 3.3.1), resources (Section 3.3.2), and performance measurement (Section 3.3.3).

#### **3.3.1 Facility layout and sterilisation flow**

We focus on the layout of the CSS facility of the hospital under study. The sterilisation process of this hospital is in-housed and resembles the layout of in-house CSSs in general (Tlahig et al., 2013). The CSS facility consists of three compartments: a decontamination space, a preparation and packing space, and storage. The decontamination space and preparation space are physically separated with trays moving from one to another via disinfection machines. Similarly, the preparation space and storage are physically separated, with trays moving from one to another via autoclaves. The CSS facility is designed such that the risk of contamination is minimised as described by the World Health Organization (2016) report on Decontamination and Reprocessing of

Medical Devices for Health-care Facilities. The layout of the CSS is visualised in Figure 3.1.

Surgical trays are requested from storage and used for surgery or at the out-patient clinic, after which they are sent to the CSS to be cleaned and restocked. The trays arrive in the decontamination space. The sterilisation process is composed of several subsequent steps. First, the trays are disassembled into RMDs and pre-cleaned, either manually or automatically, to remove coarse dirt from the RMDs. These steps are performed in the decontamination space. Following pre-cleaning, the RMDs are washed in disinfection machines, after which the trays are moved to the preparation space. The RMDs are subsequently manually assembled in their correct tray configurations. The assembly stage includes a check of all tools for maintenance and/or replacement in case of damage as explained by Fineman and Kapadia (1978). The trays are then manually wrapped in special paper and sterilised in autoclaves. Afterwards, the trays are restocked in the storage facility.

Although the described process is similar for most CSS facilities, there are local differences. In the hospital under study, there are two such exceptions. First, the hospital has a subsidiary location without a CSS. The trays from this location are transported to the main CSS facility in batches. Second, not all trays can be combined in one disinfection machine charge. Trays used for eye surgery and for anaesthetic purposes are disinfected separately.

### 3.3.2 Resources

The resources of the RMD cycle consist of surgical trays, machines, workstations, and staff. The staff is divided into two teams: one working in the preparation space (pre-cleaning) and the other in the decontamination space (post-cleaning). In general, all staff members are multi-skilled and can perform every task, but transitioning between both spaces requires changing clothes for hygienic reasons. To minimise the number of transitions between the preparation and decontamination spaces on one day, an employee should not make many of those transitions.

Pre-cleaning is performed manually by a pre-cleaning operator at a dedicated

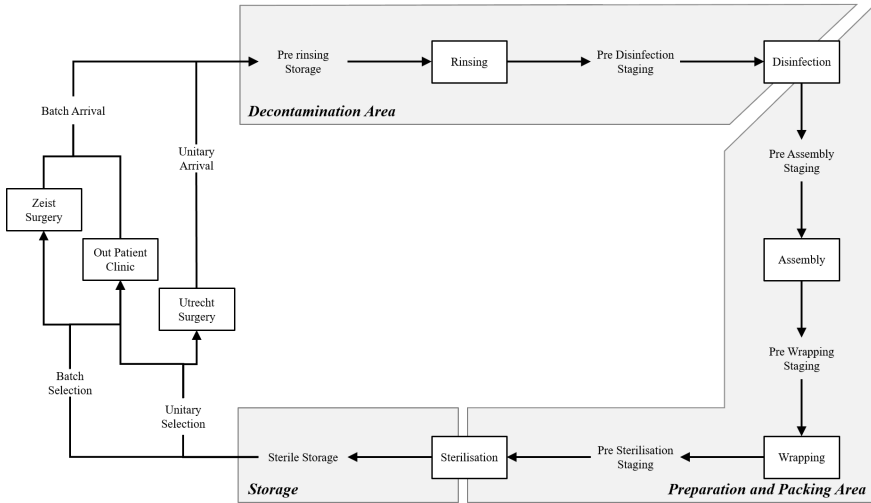


Figure 3.1: Conceptual model of the sterilisation process.

workstation. The fully automated disinfection machines, located between the decontamination and preparation spaces, only require manual interaction for loading and unloading.

After unloading by a post-cleaning operator, all RMDs are manually checked for damage and scanned, before being assembled into the trays on a dedicated workstation. The assembled trays are then manually wrapped on another dedicated workstation. Sterilisation is fully automated and performed by autoclaves located between the preparation space and the storage.

### 3.3.3 Performance measurement

Our proposed approach focuses on evaluating the performance of the RMD cycle within the hospital. The goal of the RMD cycle is to ensure that surgeries proceed as planned. To measure its success, three Key Performance Indicators (KPIs) are used that reflect the impact on the surgical schedule. These are:

- **Alternative Sets:** the proportion of surgeries that had to be performed with replacement RMDs. Some surgeons have a preferred set of RMDs. If necessary, alternative RMDs can be used as a replacement, despite the

surgeon's preference.

- **Delays:** the proportion of surgeries that are delayed due to RMDs unavailability. A surgery is delayed if the preferred or alternative RMDs is unavailable at the scheduled surgery time and becomes available within 2 hours after the scheduled surgery time.
- **Reschedules:** the proportion of surgeries that are rescheduled due to RMD unavailability. A delay in availability of preferred or alternative RMD sets of more than 2 hours results in a rescheduled surgery.

To gauge the impact of each component on the RMD cycle, additional KPIs are used to monitor resource usage. These monitoring indicators enable the assessment of potential interventions. The **utilisation rate**, defined as the ratio of time in use and total working hours, is used to assess the capacity of machines, workstations, and operators. The **queue length** in number of trays ahead of all steps in the CSS indicates potential bottlenecks. A reason for surgical schedule disruptions is the unavailability of trays. Hence, the **unavailability** of each tray is tracked as the ratio of stockout time to total time.

Preventing stockouts would be a more effective approach than simply monitoring their occurrences. Therefore, we introduce a KPI based on what we refer to as the **"tray pressure"**. Tray pressure can be considered as the virtual tray stock and is calculated per tray as the difference between the current stock level and the expected requirement for that tray in the next 24 hours. The turnaround time of the CSS is lower than 4 hours, hence 24 hours window give a large time to adjust the operations and prevent the stockout from occurring. If we define  $t$  as time,  $I(t)$  as the inventory of a tray at time  $t$ , and  $\bar{D}$  as the stochastic tray requirement for the next 24 hours, we can define  $TP(t)$  as follows:

$$TP(t) := (I(t) - E(\bar{D}))^- . \quad (3.1)$$

If  $TP(t)$  is positive, it implies (in expectation) a stockout within the next 24 hours, based on the current inventory level. This metric can be utilised, for example, to prioritise trays during the sterilisation process. To evaluate the temporal evolution of this metric, we integrate over time as follows:

$$\overline{TP}(t) := \frac{1}{t} \int_0^t (I(t) - \mathbb{E}(\bar{D}))^- dt. \quad (3.2)$$

## 3.4 Model Building

To assess current performance and the impact of strategic, tactical and operational changes, we model the CSS using DES. In this section, we present our model.

### 3.4.1 Data collection and pre-processing

To ensure comprehensive data for this study, an extensive analysis was conducted using the hospital's Enterprise Resource Planning (ERP) system. We retrieved data of 2021, and after excluding data related to COVID-19 pandemic restrictions in the Netherlands, a total of 28 weeks of data were used. To complement and enhance the data, on-site observations and interviews with the operators involved in the sterilisation and tray preparation processes were conducted. This approach allowed for detailed insights into the procedures and activities involved in the process, which may not have been captured in the ERP data. The datasets used during the current study are not publicly available due to confidentiality reasons but are available from the corresponding author upon reasonable request.

#### 3.4.1.1 Resources

The CSS operators work in shifts of approximately 8 hours with several breaks. Table 3.1 presents the capacity of the resources currently used by Diakonessenhuis and the corresponding data source.

The hospital under study uses 1213 different types of surgical trays. To simplify the analysis, we grouped the tray types into three clusters using a constrained K-means algorithm with feature selection, following the algorithm of

Table 3.1: Diakonessenhuis RMD cycle resources.

Resource	Quantity		Source
Rinsing Workstations	2		On-site obs.
Resetting Workstations	2		On-site obs.
Wrapping Workstations	2		On-site obs.
Disinfection Machines	4		On-site obs.
Autoclaves	3		On-site obs.
Pre-Cleaning Operators	Weekdays	1 from 7.30 AM - 9:45 AM	Interview
		2 from 9.45 AM - 5 PM	
		1 from 5 PM - 6:30 PM	
Post-Cleaning Operators	Weekends	1 from 8 AM - 12:30 AM	Interview
	Weekdays	6 from 7.30 AM - 9:45 AM	
		9 from 9.45 AM - 5 PM	
	Weekends	3 from 5 PM - 6:30 PM	
		1 from 8 AM - 1 PM	
Trays	2925	1213 different types	ERP

Bradley et al. (2000); Wagstaff et al. (2001). For each tray type, we calculated the expected weekly demand, the number of surgeries and outpatient clinic procedures requiring that tray type, and the current number of trays of that type in the system. The algorithm generated clusters with a minimum size of 25 tray types, ensuring that we obtained meaningful groups of trays for analysis rather than unmanageable outliers or excessively large clusters that a standard classification algorithm might produce.

Table 3.2: Constrained K-Means Analysis: Tray Types Clustering

Cluster	Number of Tray types	Use	Current Stock	Number of Procedures	Expected Weekly Demand	Criticality
0	32	Surgeries	9.97	59.94	13.98	1.25
1	771	Surgeries	2.15	5.50	0.78	0.6
2	410	Outpatient	2.35	1	1.88	-

Table 3.2 provides a breakdown of the tray clusters identified through the constrained K-means algorithm. Cluster 0 comprises the most frequently used trays in surgeries. These trays have a high criticality and a larger base stock (average of 9.97). The criticality of a tray type reflects its necessity in surgical procedures. To determine the criticality of a tray type, we calculate the expected number of trays of that type required for each surgery. The criticality

of a tray type is defined as the maximum expected number of trays needed for any surgery. If all possible configurations of a surgery require exactly one tool of a given tray type, its criticality is 1. If multiple trays of the same type are required, the criticality can be greater than 1. On the contrary, if not all surgical configurations require one tool of the tray type, the criticality can be less than 1. More information about the criticality calculation can be found in 3.A.

Cluster 1 includes all other surgical trays that are less commonly used and more specific to certain types of surgeries. Finally, Cluster 2 consists of all the trays used in outpatient clinics.

### 3.4.1.2 Service times

Both the disinfection machines and the autoclave operate on 60-minute programs. However, the durations of manual steps within the CSS are not precisely recorded in the hospital's ERP. To compensate for this, we empirically collected data on these durations throughout the day. Following established practices in the literature (see Baker and Trietsch (2009); Mohan (2007); Robb and Silver (1993)), we assumed a lognormal distribution for these manual operations and fit the distribution's parameters to the collected data. The results of this fitting process are presented in Table 3.3.

Table 3.3: Service times for all the processes inside the CSS.

Process	Type	Duration (minutes)		Lognormal Parameter	
		Average	Std.	$\mu$	$\sigma$
Disinfection Machine	Deterministic	60			
Autoclave	Deterministic	60			
Pre-Cleaning per tray	Lognormal	1	1.5	-0.256	0.262
Assembly per tray	Lognormal	2	1	0.253	$9.39 \cdot 10^{-4}$
Wrapping per tray	Lognormal	0.5	0.2	-0.333	$4.16 \cdot 10^{-4}$
Disinfection M. Loading	Lognormal	2	0.3	0.296	$9.34 \cdot 10^{-4}$
Disinfection M. Unloading	Lognormal	0.5	0.2	-0.333	$4.16 \cdot 10^{-4}$
Autoclave Loading	Lognormal	1	0.3	$-1.87 \cdot 10^{-2}$	$1.40 \cdot 10^{-4}$

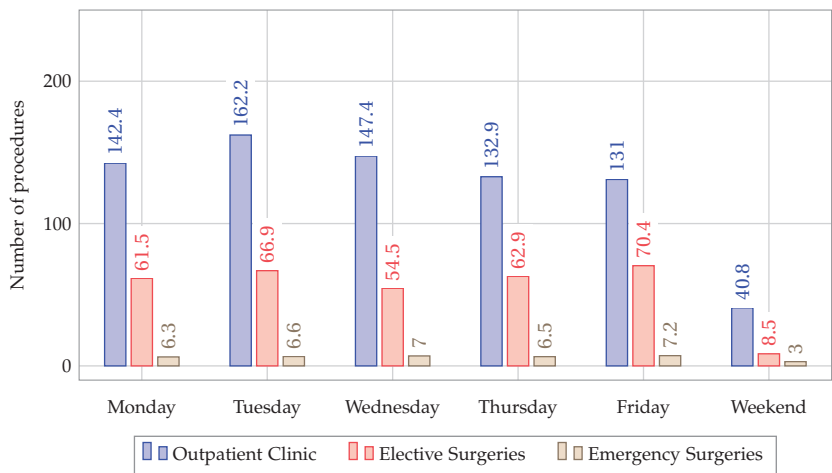
### **3.4.1.3 Tray Demand: Surgeries and Outpatient Clinic**

To model the demand for the outpatient clinic, we leveraged a dataset of log records containing tray movements within the system, which consisted of 321761 rows extracted from the hospital's ERP. A sample snapshot of the dataset is presented in 3.B. We filtered the dataset to isolate trays designated for the outpatient clinic and modelled the demand for the clinic using a Poisson process.

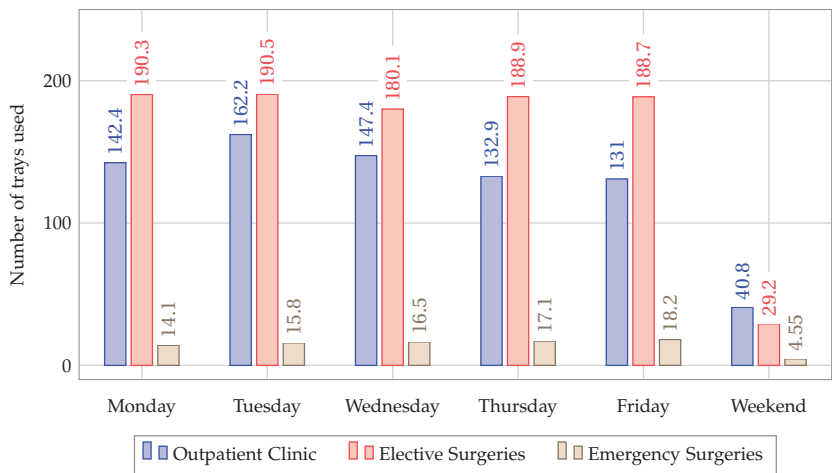
To model the inflow of surgeries at the hospital, we extracted a surgery log data set of 50860 rows from the hospital's ERP. A snapshot of the surgery data set and the retrieved input for our model is available in 3.C. We assumed that the number of surgeries of each type followed a Poisson distribution. To model the surgical demand pattern, we assumed that the surgeries' durations were lognormally distributed, as is common in surgery scheduling literature (see e.g., Zhu et al. (2019), May et al. (2000), or Schneider et al. (2020)).

We utilised the surgery log data set to map surgery types to their corresponding tray configurations and assessed the probability of each configuration. In contrast to outpatient procedures, where only a single tray is used per procedure, surgeries may require multiple trays, and varying configurations of trays may be employed for the same surgery type. By mapping the trays to the surgery demand, we can factor in the interdependence of tray demand between those typically used for the same surgeries or scheduled surgeries within the same day.

Figure 3.2 presents the results of our analysis, displaying the number of procedures occurring on each weekday as well as the corresponding volume of tray use. While the majority of trays are used for surgeries, outpatient clinic procedures are the most frequent, representing over 41.8% of the trays used. Therefore, any comprehensive model of the RMD cycle must account for outpatient demand. Similarly to Reymondon et al. (2007), Figure 3.2 also reveals that only 10.1% of surgeries are emergencies, indicating significant opportunities for planning and prioritisation strategies in the RMD sterilisation process.



(a) Average number of procedures per weekday.



(b) Average number of trays used per weekday.

Figure 3.2: Weekly Demand

### 3.4.2 Components logic

Our model relies on surgery generation procedures to generate the demand for trays and subsequently the pace of the RMD cycle. Therefore, this section details the implementation of the surgery generation procedure and of the logic behind the sterilisation process cycle with respect to queues and machine operations.

#### 3.4.2.1 Surgery generation

To generate tray arrivals in the CSS, the surgery schedule plays a crucial role. However, it is challenging to obtain the exact historical surgery schedule, and even more so to capture the intricate decision-making process of the hospital's surgery planners for future schedules. To address this challenge, we propose an algorithm that closely mimics the surgical schedule generation process. We generated input data for our algorithm using the data described in Section 3.4.1.

The surgical schedule generation algorithm is presented in Algorithm 3.1. The algorithm requires several inputs including the simulation run length, surgery types, tool configurations, operating rooms, surgery duration, and average frequency per surgery per weekday, all of which are obtained from the source data. Its output is a schedule per operating room detailing the surgeries, their start times, and preferred tool configurations. This enables the simulation to spread surgeries across operating rooms and parallelise them, as is typical in a real-world hospital setting.

In Step 3, we initialise the schedule for each operating room  $o$  and day  $t$ . We generate a schedule for each day  $t$  up to the run length. For each day, we initialise the list of surgeries to be scheduled for that day  $\mathcal{S}$  as an empty set and set the expected total surgery duration  $E_o$  to 0. The weekday corresponding to  $t$  is determined in Step 7.

Subsequently, for each surgery type  $s \in \mathcal{S}$ , we draw the number of surgeries of type  $s$  to be performed on day  $t$  in Step 10, their durations in Step 11 and preferred configurations in Step 12. All surgeries of each surgery type are

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**Algorithm 3.1** Surgery generation algorithm.

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**1: Input:**

Run length  $T_{RunLength}$   
Set of surgery types  $\mathcal{S}$   
Set of surgery tool configurations  $\mathcal{C}$   
Average frequency per weekday  $d$  of surgery  $s$   $\lambda_{s,d}$ ,  
Surgery duration parameters  $\mu_s, \sigma_s$ ,  
Set of ORs  $\mathcal{O}$   
Daily time span  $T_{span}$ .

**2: Output:** Schedules  $P_{o,t}$  per OR  $o$  for each day  $t$ .**3: Initialize**  $\mathcal{P}_{o,t} \leftarrow \emptyset, \forall o, t$ **4: for**  $t = 1, \dots, T_{RunLength}$  **do**5:   Initialise the list of surgeries to schedule  $\mathcal{L} \leftarrow \emptyset$ .6:   Initialise the expected total surgery duration per OR  $E_o \leftarrow 0$ .7:   Find the weekday  $d \leftarrow t \bmod 7$ 8:   **for**  $s \in \mathcal{S}$  **do**9:     Draw  $N_{s,t}$  surgeries of type  $s$  from  $Poisson(\lambda_{s,d})$ 10:     **for**  $n = 1, \dots, N_{s,t}$  **do**11:       Draw duration  $\tilde{t}$  from  $Lognormal(\mu_s, \sigma_s)$ .12:       Find a preferred configuration  $c$  from  $\mathcal{C}$  for surgery  $s$ .13:       Add surgery  $s$  to  $\mathcal{L}$ .14:   **for** surgeries  $s$  in  $\mathcal{L}$  **do**15:     Find OR  $o^*$  with the lowest total expected surgery time  $E_{o^*}$ .16:     Add surgery  $s$  in OR  $o^*$  by adding  $s$  to  $\mathcal{P}_{o^*,t}$ .17:      $E_{o^*} \leftarrow E_{o^*} + \mu_t$ 18:   **for**  $o \in \mathcal{O}$  **do**19:      $\gamma \leftarrow \frac{E_o}{T_{span}}$ 20:     For each scheduled surgery  $s \in \mathcal{P}_{o,t}$ , set start time  $t$  to  $t/\gamma$ .

added to  $\mathcal{L}$  in Step 13. Next, we iterate over the list of surgeries to schedule, in each iteration search for the OR with the smallest value  $E_o$  in Step 15. Note that this corresponds to a worst-fit heuristic, see, e.g., Shi et al. (2016). Subsequently, we update  $E_o$  in Step 17. In the last loop, we adjust the starting times of the surgeries such that all surgeries start spread evenly over the day in Step 20. This way, we ensure that trays arrivals are spread over the day, which resembles the actual situation.

#### **3.4.2.2 Queues**

In front of the rinsing, assembling, and wrapping workstations, as well as the disinfection machines and autoclaves, trays are queued for processing. All these queues operate as First In First Out (FIFO) queues. To model the batch arrivals from the outpatient clinic and the subsidiary locations, we use batch queues. Between the arrival times of the batches, all trays are collected and queued and inserted into the rinsing queue at the preset batch arrival times.

#### **3.4.2.3 Machine Fill up**

The disinfection machines and autoclaves have limited capacity. The disinfection machine loading rack consists of four layers, each with a capacity of 12 size units, where trays of different sizes are placed. Together with Subject Matter Experts (SMEs), we have assigned each tray to a size category with a fixed size. Each disinfection machine has a total capacity of 48 size units. Trays are picked from the queue and added to the disinfection machine until the next tray does not fit, then the operators search for the next tray in the queue that fits, repeating until no more trays can be added. Due to hygiene regulations, certain trays, such as those used for anaesthetic purposes, are cleaned separately.

In the autoclave, trays are placed in uniformly sized baskets and the autoclaves are filled according to pure FIFO discipline, with each autoclave having a capacity of 30 trays.

As observed on-site, operators do not always wait for a machine to become completely full before starting it. To maintain a continuous flow, they com-

mence the machines once a minimum quantity has been reached. To reflect this behaviour, we introduce thresholds  $\tau_{dis} = 20\%$  and  $\tau_{ster} = 50\%$  to ensure that a machine is loaded if it is free and there are enough trays to fill it to at least  $\tau$ . These thresholds are calibrated to match the weekly number of machine cycles observed on-site. The risk of tray deterioration and contamination is higher before disinfection, thereby increasing the urgency to process them through the disinfection machines. Trays are safer to store after disinfection and prior to sterilisation, explaining the difference in threshold levels for disinfection and sterilisation.

### 3.4.3 Model validation and verification

To determine the simulation's warm-up period, we use MSER-m heuristic, introduced by White (1997) and White et al. (2000) to determine the optimal truncation point for minimizing the marginal confidence interval and reducing bias. The MSER-m method uses groups of  $m$  data points to perform the analysis, increasing its robustness in removing bias White et al. (2000). In this analysis, the simulation output data points were already grouped by weeks to account for daily variations, and groups of 2 data points (MSER-2) were used instead of the more common 5 data points (MSER-5), as 5 weeks provided too broad a granularity.

Table 3.4: Warm-up period: Results of the MSER-2 analysis

KPI	Optimal Truncation			6 weeks Truncation	
	$d^*$	95% CI Width	in % of mean	95% CI Width	in % of mean
Alternative Set Prob.	4	$\pm 2.67 \cdot 10^{-2}$	$\pm 4.57\%$	$\pm 2.69 \cdot 10^{-2}$	$\pm 4.63\%$
Delay Prob.	6	$\pm 6.48 \cdot 10^{-4}$	$\pm 58.4\%$	$\pm 6.48 \cdot 10^{-4}$	$\pm 58.4\%$
Rescheduling Prob.	2	$\pm 3.56 \cdot 10^{-3}$	$\pm 18.3\%$	$\pm 3.63 \cdot 10^{-3}$	$\pm 18.8\%$
Pre Cleaning Queue	2	$\pm 0.265$	$\pm 2.73\%$	$\pm 0.271$	$\pm 2.79\%$
Disinfection Queue	2	$\pm 0.129$	$\pm 1.00\%$	$\pm 0.130$	$\pm 1.01\%$
Assembly Queue	2	$\pm 9.53 \cdot 10^{-2}$	$\pm 1.62\%$	$\pm 9.76 \cdot 10^{-2}$	$\pm 1.65\%$
Wrapping	2	$\pm 3.47 \cdot 10^{-2}$	$\pm 3.87\%$	$\pm 3.47 \cdot 10^{-2}$	$\pm 3.88\%$
Sterilisation	2	$\pm 0.339$	$\pm 2.10\%$	$\pm 0.346$	$\pm 2.14\%$

The results of the MSER-2 analysis are presented in Table 3.4. This experiment consisted of 10 replications and a 3-year (156-week) run length. For each KPI, the table shows the optimal truncation point, which corresponds to the warm-

up data that should be excluded from the output analysis to eliminate the initial bias. The probability of a surgery being delayed had the largest truncation point, and a conservative approach was taken by using a warm-up period of 6 weeks to remove the initial bias for all KPIs. In addition, Table 3.4 displays the corresponding marginal 95% confidence interval for each outcome.

To minimise the computational impact of the warm-up period of 6 weeks, a run length of 2 years (104 weeks) added to the 6 weeks of warm-up was used, as recommended by Robinson (2014), which reduces the need for replications and therefore warm-up periods. To determine the appropriate number of replications, an experiment of 100 replications was conducted to study the convergence and the width of the 95% confidence interval for the KPIs. As demonstrated by Figure 3.3 using the average queue length ahead of pre-cleaning as an example, 30 replications are sufficient to observe convergence of the average values and the 95% confidence interval. This pattern holds true for all KPIs, ensuring that 30 replications are adequate to eliminate any bias caused by stochasticity and ensure a steady state.

Table 3.5: 95% confidence interval after 30 replications.

KPI	Mean	95% CI Width	in % of mean
Alternative Set Prob.	$4.29 \cdot 10^{-2}$	$\pm 7.08 \cdot 10^{-4}$	$\pm 1.65\%$
Surgical Delay Prob.	$1.95 \cdot 10^{-4}$	$\pm 5.56 \cdot 10^{-5}$	$\pm 28.44\%$
Surgery Rescheduling Prob.	$1.67 \cdot 10^{-3}$	$\pm 1.34 \cdot 10^{-4}$	$\pm 8.03\%$
Pre Cleaning Queue	9.07	$\pm 0.154$	$\pm 1.70\%$
Disinfection Queue	12.1	$\pm 0.145$	$\pm 1.20\%$
Assembly Queue	5.52	$\pm 6.25 \cdot 10^{-2}$	$\pm 1.13\%$
Wrapping	0.804	$\pm 2.10 \cdot 10^{-2}$	$\pm 2.61\%$
Sterilisation	11.0	$\pm 3.74 \cdot 10^{-2}$	$\pm 0.34\%$

Table 3.5 displays the 95% confidence intervals obtained from 30 replications. For the majority of the indicators, the confidence intervals are relatively tight and provide accurate results. However, the intervals for surgical delay probability and rescheduling probability are wider. These events are fortunately extremely rare with an average of 35.86 and 307.12 occurrences per run (104 weeks) respectively. This rarity results in a high volatility in the results and a single event can significantly impact the simulation outcome. It is estimated that more than 980 replications would be required to reduce the 95% confidence interval to 5% of the mean value (Robinson, 2014). Although 30 replications may be considered imprecise for these two indicators, it is a trade-off

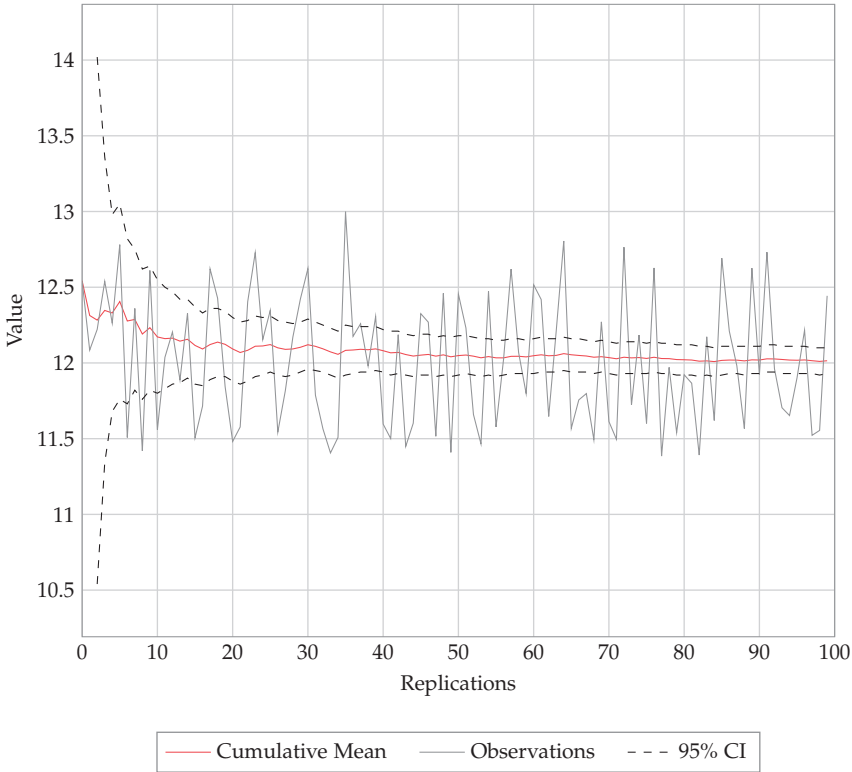


Figure 3.3: Pre-Cleaning queue length cumulative mean and confidence interval by number of replications.

made in consideration of the computational cost that would come with obtaining narrower intervals.

#### 3.4.4 Model validation

The proposed DES approach has undergone extensive development and validation through collaboration with the hospital management team.

The tray makespan, defined as the time elapsed between tray arrival at the CSS and its placement in sterile storage, is computed by our model. Our model provides a median tray makespan of 3 hours and 18 minutes and a 95<sup>th</sup> percentile of 4 hours and 46 minutes, which have been confirmed by CSS

operators and management to closely reflect the actual operations of the CSS.

The CSS does not have precise records of queue lengths or tray-level indicators, so the only available operational data for quantitative validation are the number of trays cleaned per week, and the number of cycles of the autoclaves and disinfection machines. To assess the accuracy of our model, we followed the method proposed by Robinson (1999) and calculated the 95% confidence interval of the difference between the means of the simulated output and the operational data extracted from the ERP. The results are presented in Table 3.6 and show that the confidence interval includes 0, indicating with 95% confidence that there is no significant difference between the simulated output and the operational values.

Table 3.6: Model Validation: Means difference analysis between operational data and simulated output

Metric per week	Op. Data	Simulated	Means difference 95% CI	
	Mean	Mean	Value	% of Op. Mean
Trays cleaned	1770.76	1772.66	[−46.6, +50.4]	[−2.63%, +2.85%]
Disinfection cycles	172.76	172.61	[−4.40, +4.08]	[−2.55%, +2.36%]
Sterilisation cycles	99.79	99.14	[−2.03, +0.72]	[−2.03%, +0.72%]

### 3.5 Experiments and computational results

The proposed DES approach has been implemented in Python (3.10), using SimPy (4.0.1), a process-based discrete-event simulation framework (see Matloff (2008); SimPy (2002)). The simulation experiments, consisting of 30 replications, a six-week warm-up period and 104 weeks of run length, were run on a Linux cluster with a Xeon Gold 6226R processor and 756GB of memory. The replications were parallelised across 30 cores to reduce computational time, and each experiment took approximately 50 minutes to run.

We initially conducted a baseline experiment that replicated the current setup of the hospital. Based on these results, we formulated potential interventions to enhance the system’s performance, which we subsequently tested. Additionally, the hospital expressed a desire to increase the volume of certain

procedures. Thus, we conducted experiments with varying demand levels to evaluate the system's capacity to handle such fluctuations, both with and without the proposed interventions.

### 3.5.1 Baseline experiment results

Table 3.7 presents the KPIs of the simulation of the baseline scenario. Contrary to the example hospital in Rupnik et al. (2019), only 1.18% of the surgeries are disrupted. Tray unavailability-induced delays are extremely rare (less than once per year). For a delay to occur, the required tray(s) need to be cleaned in less than 2h but the entire sterilisation process requires the tray to go through the disinfection machine and the autoclaves which together take more than 2h; the entire CSS process lasts 3h 18m on average. Hence the specific tray(s) need to be already in the sterilisation process to be ready before the surgery is rescheduled, leaving almost no adaptation possibility for the CSS.

Table 3.7: KPIs and corresponding standard deviations of the baseline scenario.

KPI	% of surgeries	Average per week		Average per year	
Surgeries	100.00 %	360.88	[ $\sigma$ : 0.63]	18765.77	[ $\sigma$ : 40.55]
Delays	$\leq 0.01$ %	0.02	[ $\sigma$ : 0.01]	0.85	[ $\sigma$ : 0.58]
Reschedules	0.04 %	0.15	[ $\sigma$ : 0.04]	7.55	[ $\sigma$ : 1.46]
Alternative Set	1.14 %	4.12	[ $\sigma$ : 0.21]	214.21	[ $\sigma$ : 9.22]

The KPIs measuring the performance of the operations within the CSS also indicate that no clear bottleneck exists. As shown in Figure 3.4, the queue lengths before each step of the CSS remain below 29 trays, which corresponds to 1 hour of tray demand. Figure 3.5 illustrates that the CSS resources are adequate to ensure the sterilisation of the trays. All resources, except for those in pre-disinfection operators, maintain an average utilisation rate below 90%, indicating a margin. The pre-disinfection operators' utilisation rate reaches 100% during weekday mornings and on weekends when only one operator is present.

Figure 3.6a reveals that stock-outs occur exclusively for tray types with low base stock levels in Cluster 1 (surgical trays with low volume) or Cluster 2 (outpatient clinic). Notably, 91% of these stock-outs involve tray types

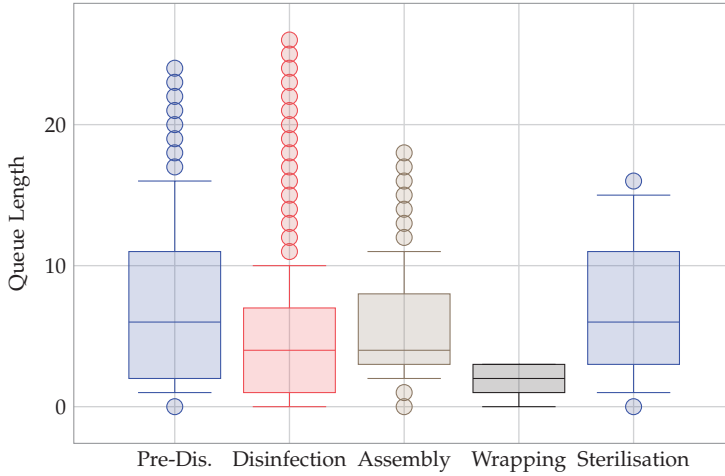


Figure 3.4: Average Queue Length in the CSS

with only one unit in their base stock (99% for base stocks under 2). Meanwhile, Figure 3.6b demonstrates that the inventory position for tray types in Cluster 0 never falls below the daily expected demand. Figure 3.6 indicates that a discrepancy exists between the base stock levels and demand for the RMDs, which is the primary cause of surgical disturbances. Moreover, it highlights that the safety level for high-usage trays (Cluster 0) is excessive, which presents opportunities for cost savings and enhancements.

### 3.5.2 RMD cycle interventions

We propose two sets of interventions to improve the current hospital-wide RMD cycle, focusing on operations changes within the CSS for the first set and variations in the base stock level of the trays for the second set.

#### 3.5.2.1 CSS operations interventions

In the baseline experiment, the utilisation of the pre-disinfection operator peaks above 90% in the early mornings and on weekends, suggesting that the resource may be under-capacitated. To address this issue, the first experiment (OP+) proposes an adjustment to the pre-disinfection operator's schedule, en-

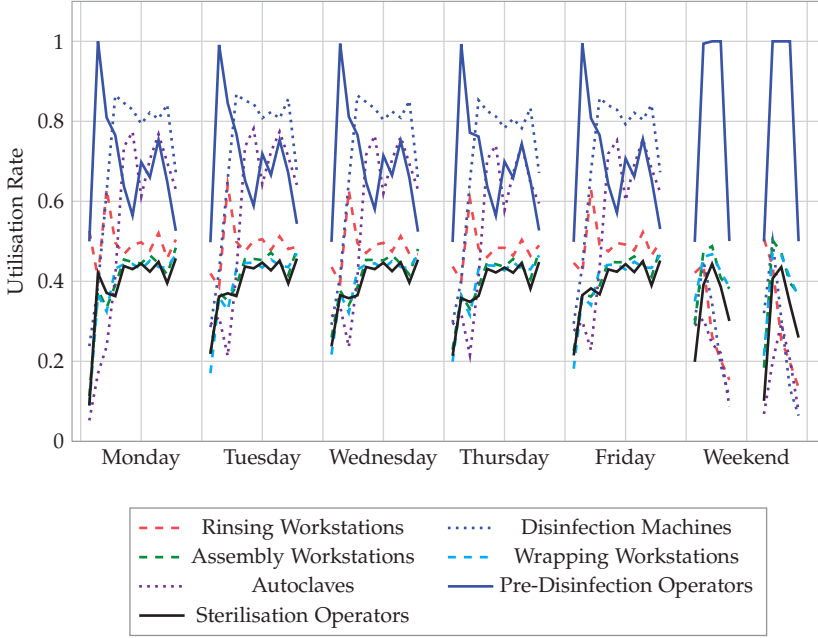


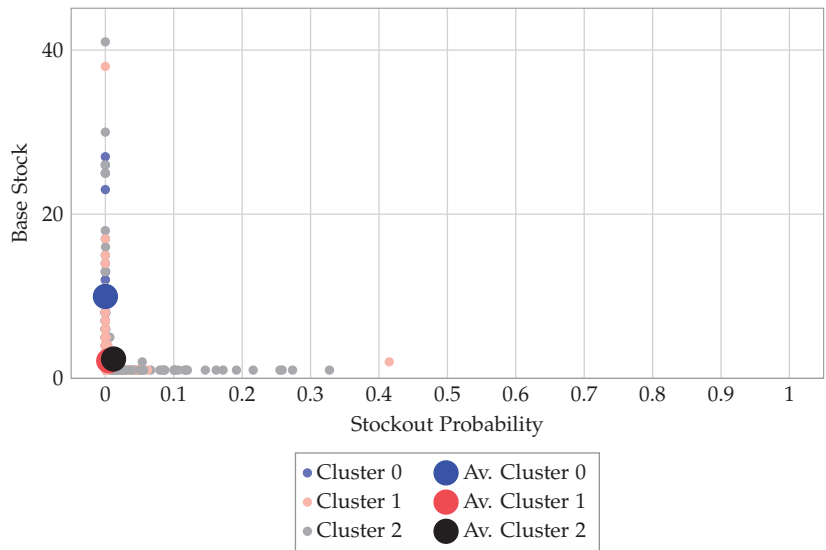
Figure 3.5: Hourly resource utilisation plot

sureing that two operators are available at all times during working hours.

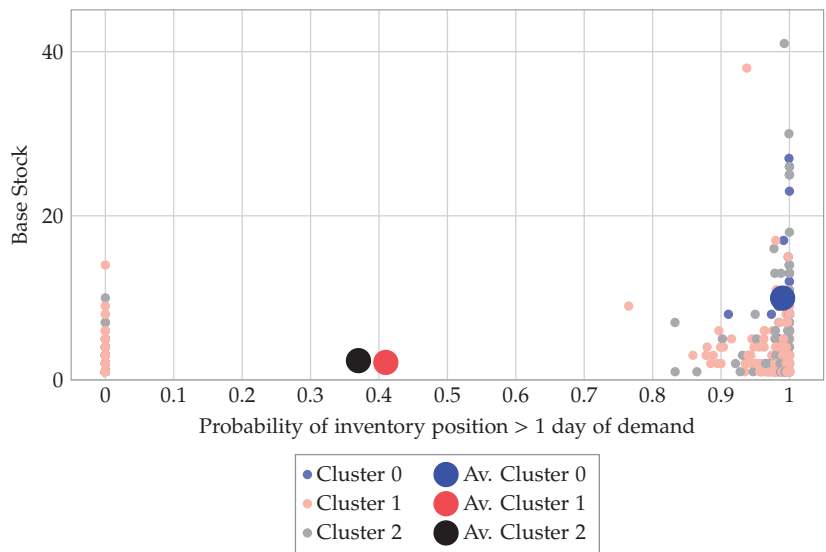
In section 3.4.2.2, we explained that the baseline queuing system operates on a FIFO basis. To improve the system, we propose two alternative prioritisation policies for the pre-disinfection queue: experiment **CR**, which involves continuous review, and experiment **DR**, which involves daily review at 2 PM. In contrast to the traditional FIFO approach, our proposed policies prioritise trays based on their level of tray pressure, which represents the degree of urgency or importance of completing a given tray. Specifically, we prioritise trays with lower sterile inventory levels compared to the forecasted demand in the next 24 hours.

### 3.5.2.2 Tray base stock interventions

Dobson et al. (2015) used the maximum daily demand as the base stock level, and we followed a similar approach by considering the demand of the busiest day of the week in three experiments. Since the CSS can sterilise trays in less



(a) Comparison of the base stock and the stockout probability of all tray types



(b) Comparison of the base stock and the probability of the stock to be larger than one day

Figure 3.6: Tray availability analysis

than 4 hours on average, it is possible to reuse some trays on the same day and have others available the next day depending on their arrival time. In experiment **BS50**, the base stock for each tray is set to the median demand on the busiest weekday, rounded up to the next integer. Experiment **BS75** corresponds to the 75<sup>th</sup> percentile, and experiment **BS95** to the 95<sup>th</sup> percentile. The reduction in the tray fleet required by the experiments (1617, 1890, and 2694 trays respectively instead of the current 2925) could lead to significant cost savings, given that the total value of surgical RMDs of a mid-size 1000-trays hospital could reach up to \$3 million, as pointed out by Lin et al. (2008).

We did not consider the maximum as in Dobson et al. (2015), as it appeared overly conservative and would have increased the total number of trays to 4432, which would have prevented any cost-savings. Additionally, we used the baseline simulation experiment to determine the base stock level, and the maximum value would have likely represented statistical anomalies rather than actual values.

### 3.5.2.3 Scenarios Results

Table 3.8: RMD cycle simulation: improving scenarios results

Scenario	Delays		Reschedules		Alternative Set	
	Values	$\Delta$ Baseline	Values	$\Delta$ Baseline	Values	$\Delta$ Baseline
Baseline	$4.53 \cdot 10^{-5}$		$4.02 \cdot 10^{-4}$		$1.14 \cdot 10^{-2}$	
<i>CSS scenarios</i>						
OP+	$5.59 \cdot 10^{-5}$	+23.4%	$4.17 \cdot 10^{-4}$	+3.73%	$1.22 \cdot 10^{-2}$	+6.84%
CR	$6.65 \cdot 10^{-5}$	+46.8%	$4.16 \cdot 10^{-4}$	+3.40%	$1.21 \cdot 10^{-2}$	+6.14%
DR	$4.97 \cdot 10^{-5}$	+10.2%	$3.99 \cdot 10^{-4}$	−0.746%	$1.22 \cdot 10^{-2}$	+7.01%
<i>Base stock strategies</i>						
BS50	$4.28 \cdot 10^{-4}$	+845%	$1.94 \cdot 10^{-3}$	+383%	$6.32 \cdot 10^{-2}$	+454%
BS75	$2.18 \cdot 10^{-4}$	+381%	$6.25 \cdot 10^{-4}$	+55.4%	$2.26 \cdot 10^{-2}$	+98.2%
BS95	$5.16 \cdot 10^{-5}$	+13.9%	$1.08 \cdot 10^{-4}$	−73.1%	$3.84 \cdot 10^{-3}$	−66.3%

Table 3.8 presents the outcomes of the proposed experiments. The adjustments suggested to the CSS operation failed to produce any improvement. The continuous prioritisation (**CR**), discrete prioritisation (**DR**), and pre-disinfection operators schedule adjustment (**OP+**) scenarios slightly underperformed com-

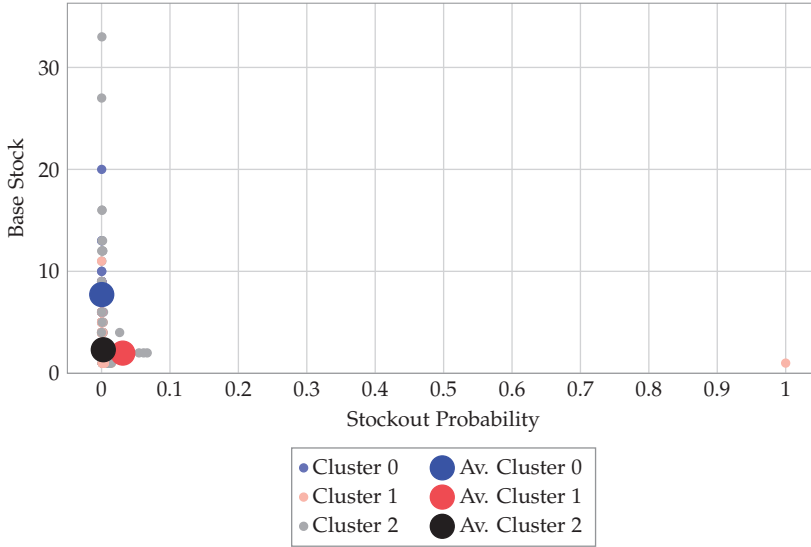
pared to the baseline. However, the observed differences are comparable the 95% confidence interval for these indicators, as presented in Table 3.5. Therefore, we conclude that these interventions do not provide significant improvement.

As previously mentioned, stock-outs occur for trays with limited base stock, which means that there might not be another tray ready to be prioritised to compensate when a stock-out occurs, thus explaining the underperformance of the prioritisation strategies.

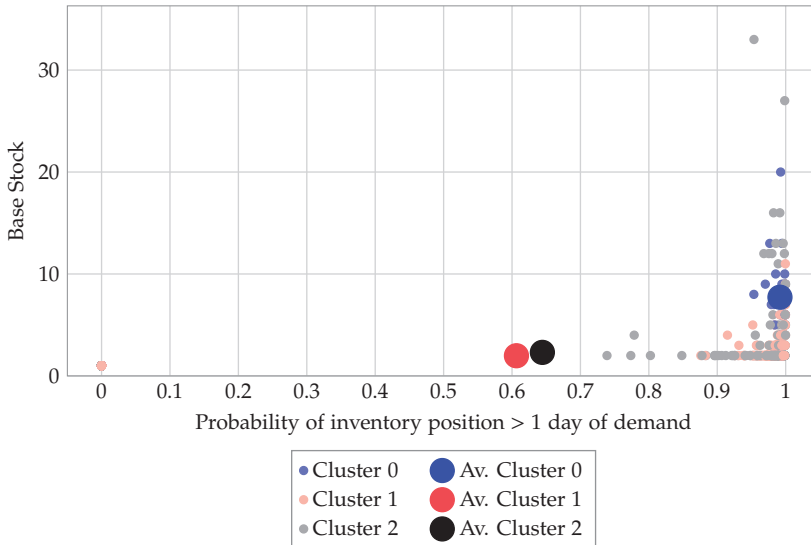
Adjusting the schedule of the pre-disinfection operators resulted in reduced utilisation during mornings and weekends but did not have a significant impact on the overall system. This suggests that despite their occasional high utilisation, this resource does not act as a bottleneck for the flow of the RMD.

The outcomes of experiments **BS50** and **BS75** are significantly inferior to the baseline, indicating that the base stock levels are set too low. However, experiment **BS95** shows a considerable improvement on most KPIs, with a reduction of over 60% in the need to reschedule procedures and use of alternative sets. This suggests a better alignment between the base stock levels and the demand, offering the potential to reduce the hospital tray fleet by more than 200 trays.

However, as illustrated in Figure 3.7, stock-outs are limited to trays with low base stock ( $\leq 2$ ), while other trays remain over-capacitated. This highlights the limitations of setting the base stock for trays based on a percentile of the daily demand. While this approach reduces the base stock and cost for high-use, large-inventory trays like those in Cluster 0, despite reducing the risk of stock out for low-inventory trays it fails to effectively increase the robustness for all low-inventory trays. Large inventory trays benefit from a pooling effect, where trays can be cleaned and reused more quickly than low-inventory trays, resulting in a disparity between the two types of trays.



(a) Comparison of the base stock and the stockout probability of all tray types



(b) Comparison of the base stock and the probability of the stock to be larger than one day

Figure 3.7: Tray availability analysis for BS95 scenario

### 3.5.3 Demand Increase

The case study hospital intends to extend its surgical capacity for certain procedures, which in turn is expected to increase the demand for these procedures. In order to assess the ability of the current RMD cycle to cope with this increased demand and the potential benefits of the proposed enhancements, we consider two experiments: **SI20** and **SI40**. These experiments correspond to an increase in the demand for the selected surgeries by 20% and 40%, respectively. Note that the anticipated increase in demand only represents a marginal increase in the overall number of surgeries performed at the hospital, as well as the number of trays cleaned (less than 8%). To fully evaluate the resilience of the system, a stress test has been proposed, which encompasses an overall increase of 25% (experiment **I25**).

Table 3.9: Demand variation results

Scenario	Trays Base Stock	Delays		Reschedules		Alternative Set	
		Values	ΔBaseline	Values	ΔBaseline	Values	ΔBaseline
Normal Demand							
Baseline	2925	$4.53 \cdot 10^{-5}$		$4.02 \cdot 10^{-4}$		$1.14 \cdot 10^{-2}$	
BS75	1890	$2.18 \cdot 10^{-4}$	+381%	$6.25 \cdot 10^{-4}$	+55.4%	$2.26 \cdot 10^{-2}$	+98.2%
BS95	2694	$5.16 \cdot 10^{-5}$	+13.9%	$1.08 \cdot 10^{-4}$	−73.1%	$3.84 \cdot 10^{-3}$	−66.3%
Demand SI 20							
Baseline	2925	$5.66 \cdot 10^{-5}$	+24.9%	$4.01 \cdot 10^{-4}$	+0.249%	$1.29 \cdot 10^{-2}$	+13.2%
BS 75	1920	$2.25 \cdot 10^{-4}$	+396%	$6.17 \cdot 10^{-4}$	+52.7%	$2.39 \cdot 10^{-2}$	+109.6%
BS 95	2713	$6.24 \cdot 10^{-5}$	+37.7%	$1.03 \cdot 10^{-4}$	−74.3%	$4.51 \cdot 10^{-3}$	−60.4%
Demand SI 40							
Baseline	2925	$8.34 \cdot 10^{-5}$	+84.1%	$3.79 \cdot 10^{-4}$	+5.72%	$1.47 \cdot 10^{-2}$	+28.8%
BS75	1938	$1.99 \cdot 10^{-4}$	+339%	$5.12 \cdot 10^{-4}$	+27.4%	$2.26 \cdot 10^{-2}$	+98.2%
BS95	2761	$5.57 \cdot 10^{-5}$	+23.0%	$9.93 \cdot 10^{-5}$	−75.2%	$4.29 \cdot 10^{-3}$	−62.3%
Demand I 25							
Baseline	2925	$1.11 \cdot 10^{-4}$	+145%	$4.29 \cdot 10^{-4}$	6.71	$2.51 \cdot 10^{-2}$	+120%
BS75	2049	$2.74 \cdot 10^{-4}$	+505%	$6.14 \cdot 10^{-4}$	+52.7%	$3.06 \cdot 10^{-2}$	+168%
BS95	2937	$1.09 \cdot 10^{-4}$	+141%	$1.28 \cdot 10^{-4}$	−68.2%	$1.01 \cdot 10^{-2}$	−11.4%

Table 3.9 presents the results of the baseline organisation and proposed base stock heuristics BS75 and BS95 for all considered demand variations. Without any adjustment to the system, the demand increase significantly deteriorates the performance of the RMD cycle.

However, the deterioration for the selective increase **SI20** and **SI40** remains moderate. The number of surgeries performed with alternative sets of RMDs would increase only slightly, from 4.1 out of 361.3 surgeries to 4.8 out of 378.02 surgeries and 5.9 out of 399.3 surgeries per week on average. The number of surgeries delayed or rescheduled on average every year would increase from 8.37 to 9.02 and 9.60 surgeries, respectively. Potential improvements need to be balanced with their cost, and management could consider these increases acceptable.

Our findings indicate that there is no significant capacity bottleneck within the current system. Specifically, we observed that the average number of trays cleaned per week increased from 1770 to 2186 for scenario **I25**, yet the queue lengths upstream of each operation remained below 50 trays in the worst-case scenario, representing less than two hours of total flow. Furthermore, we noted that the overall resource utilisation rate did not exceed 0.9, with the exception of the morning and weekend hours for the pre-disinfection operators. The base stock level remains the main challenge, even with an increase in demand, the CSS would be able to accommodate such an increase.

The results of base stock scenarios **BS75** and **BS95**, outlined in Table 3.9, corroborate this analysis. Adjusting the tray base stock to the 95<sup>th</sup> percentile of the busiest day demand outperforms the baseline situation. However, it can be seen that the performance of such a heuristic tends to decrease with higher demand. A finer heuristic with a more individual approach to each tray, tailoring the base stock to the true nature and characteristics of the demand for each tray type, might provide a larger reduction for high-use trays and more robustness and safety for low-use ones.

### 3.6 Conclusion and Future Work

This study investigated the intricate flow of the RMD system within a hospital, which involves several departments such as CSS, surgery, and outpatient clinics. Our study highlights the critical importance of taking an integrated and holistic approach to the RMD system, in order to fully understand its flow and identify areas for improvement.

We proposed a comprehensive DES model for the entire flow of sterile surgical trays in a hospital, which takes the closed-loop nature of the flow into account. Our model included a novel method to generate surgeries and outpatient procedures, which was key to modelling the entire RMD flow comprehensively. These procedures constituted both the demand for sterile trays and the source of trays to clean, making them critical for understanding the RMD cycle. Incorporating this surgery generation procedure allowed us to comprehensively model the CSS operations and the base stock of the trays, enabling us to identify areas for improvement that would not have been visible from a more limited perspective. Our model provided a more comprehensive understanding of the RMD cycle and its flow, which can be used to optimise and improve the system in the future.

We used our model to analyse the RMD flow of a Dutch hospital and measure its impact in terms of surgery and outpatient procedure disruption, to ensure the quality of care provided. This analysis provided us with valuable insights into the system's behaviour and potential improvements. It enabled us to devise different interventions to improve the CSS operations as well as the base stock level. We found that the CSS is able to cope with an increase in demand but that the main challenge for this hospital is to adjust its tray fleet. We proposed and tested heuristic methods to better align the base stock with the demand for trays. One of the key contributions of our study is that it highlights the necessity of studying the base stock and CSS operations together. Indeed, without the integrated, comprehensive analysis of the entire RMD flow, including the surgical schedule, we could not have identified that the base stock was the main issue when analysing solely the performance of the CSS.

As future work, it would be a valuable addition to the model to incorporate tray composition, thus enabling a more comprehensive analysis of the RMD flow. Additionally, there is potential in using the model to devise surgical planning guidelines aimed at reducing the likelihood of tray stock-outs. We acknowledge that the heuristics we proposed for base stock dimensioning were based on a one-rule-fits-all approach, and that developing finer heuristics tailored to the demand characteristics of each tray might provide future researchers with a larger reduction for high-use trays and more robustness and safety for low-use ones.

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## Bibliography

- Baker, K. R. and Trietsch, D. (2009). *Principles of Sequencing and Scheduling*. John Wiley and Sons.
- Beliën, J. and Demeulemeester, E. (2007). Building cyclic master surgery schedules with leveled resulting bed occupancy. *European Journal of Operational Research*, 176(2):1185–1204.
- Beliën, J., Demeulemeester, E., and Cardoen, B. (2009). A decision support system for cyclic master surgery scheduling with multiple objectives. *Journal of Scheduling*, 12(2):147–161.
- Bijvank, M. and Vis, I. F. (2012). Inventory control for point-of-use locations in hospitals. *Journal of the Operational Research Society*, 63(4):497–510.
- Bradley, P. S., Bennett, K. P., and Demiriz, A. (2000). Constrained k-means clustering. *Microsoft Research, Redmond*, 20(0):0.
- Calegari, R., Fogliatto, F. S., Lucini, F. R., Anzanello, M. J., and Schaan, B. D. (2020). Surgery scheduling heuristic considering or downstream and upstream facilities and resources. *Bmc Health Services Research*, 20(1):684.
- Cardoen, B., Beliën, J., and Vanhoucke, M. (2015). On the design of custom packs: Grouping of medical disposable items for surgeries. *International Journal of Production Research*, 53(24):7343–7359.
- Cardoen, B., Demeulemeester, E., and Beliën, J. (2010). Operating room planning and scheduling: A literature review. *European Journal of Operational Research*, 201(3):921–932.
- Demeulemeester, E., Beliën, J., Cardoen, B., and Samudra, M. (2013). Operating room planning and scheduling. *International Series in Operations Research and Management Science*, 184:121–152.
- Di Mascolo, M. and Gouin, A. (2013). A generic simulation model to assess the performance of sterilization services in health establishments. *Health Care Management Science*, 16(1):45–61.
- Diamant, A., Milner, J., Quereshy, F., and Xu, B. (2018). Inventory management of reusable surgical supplies. *Health Care Management Science*, 21(3):439–459.

- Dobson, G., Seidmann, A., Tilson, V., and Froix, A. (2015). Configuring surgical instrument trays to reduce costs. *Iie Transactions on Healthcare Systems Engineering*, 5(4):225–237.
- Fineman, S. J. and Kapadia, A. S. (1978). Analysis of the logistics of supplying and processing sterilized items in hospitals. *Comput Oper Res*, 5(1):47–54.
- Fügener, A., Hans, E. W., Kolisch, R., Kortbeek, N., and Vanberkel, P. T. (2014). Master surgery scheduling with consideration of multiple downstream units. *European Journal of Operational Research*, 239(1):227–236.
- Guerrero, W. J., Yeung, T. G., and Guéret, C. (2013). Joint-optimization of inventory policies on a multi-product multi-echelon pharmaceutical system with batching and ordering constraints. *European Journal of Operational Research*, 231(1):98–108.
- Latorre-Núñez, G., Lüer-Villagra, A., Marianov, V., Obreque, C., Ramis, F., and Neriz, L. (2016). Scheduling operating rooms with consideration of all resources, post anesthesia beds and emergency surgeries. *Computers & Industrial Engineering*, 97:248–257.
- Lin, F., Lawley, M., Spry, C., McCarthy, K., Coyle-Rogers, P. G., and Yih, Y. (2008). Using simulation to design a central sterilization department. *Aorn Journal*, 88(4):555–556,558,561–567.
- Little, J. and Coughlan, B. (2008). Optimal inventory policy within hospital space constraints. *Health Care Management Science*, 11(2):177–183.
- Matloff, N. (2008). Introduction to discrete-event simulation and the simpy language. Davis, CA. *Dept of Computer Science. University of California at Davis*. Retrieved on August, 2(2009):1–33.
- May, J. H., Strum, D. P., and Vargas, L. G. (2000). Fitting the lognormal distribution to surgical procedure times. *Decision Sciences*, 31(1):129–148.
- Mohan, S. (2007). A lognormal approximation of activity duration in pert using two time estimates. *Journal of the Operational Research Society*, 58(6):827–831.
- Moosavi, A. and Ebrahimnejad, S. (2018). Scheduling of elective patients considering upstream and downstream units and emergency demand using robust optimization. *Computers and Industrial Engineering*, 120:216–233.
- Moosavi, A. and Ebrahimnejad, S. (2020). Robust operating room planning

- considering upstream and downstream units: A new two-stage heuristic algorithm. *Computers and Industrial Engineering*, 143:106387.
- OECD (2021). OECD Health Statistics 2021. [https://stats.oecd.org/Index.aspx?DatasetCode=HEALTH\\_STAT](https://stats.oecd.org/Index.aspx?DatasetCode=HEALTH_STAT).
- OECD and European Union (2020). Health at a glance: Europe 2020. <https://www.oecd-ilibrary.org/content/publication/82129230-en>.
- Ozturk, O., Espinouse, M. L., Di Mascolo, M., and Gouin, A. (2010). Optimizing the makespan of washing operations of medical devices in hospital sterilization services. *2010 Ieee Workshop on Health Care Management, Whcm 2010*, page 5441278.
- Reymondon, F., Marcon, E., and Pellet, B. (2007). Optimisation des stocks de dispositifs médicaux réutilisables par la différenciation retardée. *Logistique and Management*, 15(1):37–48.
- Reymondon, F., Pellet, B., and Marcon, E. (2006). Methodology for designing medical devices packages based on sterilisation costs. *Ifac Proceedings Volumes (ifac-papersonline)*, 12(1).
- Reymondon, F., Pellet, B., and Marcon, E. (2008). Optimization of hospital sterilization costs proposing new grouping choices of medical devices into packages. *International Journal of Production Economics*, 112(1):326–335. Special Section on Recent Developments in the Design, Control, Planning and Scheduling of Productive Systems.
- Robb, D. and Silver, E. (1993). Scheduling in a management context - uncertain processing times and nonregular performance-measures. *Decision Sciences*, 24(6):1085–1108.
- Robinson, S. (1999). Simulation verification, validation and confidence: A tutorial. *Transactions of the Society for Computer Simulation*, 16(2):63–69.
- Robinson, S. (2014). *Simulation: The Practice of Model Development and Use*, 2nd edition. Bloomsbury Publishing.
- Rossi, A., Puppato, A., and Lanzetta, M. (2013). Heuristics for scheduling a two-stage hybrid flow shop with parallel batching machines: Application at a hospital sterilisation plant. *International Journal of Production Research*, 51(8):2363–2376.

- Rupnik, B., Narding, R., and Kramberger, T. (2019). Discrete event simulation of hospital sterilization logistics. *Tehnicki Vjesnik*, 26(5):1486–1491.
- Samudra, M., Van Riet, C., Demeulemeester, E., Cardoen, B., Vansteenkiste, N., and Rademakers, F. E. (2016). Scheduling operating rooms: achievements, challenges and pitfalls. *Journal of Scheduling*, 19(5):493–525.
- Schneider, A. J. T. (2020). *Integral Capacity Management & Planning in Hospitals*. PhD thesis, University of Twente, Netherlands.
- Schneider, T. A. J., Van Essen, T. J., Carlier, M., and Hans, E. W. (2020). Scheduling surgery groups considering multiple downstream resources. *European Journal of Operational Research*, 282(2):741–752.
- Shi, P., Dexter, F., and Epstein, R. H. (2016). Comparing policies for case scheduling within 1 day of surgery by markov chain models. *Anesthesia and Analgesia*, 122(2):526–538.
- SimPy (2002). SimPy 2002-2020. <https://simpy.readthedocs.io/en/latest/index.html>. [Online; accessed 7-February-2023].
- Tlahig, H., Jebali, A., Bouchriha, H., and Ladet, P. (2013). Centralized versus distributed sterilization service: A location allocation decision model. *Operations Research for Health Care*, 2(4):75–85.
- Van De Klundert, J., Muls, P., and Schadd, M. (2008). Optimizing sterilization logistics in hospitals. *Health Care Management Science*, 11(1):23–33.
- Wagstaff, K., Cardie, C., Rogers, S., Schrödl, S., et al. (2001). Constrained k-means clustering with background knowledge. In *Icml*, volume 1, pages 577–584.
- White, K. P. (1997). An effective truncation heuristic for bias reduction in simulation output. *Simulation*, 69(6):323–334.
- White, K. P., Cobb, M. J., and Spratt, S. C. (2000). A comparison of five steady-state truncation heuristics for simulation. *2000 Winter Simulation Conference Proceedings (cat. No.00ch37165)*, 1:755–60 vol.1.
- World Health Organization (2016). Decontamination and reprocessing of medical devices for health-care facilities.
- Zhu, S., Fan, W., Yang, S., Pei, J., and Pardalos, P. M. (2019). Operating room planning and surgical case scheduling: a review of literature. *Journal of Combinatorial Optimization*, 37(3):757–805.

## Appendix 3.A Tray Criticality

The criticality of a tray measures the necessity of a tray for surgery to be performed. With  $Surgeries(t)$  defining the set of surgeries using trays of type  $t$ ,  $Conf(s)$  the set of RMDs configuration that could be used for surgeries  $s$ , the criticality of a tray type  $t$   $\gamma_t$  is computed as the following.

$$\gamma_t = \sup_{s \in Surgeries(t)} \left\{ \left[ \sum_{C \in Conf(s)} \sum_{\theta \in C} 1_{\theta=t} \right] / |Conf(s)| \right\} \quad \forall t \in Tray\ Types \quad (3.3)$$

Hence if tray type  $t$  is only used in one surgery and is used in half of the possible configurations of this surgery, its criticality is  $\gamma_t = 0.5$

## Appendix 3.B Snapshot of the tray log dataset extracted from the ERP

Table 3.10: A snapshot of the usage log of RMDs in the hospital. Source: the hospitals' ERP system

Set ID	Set Name	Activity	Time	Date	Set Type ID
1	BASE TRAY	Reset	10:53:05	19-2-2020	E1
2	COLOSCOPE	On OR	10:54:44	19-2-2020	E2
3	SURG.DERMA	Wrapping Room	10:57:04	19-2-2020	E3
4	ENDO EYE 0	Wrapping Room	10:57:17	19-2-2020	E4
4	ENDO EYE 0	Reset	10:57:22	19-2-2020	E4

## **Appendix 3.C      Snapshot of the surgery log dataset extracted from the ERP**

Table 3.11: A snapshot of the surgery log. Source: the hospitals' ERP system

Surg. ID	Date	Surgery Type	OR	Tray ID	Start	End
1	07/04/2021	LAPAROSCOPY DIAGN.	UH7	10	19:30	20:32
1	07/04/2021	LAPAROSCOPY DIAGN.	UH7	11	19:30	20:32
2	21/12/2021	SECTIO CAESAREA	UH6	12	19:00	19:51
3	09/07/2021	URETHROTOMY	UH8	13	18:40	19:04
4	14/03/2021	ABCES TRTMNT -(+ PCH)	UH8	14	17:23	18:17
5	28/07/2021	URETERORENOSCOPY	UH6	15	16:48	17:42
5	28/07/2021	URETERORENOSCOPY	UH6	16	16:48	17:42

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## 4 | Optimising Department Allocation in Hospital Layouts: A Simulation Metaheuristic Approach

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**Abstract** Patient arrivals in hospitals exhibit significant variability, requiring efficient positioning of departments to optimise room resource usage. This study proposes a novel approach to the Hospital Layout Problem (HLP) in the context of fully flexible nursing room setups. By strategically placing department centres and using the flexibility of nursing rooms, our method dynamically accommodates patients close to the centres, accounting for the departments' variability. To achieve efficient layouts, we develop a Hybrid TABU Search and simulation methodology that prioritises compact and connected departments, minimising cross-departmental movement. Incorporating a graph-based formulation of the HLP and a novel quantitative assessment method, we evaluate patient misplacement within flexible layouts. This research optimises resource usage and addresses the complexities of modern healthcare environments. It emphasises the importance of nursing unit layouts for enhancing operational efficiency and offers a practical methodology for efficient layout design and performance evaluation. In a newly constructed Danish hospital, our approach successfully reduces patient misplacement disruptions by over 45% compared to an initial benchmark developed by the hospital management.

**Keywords:** *Hospital Layout Problem, Hospital Logistics, Hospital Flexibility, Sim-Heuristic, TABU Search, Simulation*

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## 4.1 Introduction

The design of hospital layouts plays a critical role in achieving high operational performance and delivering quality care to patients in complex health-care environments. With a wide range of medical specialities and limited resources, hospitals face the challenge of managing highly stochastic demand (Hall, 2012). Since the 1970s, extensive research efforts have been dedicated to optimising hospital layouts to enhance internal flow, reduce costs, improve productivity, and support patient recovery (Arnolds and Nickel, 2015; Drira et al., 2007).

The variable demand for care in hospitals, however, poses challenges in capacity planning, resource management, and in predicting space requirements during hospital construction (Hall, 2012), which makes the Hospital Layout Problem (HLP) a complex task. Resource sharing and flexibility have emerged as common approaches to address uncertainty in demand and resource limitations (De Neufville et al., 2008).

In our study, we focus specifically on the layout of nursing units within hospitals, where beds and rooms can be shared. This setting provides an opportunity to leverage flexibility and achieve high-performance hospital layouts. Nonetheless, as highlighted by Bekker et al. (2017), uncontrolled flexibility can introduce inefficiencies in traffic flow and increase practitioners' workload, thereby undermining the intended benefits.

To address these challenges, we propose a novel version of the HLP that integrates flexibility into the layout design process while mitigating its staff and material flow increase drawbacks. Our approach incorporates a simulation-based evaluation of layout performance, specifically quantifying flexibility issues at the operational level to assess the strategic performance of a layout. This evaluation simulation includes a bed allocation heuristic that assigns room to patients optimising their positioning as close to their department centres as possible. This contribution effectively transforms the department allocation problem into a centre allocation problem and accommodates the dynamic nature of medical department sizes. Building upon this, we develop a hybrid TABU search and simulation heuristic framework to generate efficient layouts.

By moving beyond the traditional static allocation of pre-sized blocks and incorporating bed allocation for improved adaptability, our research offers a novel perspective on the HLP. It provides valuable insights into optimising hospital layouts to enhance operational performance and resource utilisation, ultimately improving the delivery of care to patients.

The remaining sections of this paper are organised as follows. In Section 4.2, we present a literature review on the HLP and hospital flexibility, and positions our research contribution. Section 4.3 introduces the use case that is the basis for our study and methodology. The details of our simulation optimisation approach are provided in Section 4.4, followed by a description of the performance evaluation simulation in Section 4.5. Section 4.6 presents the computational results obtained from our approach, and Section 4.7 concludes the paper and discusses our findings.

## **4.2 Literature Review**

The design and layout of healthcare facilities are critical aspects of Operations Management (OM) and Operations Research (OR) within the healthcare industry. HLP, originated as a subcase of the Facility Layout Problem (FLP), focuses on the positioning of departments and specific facilities within hospitals. Earlier studies by Delon (1970); Delon and Smalley (1970); Whitehead and Eldars (1965) approached HLP from a theoretical mathematical perspective, adapting FLPs to hospitals. However, recent years have witnessed increased interest and research in HLPs, as indicated by the 81 relevant articles identified by Benitez et al. (2019). Contemporary approaches, as highlighted by Jamali et al. (2020), involve collaborative efforts between architects and researchers, using optimisation techniques to improve the operational usability and constructability of healthcare facility layouts.

### **4.2.1 A wide range of HLPs**

The field of HLP encompasses a wide range of considerations, ranging from positioning entire medical departments in the entire hospital to specific activ-

ities inside specific subparts of the hospital, such as the Operation Theatre (OT) (Assem et al., 2012), or the Emergency Department (ED) (Rismanchian and Lee, 2017). Jamali et al. (2020) notes that the exact definition of HLP lacks consensus, as it relies on the specific scope considered.

One frequent aspect of HLPs revolves around the interrelationships among different elements and their positioning. The integration of related elements, such as OTs and Intensive Care Units (ICUs), can lead to synergistic benefits, which can be achieved through the use of adjacency matrices or activity graphs (see (Chraibi et al., 2013, 2014; Cubukcuoglu et al., 2022; Delon, 1970; Holst, 2015)). Hicks et al. (2015) identifies patients, families, staff, medications, supplies, equipment, and information as critical flows to consider for optimising hospital layouts. Comprehensive approaches consider the quantitative incorporation of these flows as suggested by Delon and Smalley (1970), or as commonly practised in the broader FLP literature (Drira et al., 2007). Building upon this Chraibi et al. (2014); Haji et al. (2006); Rismanchian and Lee (2017) strategically plan circulation paths to optimise these flows. Additionally, researchers like Bate and Robert (2006) and Becker and Parsons (2007), propose the use of evidence-based design methods and draw insights from innovative solutions implemented in other hospitals, offering a qualitative perspective on enhancing hospital layouts.

The field of HLPs, inherits methods from FLP literature, particularly Quadratic Assignment Problem (QAP). However, QAP formulations are known to be highly complex and NP-Hard (see (Cornuéjols et al., 1983; Garey and Johnson, 1979; Heragu, 2022)), leading to heuristic-based approaches (e.g. (Elshafei, 1977)), or decomposition techniques, (e.g. (Helber et al., 2016; Holst, 2015)). Other HLPs approaches often leverage concepts from Strategic Layout Planning (SLP) and Graph Theoretic Approach (GTA) to maximise closeness between related components. However, Jamali et al. (2020) notes that these conventional formulations of QAP, SLP, and GTA are inadequate to capture the dynamic nature of hospital demands. To address this limitation, Chraibi et al. (2013, 2014); Haji et al. (2006) introduce "Floating Facilities (FF)" allows activities to freely occupy adjustable spaces within the hospital layout, incorporating architectural design principles described by Michalek et al. (2002). Boucherie et al. (2012) highlights that department positioning is frequently undertaken within established hospital settings. Approaches such as Butler et al. (1992) aim to optimise the placement of departments by minimising the

need for extensive adjustments to fit within existing physical boundaries, a technique referred to as "maximising the goodness of the fit".

For a comprehensive overview of proposed HLP approaches and their solution methodologies, refer to the detailed table in Section 4.A.

#### **4.2.2 Including hospital variability into HLP**

Our research focuses on nursing unit placement within a new hospital facility. According to Rashid (2015), the predominant flows within nursing units revolve around the internal movement of staff, as patients typically stay within their individual rooms with limited interdepartmental mobility. Consequently, our focus diverges from the conventional HLP as the significance of interdepartmental relations and flows is reduced.

Hall (2012) explains that the variability in patient arrivals exhibits hourly, daily, weekly, and seasonal variations, while their Length of Stay (LOS) is influenced by various factors, resulting in high variability. This combination of patient arrivals and LOS directly impacts the demand for nursing units and, thereby, their size. Consideration of this highly variable nature is crucial aiming for efficient hospital layouts. Utley and Worthington (2012) discuss using queuing methods to estimate resource demands and determine size requirements for nursing units. Department dimensioning approaches can pursue different objectives, such as maximising profits (e.g. (Wang et al., 2009)), balancing bed availability probabilities (e.g. (de Bruin et al., 2010; Kao and Tung, 1981)), or combining different objectives (e.g. Zhou et al. (2018)).

Strategic department dimensioning techniques could be incorporated within what Drira et al. (2007) classifies as a static FLP-based approach. Such implementation, however, may overlook the operational stochasticity associated with demand variability. To address this issue, a framework proposed by Boucherie et al. (2012) includes a simulation-based evaluation of layout performance. Similar evaluations can be found in various other studies (see (Cubukcuoglu et al., 2020; Kritchanhai and Hoeur, 2018; Sasanfar et al., 2021; Wang et al., 2015; Wurzer, 2012)). In line with this approach, Zuo et al. (2019) and Butler et al. (1992) propose optimisation-simulation methods, where the

layout is iteratively improved based on simulation evaluation. Expanding this concept, Munavalli et al. (2022) propose a genetic algorithm coupled with simulation to reduce waiting and cycle times for an eye clinic.

In nursing unit planning, strategic-level decisions involve the positioning and dimensioning of units in terms of the number of beds or rooms, while the operational-level evaluation focuses on patient-to-bed allocations within the units. Extensive reviews on bed allocation strategies and management have been provided by Hall (2012) and He et al. (2019).

Flexibility in nursing units allows for the sharing of beds, mitigating the challenges associated with strict unit dimensioning (Bekker et al., 2017). Bekker et al. (2017) proposes various bed allocation policies ranging from fully flexible setups, where any patient can use any bed, to separate ward setups where beds are assigned to specific departments. Additional strategies include the use of a common buffer of flexible beds for patients exceeding department capacity and admission rules based on department hierarchy or predefined thresholds.

van Essen et al. (2014) combines separate ward setups with full flexibility by strategically grouping departments, enabling flexibility, resource pooling, and reduced demand uncertainty within clusters. The potential benefits of fully flexible beds in increasing and optimising bed utilisation are commonly recognised (see (Bekker et al., 2017; de Bruin et al., 2010; Hall, 2012)). Bekker et al. (2017); Holm et al. (2013) points out that fully flexible setups, however, could also result in increased staff and material movements as well as avoidable flow crossings. In conclusion, Bekker et al. (2017) suggests that hybrid approaches, such as overflow or threshold policies, demonstrate promising outcomes in effectively managing demand peaks.

### 4.2.3 Our contribution

Our research contributes to the HLP field by addressing the challenges of patient demand variability and incorporating the flexibility of beds into the hospital layout of nursing units. Building upon the strategic-operational decomposition proposed by Boucherie et al. (2012), our approach strategically

positions the centre of the nursing unit within the hospital and allocates patients in close proximity to these centres at the operational level. Unlike traditional approaches, we leverage the flexibility of resources, particularly beds, to strategically position the unit centres rather than pre-determining and pre-sizing activities.

This centric approach simplifies the HLP problem, allowing us to incorporate operational-level flexibility and achieve improved bed occupancy, in line with studies by Bekker et al. (2017); de Bruin et al. (2010); Hall (2012). To address concerns raised by Bekker et al. (2017); Holm et al. (2013) regarding staff travel, our system accommodates fully flexible beds while prioritising the allocation of patients near the centres of their respective departments, recreating departmental structures.

To evaluate the performance of our approach, we adopt a simulation meta-heuristic framework similar to Munavalli et al. (2022), employing a TABU search algorithm and conducting a simulation-based evaluation. By adopting this research methodology, we contribute to the development of efficient hospital layouts that effectively manage patient demand variability and optimise staff movement.

### **4.3 Use Case and Methodology**

In 2007, Denmark initiated a comprehensive hospital reform consolidating small hospitals into larger ones, closing 18 and planning to close 9 more, while constructing 6 new "super" hospitals. Danish Ministry of Health (2021) reports that the goal was to ensure large patient areas of over 300,000 inhabitants per hospital, thereby generating sufficient demand for specialised medical services and ultimately enhancing the quality of care and operational efficiency. The Nyt Hospital Nordsjælland (NHN), a "super" hospital under construction in Hillerød, approximately 40 km northwest of Copenhagen, serves as a case study for nursing wards HLP.

The architectural design of the NHN by Herzog & De Meuron (2014) features a three-level ground sub-structure housing key dynamic facilities like service

spaces, OTs, ICUs, the ED, and diagnostic rooms. The nursing wards are accommodated in a two-level four-leaf-clover structure that provides a view of an internal garden. Figure 4.1 presents architectural visualisations of the NHN, showcasing the integration of nature into the design and a standardised patient room with a view of the natural environment. According to Davidovici (2021), the incorporation of nature and individual patient rooms aims to enhance the healing process, aligning with previous research by Rashid (2015). Notably, all rooms in the NHN are individual, making bed and room allocations synonymous.



(a) Aerial visualisation of the top floors of the NHN hosting the nursing units



(b) Visualisation of one of the standardised rooms of the NHN with a view on the inner courtyard

Figure 4.1: Visualisations of the NHN (source: Herzog & De Meuron (2014))

The NHN is a medium-sized hospital featuring 14 specialised departments comprising 456 individual patient bedrooms. The hospital's grounded structure includes an extra 114 beds allocated for the ED and ICUs. The nursing rooms throughout the hospital have a standardised design, facilitating their use for patients from any department, except for the paediatrics and neonatal departments. In these areas, larger rooms have been incorporated to cater for both patients and their parents.

Figure 4.2 depicts a floor plan of the nursing ward area within the four-leaf-clover structure. Both floors share an identical layout. The red region represents technical areas (storage spaces, break rooms, elevators), while the green areas indicate administrative zones. As highlighted by Davidovici (2021), the layout features a main street with rooms on both sides. The paediatrics and neonatal departments occupy the right petal of the four-leaf clover. This case

study aims to optimise the arrangement of the remaining 12 medical specialities within the remaining 401 rooms across the two levels while avoiding direct passage through the paediatrics and neonatal departments. These two departments create distinct boundaries within the "circular" four-leaf-clover structure, effectively transforming the problem into locating the departments in two interconnected corridors facilitated by 12 elevators.

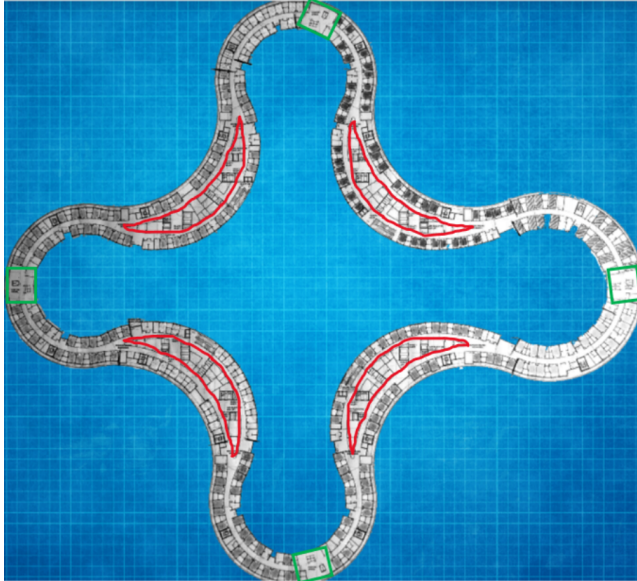


Figure 4.2: Floor-plan of one of the levels of the four-leaf-clover.

Whilst this configuration may resemble the Double-Row Layout Problem (DRLP) described by Chung and Tanchoco (2010) or the Corridor Allocation Problem (CAP) presented by Amaral (2012), the flow between rooms or departments is not a concern in this particular use case and is therefore not an objective. Additionally, these two problems are static FLPs and do not account for the flexibility inherent in the NHN scenario.

#### 4.3.1 A graph representation

In the context of the NHN, conventional QAP methods aim to allocate all rooms to corresponding departments (Drira et al., 2007). These methods, however, do not consider the flexibility of rooms or the variability in department

sizes. SLP or GTA graph-based formulations are designed to capture the relationships between activities to be positioned, which is not suitable for positioning independent nursing units within the NHN. In this context, it is important to consider the relationships between neighbouring rooms and whether patients are from the same department or not. Therefore, a graph-based modelling approach that focuses on room relations and locations rather than activity relations, as in SLP or GTA approaches, becomes particularly relevant for the NHN case.

Our proposed approach models the hospital layout as a weighted graph. Each room in the hospital is a vertex of the graph and separated vertices for elevator doors on each level have been added. Using the floor plan depicted in Figure 4.2, edges are established between adjacent rooms and rooms facing each other across the corridor. Additionally, edges connect the elevator doors to the nearest rooms, ensuring connectivity between the two corridors. In our model, distances are measured based on the number of rooms, although alternative metrics such as metric distances or travel time could be used without loss of generality.

Edges connecting adjacent rooms or rooms separated by the corridor are assigned a weight of 1. Following discussions with the NHN management, edges crossing the administrative area carry a cost of 10, while edges representing elevators have a cost of 50, reflecting the preference to avoid floor changes. The sensitivity of these values will be further explored in Section 4.6. Figure 4.3 illustrates a representative example of the constructed graph, where elevators are depicted in red, rooms in grey and administrative areas crossings in green.

### 4.3.2 Key Performance Indicators (KPIs) of the layout performance

The NHN management aims to strike a balance between the flexibility of the fully flexible nursing wards and the desired resemblance to a traditional separate department setup. The flexibility addresses the limitations of a rigid departmental arrangement to accommodate variable demand, while the traditional separate department approach aims to prevent patient mixing and upsurging staff and material flow, which are identified as flexibility issues by

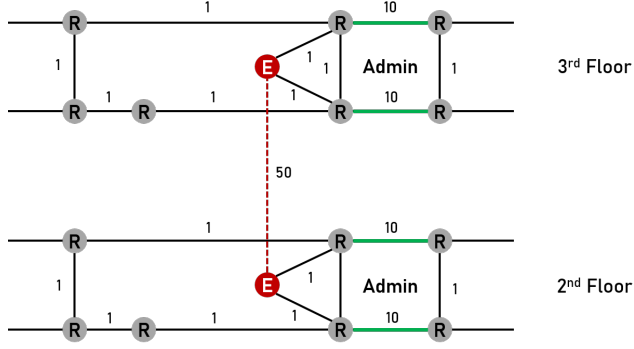


Figure 4.3: Example of the graph representation of the hospital layout.

Holm et al. (2013) and Bekker et al. (2017). To assess the performance of the layout, two KPIs are proposed: *compactness*, which measures the tightness of departments at the operational level, and *connectedness*, which evaluates patient crossing and approximates avoidable mixing flows.

#### 4.3.2.1 Compactness $\kappa$

For each daily period (morning, afternoon, evening, and night), we evaluate the distance of each assigned patient from the centre of their respective department. This distance is calculated as the shortest path within the graph representation of the hospital. Our nearest patient allocation heuristic aims to maximise department compactness. The total distance is theoretically bounded by the patient allocation within the hospital without any collisions with patients from other departments.

The discrepancy between each patient's distance to their department centre and the optimal distance in the collision-free hospital is summed across all simulation periods and patients. This sum is then compared to the number of accommodated patients and their LOS to determine the compactness  $\kappa$ . This value represents the average distance between the actual patient placement and the theoretical best placement unaffected by other departments.

Let  $T$  denote the set of time periods in the simulation,  $P(t)$  represent the set of patients in the hospital at period  $t \in T$ ,  $x_p$  indicate the position of patient

$p \in P(t)$  within the hospital,  $x_p^*$  denote the theoretical optimal allocation,  $\lambda_p$  its LOS, and  $c_p$  represent the position of the centre of the department to which patient  $p \in P(t)$  belongs. The compactness  $\kappa$  can be expressed using Equation (4.1).

$$\kappa = \frac{1}{|P|} \cdot \sum_{t \in T} \sum_{p \in P(t)} \frac{\text{dist}(x_p, c_p) - \text{dist}(x_p^*, c_p)}{\lambda_p} \quad (4.1)$$

#### 4.3.2.2 Connectedness $\gamma$

Using graph theory terminology, for each department and time period, we define the central connected component as the connected component that includes the department's centre in the department subgraph of the entire layout's graph. This subgraph comprises all the rooms that are either available or occupied by patients belonging to the same department, including the centre of the department. The central connected component can be viewed as the core of the department.

The distances between each patient's room and their respective central connected component are computed for all time periods and averaged across all patients based on their LOS. These distances are calculated using the shortest path within the graph representation to any vertex within the central connected component. The connectedness metric favours traditional ward setup with connected departments and penalises isolated patients. The connectedness  $\gamma$  value represents the average number of rooms occupied by another department between a patient and their connected component.

Using the same notations as in Equation (4.1), with  $C_t(p)$  representing the central connected component of the department to which patient  $p \in P(t)$  belongs at period  $t \in T$ , the connectedness  $\gamma$  can be expressed as shown in Equation (4.2).

$$\gamma = \frac{1}{|P|} \cdot \sum_{t \in T} \sum_{p \in P(t)} \frac{\text{dist}(x_p, C_t(p))}{\lambda_p} \quad (4.2)$$

### **4.3.3 Average Patient Misplacement (APM)**

The hospital places equal importance on two KPIs. The objective of the approach is to minimise the combined value of both compactness and connectedness, which corresponds to the average total misplacement of a patient (APM) and is expressed in a number of rooms distance.

## **4.4 Strategic optimisation–simulation positioning of departments**

Our approach combines a tabu search as proposed by Glover (1986) with a simulation-based evaluation of the objective function. The search procedure generates layouts at the strategic level and their performance is evaluated at the operational level by the simulation. The hospital layout of the NHN consists of two corridors interconnected by 12 elevators. As all beds within the hospital are flexible, the departments are defined, on the operational level, by the rooms occupied by their patients. Although this flexible definition allows departments to vary in shape and position, to be mixed and disconnected, the objective is to create a layout that emulates a more traditional setup with separate departments. To achieve this, we anchor the flexible departments around fixed centres at a strategic level and a nearest allocation heuristic is employed to allocate rooms at the operational level, thereby limiting the movement of these flexible departments. By arranging the departments in a sequential order between the two floors and appropriately distributing their centres, we effectively allocate the available corridor space to meet the demands of each department. This process results in a layout closely resembling a series of distinct departments occupying consecutive sections of the corridors. The proposed tabu search algorithm is designed to explore and find efficient department orders that minimise APM.

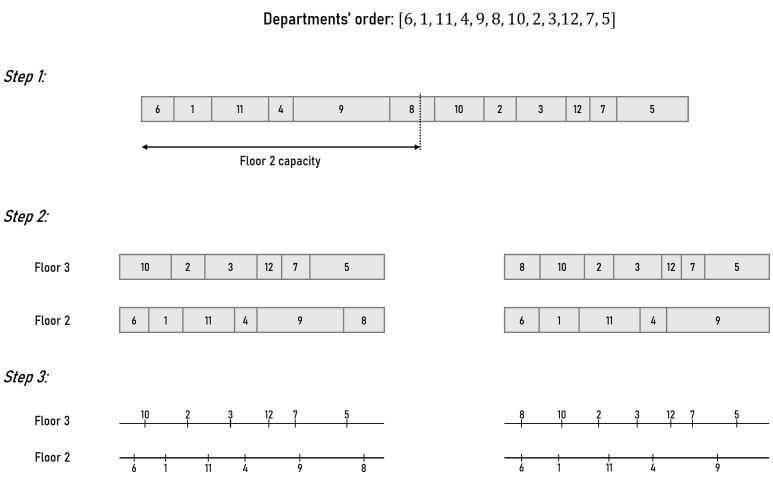


Figure 4.4: Scheme of department centres generation procedure

4.4.1 Transforming Departments Order into Departments Centres

Figure 4.4 illustrates the process of converting an ordered list of departments into their respective department centres, which serve as input for the operational simulation model. The transformation involves three key steps.

In Step 1, a Monte Carlo simulation estimates the patients’ arrival per period for each department over a year, determining the proportion of NHN rooms that should be allocated to each department. This simulation is conducted prior to the tabu search algorithm, as it is independent of the departments’ order.

In Step 2, rooms are preallocated based on the hospital’s structure in a traditional separated wards approach. Initially, all the first departments of the order that can be accommodated on Floor 2 are positioned, same for the last departments on Floor 3. Two scenarios are built with the "middle" department, which would be split across floors. The first scenario assigns the middle department to Floor 2, the second assigns it to Floor 3. Within each floor, rooms are redistributed again based on departments’ demand, ensuring equitable spacing.

In Step 3, for each department in each scenario, a centre is determined by identifying the room that minimises the distance to other rooms.

This process generates two lists of department centres. The operational simulation evaluation is then used for both scenarios, to solely keep the one providing the most favourable outcome.

#### 4.4.2 Sim-heuristic framework

In line with Munavalli et al. (2022), our approach adopts a metaheuristic framework that integrates our simulation-based performance evaluation. This framework, known as "sim heuristics" and discussed by Juan et al. (2015), has demonstrated its effectiveness in exploring a wide range of solutions while considering real-life stochasticity. However, sim-heuristic methods are highly computationally demanding due to the need for running multiple replications to ensure credibility in the simulation. To address this challenge, Juan et al. (2015) propose a deterministic pre-evaluation step to assess the potential for improvement of a solution before engaging in full stochastic evaluation and its associated replications. This strategy uses the notion that a solution yielding favourable outcomes in the stochastic problem will likely perform well in a deterministic instance of the problem.

Our tabu-search algorithm, depicted in Algorithm 4.1, integrates this deterministic pre-evaluation technique namely *Evaluate\_Det* in Algorithm 4.1. *Evaluate\_Stoch* corresponds to the full stochastic evaluation. Both evaluations are detailed in Section 4.5.

The proposed Algorithm 4.1 is built around a classical tabu-search structure, encompassing diversification and intensification procedures as suggested by Gendreau and Potvin (2014), and uses a time-limit stop criterion.

##### Initialisation: Line 1

The *Construct\_Initial()* function implements a department assignment algorithm based on the departments' expected size requirement and standard deviations. Its goal is to distribute departments evenly across floors, with

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**Algorithm 4.1** Tabu Search

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**Input:**

Time limit  $t_{lim}$   
 Stall limit  $stall_{lim}$

**Output:**

Best Solution  $best$

1: **Initialise**

$sol \leftarrow Construct\_Initial()$  ▷ Construct an initial solution  
 $Evaluate\_Det(sol), Evaluate\_Stoch(sol)$  ▷ Evaluate the solution  
 $best, currentBest, current \leftarrow sol$  ▷ Initiate the best and current solutions  
 $tabu \leftarrow [ sol ]$  ▷ Initiate the tabu list  
 $t_{last} \leftarrow 0$  ▷ Initiate the time since last improvement

2: **while**  $t < t_{lim}$  **do**

3:  $neighbours \leftarrow Generate\_Neighbourhood(current)$   
 4:  $new \leftarrow null$   
 5: **for**  $sol \in neighbours$  **do**  
 6:     **if**  $sol \notin tabu$  **then**  
 7:          $Evaluate\_Det(sol)$   
 8:         **if**  $Accept\_Det(currentBest, sol)$  **then**  
 9:              $Evaluate\_Stoch(sol)$   
 10:         **if**  $(new \text{ is null}) \vee (sol \text{ better than } new)$  **then**  
 11:              $new \leftarrow sol$   
 12:          $Insert(sol, tabu)$  ▷ Update the tabu list  
 13:     **if**  $new \text{ is null}$  **then** ▷ If all the neighbours were in the tabu list  
 14:          $current, currentBest \leftarrow Diversify(current)$   
 15:          $t_{last} \leftarrow 0$   
 16:     **else**  
 17:          $current \leftarrow new$   
 18:         **if**  $current \text{ better than } currentBest$  **then**  
 19:              $currentBest \leftarrow current$   
 20:              $t_{last} \leftarrow 0$   
 21:             **if**  $current \text{ better than } best$  **then**  
 22:                  $best \leftarrow current$   
 23:         **else if**  $t_{last} > stall_{lim}$  **then**  
 24:              $current, currentBest \leftarrow Diversify/Intensify(current, best)$   
 25:              $t_{last} \leftarrow 0$

---

lower standard deviation departments closer to the corridor ends. This approach ensures that departments with higher size variations are not confined to the less flexible end-sections where space constraints may be challenging to accommodate their needs.

Departments are ranked by ascending standard deviation, and the algorithm assigns the first department to the second floor, adjacent to one end of the corridor, followed by the second department on the third floor. The third department serves as the "middle" department of Section 4.4.1 procedure. Subsequently, the remaining departments are iteratively assigned to the floor with the largest remaining available space. This iterative assignment strategy, referred to as a "worst-fit heuristic" in the context of bin-packing (Johnson, 1974), aims to balance the expected demand among the available spaces. The resulting department order is the concatenation of the second-floor departments, the "middle" department and the third-floor departments.

The initial solution undergoes both deterministic and stochastic evaluations, establishing benchmarks for the best, current best, and current solutions. It also serves as the foundation for initialising the tabu list. Concurrently, the counter for iterations without observed improvements, denoted as  $t_{last}$ , is set to zero.

#### **Iteration: Lines 3 - 12**

A neighbourhood of solutions is generated by swapping every pair of adjacent departments within the current solution. These new solutions are evaluated deterministically in parallel for improved performance, excluding tabu solutions (solutions visited previously).

Deterministic solutions are accepted based on the comparison of their objective values with the current best solution using a threshold  $\tau_{det}$ . Accepted solutions undergo stochastic evaluation. The solution with the best stochastic evaluation becomes the new current solution. If no solutions meet the deterministic acceptance criterion, the best deterministic solution is chosen, stochastically evaluated, and adopted as the new current solution.

The stochastic evaluation in our approach involves conducting multiple replications to reach a steady state and obtain reliable simulation outputs, there-

fore being computationally expensive. The deterministic acceptance criterion serves to reduce the number of layouts that need to undergo stochastic evaluation. It focuses on evaluating layouts that have the potential for improvement, thereby accelerating the overall search process.

### State Update: Lines 13 - 25

If all generated neighbour solutions are in the tabu list, a diversification procedure is employed. Otherwise, the best and current best solutions are updated if an improvement is found.

When no improvement is observed for a period exceeding the stall limit  $t_{stall}$ , diversification and intensification procedures are alternately applied. Diversification generates a new current solution by randomly selecting and performing a certain number  $n_{div}$  of swaps between any departments from the current best solution. The intensification first comes back to the best solution and performs a small number  $n_{int}$  of random swaps between any departments. The current best solution aims to identify the local optimum, while the best solution aims for the global optimum.

Parameter values of our approach are presented in Table 4.1. The values have been determined through preliminary tests, as thorough parameter tuning would be computationally intensive. The tabu-search framework efficiently explores a vast solution space and provides satisfactory solutions within a reasonable time.

Table 4.1: Tabu-Search Sim-heuristic Parameters

Parameter	Value	Range of tested values
Tabu list length	100	[50, 100, 250, 1000]
Deterministic acceptance threshold $\tau_{det}$	0.3	[0.05, ..., 0.45]
Number of swaps for the diversification $n_{div}$	3	[1, 3, 5, 8]
Number of swaps for the intensification $n_{int}$	1	[1, 2, 3]
Stall limit $t_{stall}$	100	[50, 100, 250, 1000]

## 4.5 Operational-level simulation performance evaluation

The operational level of our approach uses a simulation to model patient arrivals and their individual LOS for each department. This simulation includes the allocation of patients to nursing wards and the evaluation of the KPIs of compactness and connectedness. The key inputs for this operational process are the patient demand and the precise locations of the department centres within the hospital.

### 4.5.1 Patients' arrival and LOS

As part of the pooling strategy outlined by Danish Ministry of Health (2021), the NHN is designed to replace the former Northern Zealand hospitals, which encompassed Frederikssund, Hillerød, and Helsingør hospitals, while also undertaking a reorganisation of medical operations to enhance efficiency and overall performance. The NHN management kindly shared the data used for the research. Although the NHN is not yet operational, the data consists of two subsets: 1) data that describes the physical infrastructure of the future hospital and 2) historical anonymous data on admissions and LOS of patients during the years 2018-2021. None of the data used are related to any ethics issues. To avoid COVID-19-related fluctuations, the analysis only uses patient data from 2018 and 2019.

In the considered departments, it is estimated by the NHN that more than 90% of admitted patients arrive from the ED without prior scheduling. To simulate the stochastic admission pattern, Poisson distributions with time-varying intensity are used, aligning with established practices in the literature (e.g., Bekker et al. (2017); Cubukcuoglu et al. (2020); Holm et al. (2013)). Additionally, to model the LOSs, log-normal distributions are employed, following common approaches (e.g., Cubukcuoglu et al. (2020); Harini et al. (2018); Marazzi et al. (1998)).

To address the inherent variabilities in patient arrival patterns and LOS, the daily time frame is divided into four periods: night (0AM-6AM), morning

(6AM-12AM), afternoon (12AM-6PM), and evening (6PM-12PM). For each department, season, day of the week, and time period, Poisson coefficients, along with log-normal  $\alpha$  and  $\beta$  coefficients, are determined. This comprehensive approach yields a total of 1344 coefficients, capturing the complexities associated with patients' arrival patterns and LOS variabilities highlighted by Hall (2012).

Danish Ministry of Health (2021) emphasises a notable shift towards reduced hospitalisation, shorter LOS, and increased utilisation of telemedicine and home care. Reorganising its medical operations following these trends, the NHN is already experiencing the anticipated decrease in room demand. However, the absence of precise data or estimates regarding this phenomenon presents challenges in accurately modelling the future demand of the NHN.

Optimal bed occupancy, as discussed by Hall (2012) and He et al. (2019), depends on specific hospital characteristics but typically ranges from 60% to 80% for inpatient departments, with a safety upper bound of 85%. To evaluate the effectiveness of our hospital layout, we have designed three occupancy scenarios targeting rates of 60%, 80%, and 90%, respectively.

Using patient arrival and LOS data provided by the NHN, we conducted a Monte-Carlo simulation to estimate the bed requirements for accommodating the demand from the original hospitals in Frederikssund and Hillerød, based on data from the 2018-2019 period (Helsingør Hospital does not have nursing wards and thus, no demand for beds).

To align the expected occupancy with the target rates of 60%, 80%, and 90%, we computed adjusting factors by modifying the arrival Poisson coefficients while maintaining the patient distribution across departments. However, adjusting LOSs globally is impractical, as they are influenced by various treatment practices and patient progress. Therefore, our approach focuses on achieving the desired target occupancy rates primarily through adjustments to patient arrivals.

### 4.5.2 The simulation model

The simulation procedure, as outlined in Algorithm 4.2, uses the occupancy coefficients of the selected occupancy scenario (e.g. 60%, 80%, or 90% target occupancy) along with the department centres  $c_d$  as inputs.

#### Initialisation: Lines 1 - 1

A matrix  $A$  represents the patient allocation with rooms as rows and time periods as columns. In Step 1, the matrix  $A$  is initialised with zeros for all rooms and time periods, indicating that all rooms are initially available. A separate matrix  $A^*$  with an extra dimension for the departments, represents the theoretical collision-free allocation used to compute the compactness as described in Section 4.3.2.1. Additionally, the KPIs, and the patient dropout counters are initialised to 0.

#### Patients Generation: Lines 3 - 7

For each time period considered, for each department, the arrival of patients is simulated using a Poisson distribution, and their LOS is created using a Log-normal distribution.

#### Patient Allocation: Lines 8 - 17

The time period of the simulations corresponds to 6 hours windows, hence to reflect the random emergency-like arrival patient observed in the NHN, the generated patients are randomly shuffled. Patients are then successively allocated using the nearest-allocation heuristic, assigning patients to the closest available rooms near their department centre. Patients without available rooms are "dropped" from the simulation, emulating the patient being redirected to another hospital.

The allocation matrices  $A$  and  $A^*$  are populated by assigning the department number to the respective room and time periods.

#### Patient Allocation: Lines 18 - 21

For all the time periods in the runtime, the KPIs are computed based on Equations (4.1) and (4.2)

---

**Algorithm 4.2** Bed Allocation Simulation Algorithm.

---

**Input:**

Set of departments  $\mathcal{D}$   
 Set of rooms  $\mathcal{R}$   
 Set of runtime time periods  $\mathcal{T}$   
 Set of warm-up time periods  $\mathcal{W}$   
 Set of time periods  $\widehat{\mathcal{T}} = \mathcal{W} \cup \mathcal{T}$   
 Poisson arrival coefficients  $\lambda_{d,t}$ ,  $\forall (d,t) \in \mathcal{D} \times \widehat{\mathcal{T}}$   
 LOS log-normal coefficients  $(\mu_{d,t}, \sigma_{d,t})$ ,  $\forall (d,t) \in \mathcal{D} \times \widehat{\mathcal{T}}$   
 Departments centres  $c_d \in \mathcal{R}$ ,  $\forall d \in \mathcal{D}$

**Output:**

Bed allocation matrix  $\mathbf{A} = [a_{r,t}]_{(r,t) \in \mathcal{R} \times \widehat{\mathcal{T}}}$   
 Compactness  $\kappa$   
 Connectedness  $\gamma$   
 Dropouts  $n_{drop}$

**1: Initialize**

Initialise the bed allocation matrix  $\mathbf{A} \leftarrow [0]_{(r,t) \in \mathcal{R} \times \widehat{\mathcal{T}}}$   
 Initialise the theoretic collision-free bed allocation matrix  $\mathbf{A}^* \leftarrow [0]_{(r,d,t) \in \mathcal{R} \times \mathcal{D} \times \widehat{\mathcal{T}}}$   
 Initialise the compactness and connectedness  $(\kappa, \gamma) \leftarrow (0, 0)$   
 Initialise the number of dropouts  $n_{drop} \leftarrow 0$

**2: for**  $t \in \widehat{\mathcal{T}}$  **do**

**3:** Initialise the list of patients to allocate  $\Pi \leftarrow \emptyset$

**4: for**  $d \in \mathcal{D}$  **do**

**5:** Draw  $n_d$  patients from  $Poisson(\lambda_{d,t})$

**6:** Draw  $n_d$  LOSs  $(l_p)_{p \in [0, n_d-1]}$  from  $LogNormal(\mu_{d,t}, \sigma_{d,t})$

**7:** Add the patient to  $\Pi = \Pi \cup [\bigcup_{p \in [0, n_d-1]} (d, l_p)]$

**8:** Shuffle the arrivals  $Shuffle(\Pi)$

**9: for**  $(d, l) \in \Pi$  **do**

**10:** Find the closest free allocation  $x = BestAllocation(c_d, \mathbf{A})$

**11: if** an allocation is possible ( $x \neq \emptyset$ ) **then**

**12:** Find the closest theoretic allocation  $x^* = BestTheoAllocation(c_d, d, \mathbf{A}^*)$

**13: for**  $\theta \in [0, l-1]$  **do**

**14:** Allocate the patient in  $\mathbf{A}$ ,  $a_{x,t+\theta} = d$

**15:** Allocate the patient in  $\mathbf{A}^*$ ,  $a_{x^*,d,t+\theta}^* = 1$

**16: else**

**17:** Increment dropouts  $n_{drop} = n_{drop} + 1$

**18: if**  $t \in \mathcal{T}$  **then**

**19:** Increment the KPIs

**20:**  $\kappa = \kappa + Compactness(\mathbf{A}, \mathbf{A}^*, t)$

**21:**  $\gamma = \gamma + Connectedness(\mathbf{A}, t)$

---

Algorithm 4.2 returns the computed KPIs evaluating the layout and the allocation matrix for visualisation and analysis purposes.

### 4.5.3 Deterministic Evaluation

The stochastic evaluation,  $Evaluate\_Stoch()$ , and the deterministic evaluation,  $Evaluate\_Det()$ , employed in the tabu-search sim-heuristic Algorithm 4.1, follow the shared structure outlined in Algorithm 4.2. In the deterministic evaluation, the LOS for each patient is determined by taking the maximum between the expected LOS calculated using the lognormal coefficients  $\mu$  and  $\sigma$ , and 1, as stated in Equation (4.3). This ensures that no patient has a null LOS. The arrival rates are set close to the expected value  $\lambda_{stoch}$ , as indicated in Equation (4.4). The Poisson arrival coefficient, corresponding to the expected arrival rate, is rounded up or down with a probability corresponding to the fractional value of the coefficient. To maintain consistency, a fixed seed is used for both the random rounding process and the random shuffling of arriving patients. These strategies ensure that deterministic runs resemble the "average" demand behaviour and can be compared.

$$LOS_{det} = \max \left\{ e^{\mu + \frac{\sigma^2}{2}}, 1 \right\} \quad (4.3)$$

$$\lambda_{det} = \lfloor \lambda_{stoch} \rfloor + \begin{cases} 1 & \text{if } rand() > \lambda_{stoch} - \lfloor \lambda_{stoch} \rfloor \\ 0 & \text{otherwise} \end{cases} \quad (4.4)$$

## 4.6 Computational Experiments

The proposed approach was implemented using Julia 1.8.5. The simulation runs of 32 replications, were parallelised on a Linux cluster with 32 cores, and a Xeon Gold 6226R processor with 256GB of memory. With this configuration, an experiment for an 80% target occupancy scenario takes approximately 1 minute to execute.

### **4.6.1 Experimental Design, Model Validation and Verification of the Stochastic Evaluation**

The objective of the proposed simulation is twofold: to account for the stochastic nature of patient arrivals and LOS patterns, and to allocate beds within the hospital. Although the model's behaviour has been verified, the simulated hospital has not yet been constructed, and the corresponding patient allocation procedure has not yet been implemented, making the notion of validation not applicable in this context. Here, the simulation serves as a means to handle stochasticity and evaluate performance within a broader strategic department allocation framework.

To accurately capture hourly, daily, and seasonal variations in patient arrivals and LOS (Hall, 2012), it is essential to use as runtime a duration that is a multiple of 1 year. Since our simulation begins with an empty hospital, a warm-up period is necessary to mitigate the resulting starting bias.

#### **4.6.1.1 Warm-up period**

In our analysis, the simulation begins in the Spring season. The warm-up period is established by focusing on the LOS of winter patients. Figure 4.5b presents a Monte Carlo simulation of the LOS for all winter patients, with Subfigure 4.5a specifically highlighting the palliative care patients arriving on Friday afternoon, who have the longest LOS among the winter patients. The results demonstrate that a 6-week duration ensures a 99.92% probability (95% CI:  $\pm 0.011\%$ ) that all winter patients have sufficient time for full hospitalisation. Hence, a 6-week warm-up period guarantees that the hospital has been populated at least once with a 99.92% probability. Therefore, a 6-week warm-up period is adopted for the analysis.

#### **4.6.1.2 Run length and Replications**

Our approach uses a fixed run length of 1 year, which corresponds to 4 seasons of 13 weeks each, and relies on replications to achieve a steady state. To determine the required number of replications, we generated 100 layouts for

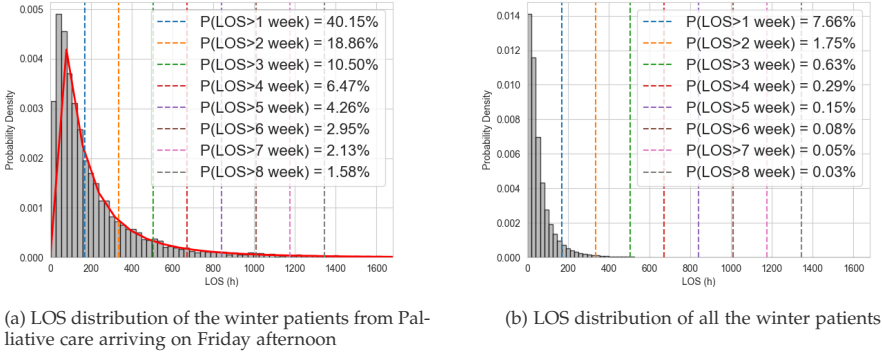


Figure 4.5: Winter patients' LOS distribution. The histogram represents the density of LOS values, The dashed lines denote weekly thresholds of 6 weeks, and the corresponding probability of exceeding these thresholds

testing. For each layout, an experiment consisting of 512 replications with a 1-year run length and a 6-week warm-up period has been run. Following the recommendations of Robinson (2014), we then focused on the Confidence Interval (CI) to determine the appropriate number of replications.

For each potential number of replications, we computed the 95% CI for the KPIs values. Table 4.2 presents the results of this CI analysis where CIs are expressed as percentages of the average value. It can be observed that scenarios with a lower target occupancy exhibit higher variability in the KPIs. This could be attributed to the fact that lower occupancy allows for more diverse room allocations, while higher occupancy scenarios are more constrained. Lower occupancy also reduces issues related to departments collisions and patient misplacements.

The KPIs values for the 60% target occupancy scenario are significantly lower compared to the other scenarios and slight changes between replications have a substantial impact. The observed APM remain under 0.3 rooms in the 60% target occupancy scenario but can reach up to 8 for the 90% one.

Table 4.2 demonstrates that 32 replications are sufficient to maintain the 95% CIs around 2% for the 80% and 90% occupancy scenarios. Although the resulting 95 % CI is larger on the 60 % occupancy scenario, the difference in terms of APM is very small (ie  $\sim 0.015$  rooms) which is considered acceptable.

Table 4.2: 95% CI analysis of the number of replications

Occupancy Scenario	KPI	Repl. for CI < 2%		Repl. for CI < 1%		CI after 32 repl.	
		median	95 <sup>th</sup> perc.	median	95 <sup>th</sup> perc.	median	95 <sup>th</sup> perc.
60%	Compactness	34	56	76	141	2.02%	3.45%
	Connectedness	37	63	82	151	2.32%	3.67%
	APM	35	61	80	135	2.12%	3.47%
80%	Compactness	19	34	65	122	1.49%	2.08%
	Connectedness	22	37	74	129	1.58%	2.19%
	APM	20	34	70	124	1.54%	2.08%
90%	Compactness	9	17	30	53	0.96%	1.33%
	Connectedness	10	18	32	58	1.00%	1.40%
	APM	10	17	32	55	0.98%	1.36%

#### 4.6.2 Baseline Layout and centre positioning impact

NHN management, in consultation with doctors and nurses, proposed a layout which follows a separated wards structure, with each bed allocated to a specific department. In order to evaluate this arrangement, we conducted an assessment using three occupancy target scenarios.

Firstly, the classical structure has been transformed by calculating the centres of the departments in the NHN layout. These centres were then used as input for our simulation model. Additionally, we proposed a hybrid layout, maintaining the proposed order of departments while computing the centres based on the demand, as described in Section 4.5.1.

Table 4.3: Performance evaluation of the layout proposed by the NHN management and of the hybrid layout with the same order but computed centres

	Occupancy Scenario	Compactness	Connectness	APM	Improvement	Patients /year	Dropouts /year
NHN layout	60%	0.11	0.11	0.22		31,088.2	0
	80%	1.06	1.16	2.22		41,420.2	2.09
	90%	3.41	3.99	7.40		46,658.8	303.12
Hybrid layout	60%	0.03	0.03	0.06	-72.7%	31,090.1	0
	80%	0.87	1.11	1.98	-11.7%	41,483.2	1.19
	90%	3.02	3.91	6.93	-6.4%	46,554.8	297.59

The evaluation results, presented in Table 4.3, highlight the effectiveness of the centre allocation procedure. For lower-occupancy scenarios, the allocation

shows a substantial reduction in APM, reaching 72.7%. However, in the 90% target occupancy scenario, the reduction is only 6.4%. This disparity can be attributed to the higher flexibility and potential for adjustments in lower occupancy setups compared to more constrained higher occupancy scenarios. Additionally, considering individual patients, the misplacements caused by the allocation in the 60% occupancy scenario remain minimal.

It is important to highlight that the total corridor length spans 1.4 km, resulting in an average separation of 6.1 meters between two adjacent rooms. By utilising the patient arrival and LOS data for each occupancy scenario, we can translate the practical implications of an APM difference of 0.01 as a daily increase in walking distance for a hypothetical medical practitioner who needs to visit all patients once each day. In the 60%, 80%, and 90% target occupancy scenarios, such a difference translates to an additional daily walk of 32 m, 43 m, and 48 m, respectively. Consequently, the hybrid layout offers substantial advantages, resulting in a respective daily reduction of 512 m, 1,032 m, and 2,256 m in walking distance for the hypothetical practitioner in the 60%, 80%, and 90% occupancy scenarios. This reduction in daily distance translates to significant improvements in operational efficiency and convenience.

Figure 4.6 illustrates the average room occupancy by department for the 80% target occupancy scenario, comparing the NHN and hybrid layouts. The hybrid scenario shows a more spacious allocation for larger departments like Pulmonary and Infections, Cardiology, Orthopaedics and Surgery, while smaller departments are more compact, resulting in reduced misplacements overall. The occupancy of rooms on the 3<sup>rd</sup> floor is significantly higher than the 2<sup>nd</sup> floor in both scenarios, indicating potential improvements by relocating smaller departments such as Gynaecology, Gastroenterology or Palliative Care to the lower floor.

### 4.6.3 Tabu Search Results

The tabu-search procedure was executed for all occupancy scenarios over a one-week period (168 hours). Figure 4.7 presents the progression of the search, showing the gap between the current best solution and the best-observed solution. The results indicate that the tabu search rapidly converges to satisfactory

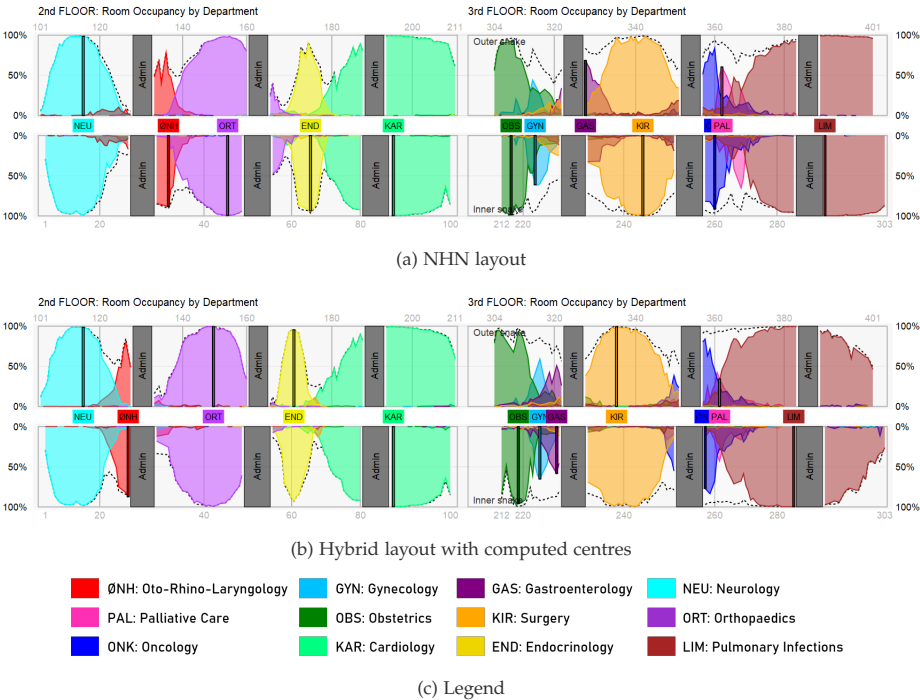


Figure 4.6: Average simulated occupancy by department of the rooms in the 80% target occupancy scenario

solutions, reaching a gap of less than 10% from the best-observed solution within the initial 1000 iterations, after which the diversification and intensification methods explore other solutions and further enhance the outcomes.

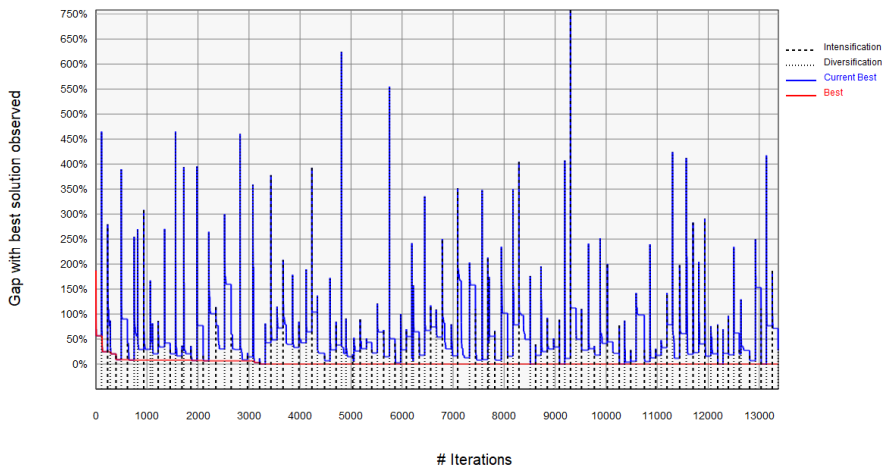


Figure 4.7: Tabu Search performance evolution for the 80% target occupancy scenario

Table 4.4 provides an overview of the iterations and solution exploration numbers across all target occupancy scenarios. The table shows a decrease in the number of iterations as the target occupancy increases. This can be attributed to two factors. Firstly, higher occupancies require accommodating more patients, resulting in increased computational time. Secondly, solutions for higher occupancy scenarios exhibit less variability in objective values, leading to a higher proportion of deterministically accepted solutions that are then stochastically evaluated, thus slowing down the search process.

Table 4.4: Tabu Search Execution Summary

Occupancy Scenario	Iterations	# solutions stoch. evaluated	# solutions det. evaluated	Diversifications	Intensifications
60%	35,134	10,330	163,790	185	153
80%	13,375	15,756	45,063	59	56
90%	5,345	19,092	22,115	19	15

Table 4.5 demonstrates the substantial improvements achieved by the tabu search algorithm compared to the baseline layout proposed by the NHN management. Notably, in the 60% target occupancy scenario, the tabu search re-

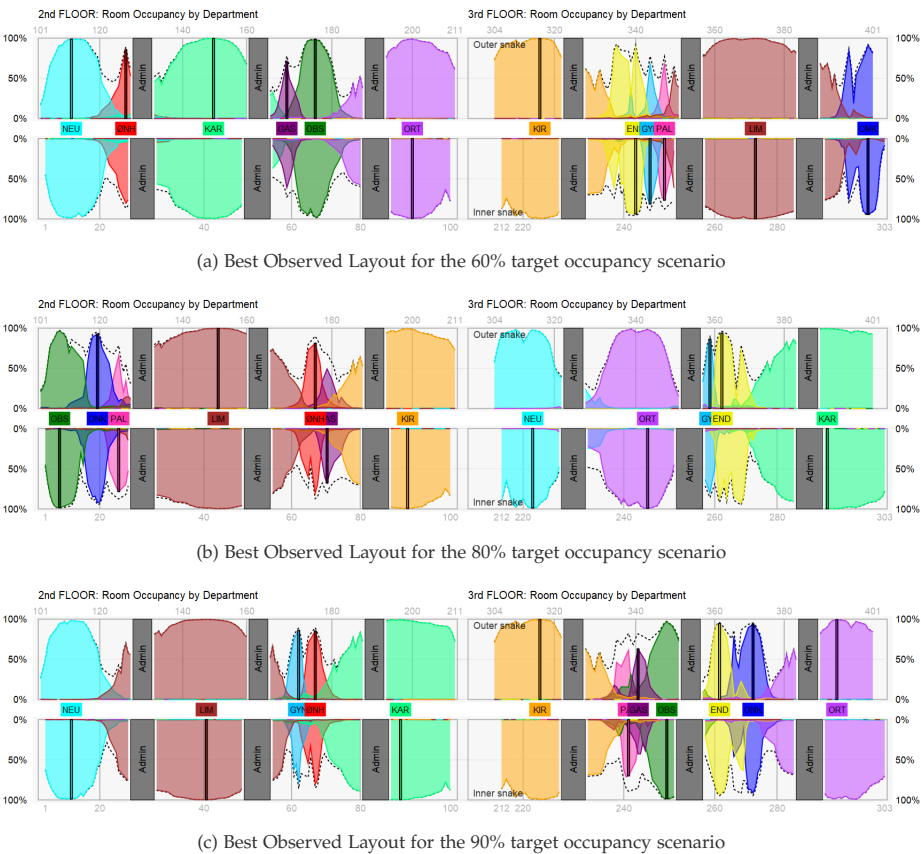


Figure 4.8: Average simulated occupancy by department of the rooms for the best layouts obtained for each scenario

Table 4.5: Performance evaluation of the best layouts found with the tabu search for the 3 occupancy target scenarios and comparisons with the best-observed and baseline layouts

Occupancy Scenario	Compactness	Connectness	APM	$\Delta_{Baseline}$	Hypothetical Daily Walk Reduction
60%	< 0.01	< 0.01	< 0.01	−98.9%	0.7 km
80%	0.22	0.27	0.49	−78.1%	7,4 km
90%	1.76	2.19	3.96	−46.5%	16,5 km

sults in neglectable APM, with less than 1 patient misplaced by 1 room. The reductions in APM are significant in the 90% and 80% target occupancy scenario, respectively 46.5% and 78.1% which translate into a significant daily walk reduction of 7.439 km and 16.512 km for a hypothetical practitioner who has to visit all patients once per day. These findings are in line with our earlier observation that higher occupancy scenarios offer limited flexibility for adjustments, resulting in lower variability in APM and consequently smaller improvements compared to lower occupancy scenarios. However, it is important to note that as the occupancy decreases, the level of disruption experienced also diminishes, reducing the importance of advanced optimisation techniques.

The pronounced disparity between the proposed layouts and the baseline scenario underscores the large impact of a poorly designed layout, leading to patient misplacements and disruptions. Thus, the importance of selecting an appropriate layout based on the actual patient demand is evident.

The outcomes, as well as the explored solutions during the tabu search (depicted in Figure 4.7), reveal a narrow range of department orders that yield similar outcomes, with a disparity of less than 20% in APM. This implies that the tabu search can effectively identify layouts within this range, thereby assisting management in making informed decisions regarding the best layout choice.

#### **4.6.4 Tabu Search Procedure Performance**

Figure 4.7 demonstrates the rapid convergence of the tabu search algorithm, achieving favorable solutions within the first 1000 iterations. Subsequently, the diversification and intensification procedures become crucial in exploring the solution space further and potentially identifying superior solutions. To assess the reliability and overall performance of the tabu search, ten experiments were conducted for each target occupancy scenario, allowing for the evaluation of result consistency and quality. Figure 4.9 depicts the evolution of the best solutions observed in the 10 Tabu Searches for the 80% target occupancy scenario. Improvements continue to emerge even after 144 hours, but the variation between the best solutions from the 10 searches tends to dimin-

ish.

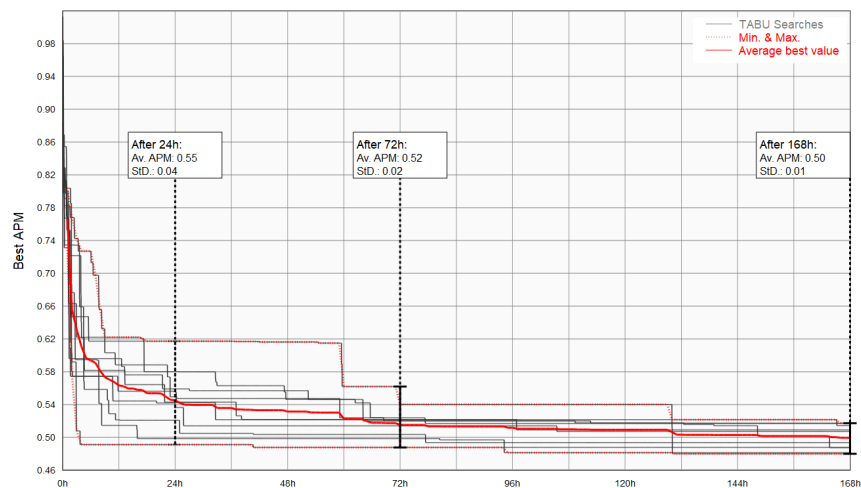


Figure 4.9: Evolution of Best Solutions in 10 Tabu Searches for the 80% Target Occupancy Scenario

Table 4.6 presents the average APM and standard deviation found across the 10 searches for all target occupancy levels. For the 60% occupancy scenario, the APM values are negligible, while for the 80% and 90% occupancy targets, the standard deviation is less than 2%. This level of variability is comparable to the 95% confidence interval of the simulation results, indicating that the solutions derived from the search procedures exhibit equivalent performance, and that, the search procedure produces reliable consistent results.

Table 4.6: Average APM and Standard Deviation of 10 Tabu Search Experiments for All Target Occupancy Scenarios

Occupancy Target	Av. Best APM	StD.	StD. in %	Simulation 95% CI
60%	< 0.01	< 0.01	-	2.12%
80%	0.50	0.01	1.99%	1.54%
90%	4.04	0.07	1.66%	0.98%

### 4.6.5 Sensitivity analysis

The cost of changing floors was determined in consultation with the NHN management and was estimated at 50 rooms (equivalent to half the corridor length or approximately 700 meters), while crossing the administrative area incurred a cost of 10 rooms. Tabu searches were conducted with varying cost parameters (10 and 200 for elevators, and 1 and 50 for administration crossings) to assess their impact on the optimisation process and resulting layouts. These variations allowed for an investigation into the sensitivity of the algorithm and its role in determining the department arrangement. The analysis of different cost settings provided valuable insights for decision-making in real-world implementations, considering the trade-offs involved in department allocation.

Table 4.7: Sensitivity Analysis of the Elevator and Administration Crossing Costs on the 80% target occupancy scenario

Elevator Cost	Administration Crossing Cost	Compactness	Connectedness
10	1	0.11	0.15
10	10	0.21	0.36
10	50	0.54	1.33
50	1	0.20	0.23
<b>50</b>	<b>10</b>	<b>0.27</b>	<b>0.33</b>
50	50	0.70	1.26
200	1	0.25	0.29
200	10	0.35	0.39
200	50	0.52	0.56

Table 4.7 presents the sensitivity analysis results for the 80% target occupancy scenario. As expected, the KPIs demonstrate a positive correlation with increasing cost parameters, particularly for administration crossing.

When examining the average room occupancy for scenarios with low and high costs for elevators and administration crossings, we observe that regardless of the elevator cost, the occupancy of departments across floors is neglectable. Such crossings are infrequent and represent extreme cases. While these cases may have a marginal impact on the overall KPIs values, they do not result in departments being allocated across different floors.

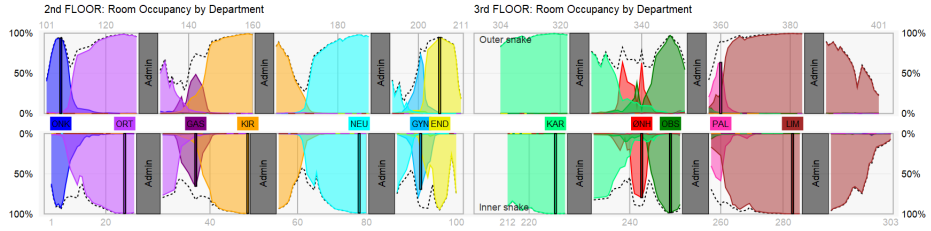
Conversely, the cost associated with administrative crossings has a significant impact on the layout. Certain departments, such as Cardiology and Pulmonary Infection, are inherently too large and require administrative crossings. In contexts where administration crossing costs are high, other departments are positioned to avoid or limit such crossings. This highlights the substantial impact of administrative crossing costs on the overall layout design.

## **4.7 Conclusions and further research**

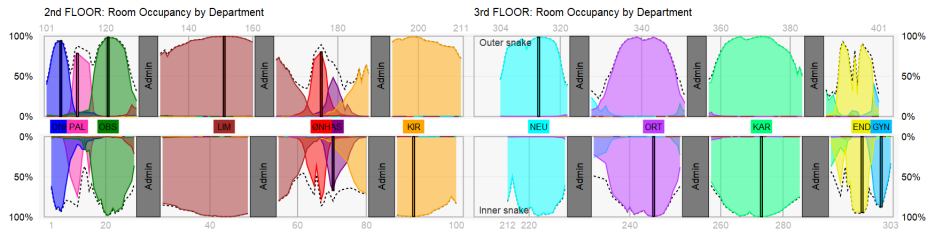
This study investigates a novel version of the HLP that specifically focuses on positioning nursing departments within a flexible setup. Unlike traditional approaches, strategically positioning fixed-size units, our key innovation lies in strategically placing department centres and using the inherent flexibility of nursing rooms to dynamically accommodate patients at an operational level. This adaptable approach allows accounting for medical departments' variability and dynamically adjusts their spatial requirements to match their actual size.

We have developed a TABU Search and simulation methodology that strategically positions department centres and employs simulation techniques to allocate patients and evaluate the performance of the proposed layout. Our methodology addresses the challenges associated with fully flexible setups, emphasising the importance of compactness and connectedness of departments to minimise cross-departmental movement. We introduce a graph-based formulation of the HLP and a novel quantitative assessment method for evaluating patient misplacements within flexible layouts.

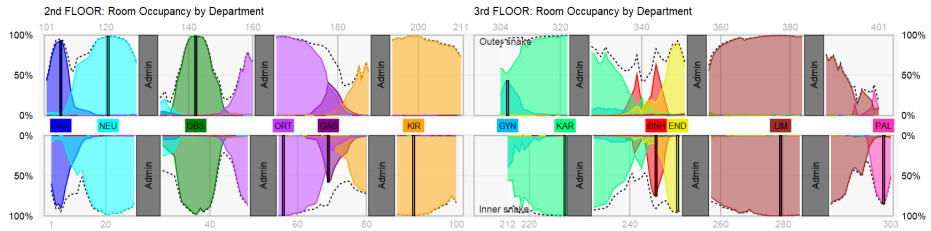
By adopting this innovative approach, our research aims to tackle the complexities and challenges of modern healthcare environments, leveraging flexibility to optimise resource utilisation. The findings of this study underscore the significance of nursing unit layouts in enhancing operational efficiency, offering a methodology for achieving efficient layouts and evaluating their performance. Our methodology manages to reduce APM by more than 45% compared to the initial baseline layout provided by the hospital management.



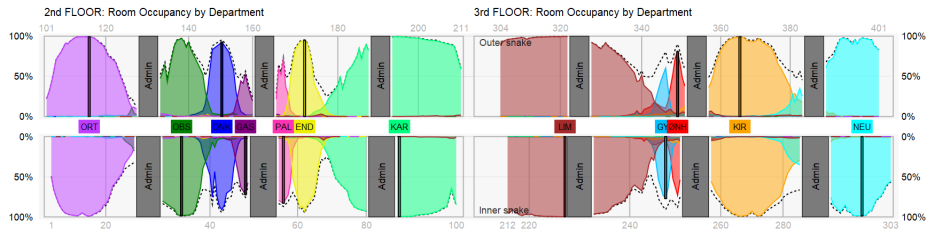
(a) Low Elevator Cost (10)



(b) High Elevator Cost (200)



(c) Low Administration Crossing Cost (1)



(d) High Administration Crossing Cost (50)

Figure 4.10: Average simulated occupancy by department of the rooms for the best layouts obtained for each of the elevator and administration crossing costs

Further research in this area holds potential for exploring alternative meta-heuristic algorithms, such as genetic algorithms, as well as more thorough parameter tuning to accelerate solution exploration and address the simulation-induced computational challenges encountered in our study. Additionally, an improved allocation heuristic could be devised to alleviate issues related to room occupancy near the edges. Indeed as edges are further from the centres their occupancy is lower but could be used to reduce patient misplacements in the middle of corridors. An additional simulation analysis could be formulated to achieve a more precise evaluation of the travel distance and time saved by workers and equipment due to the enhanced layouts. Such an analysis would offer a more accurate estimate than the hypothetical scenario of a worker visiting all patients daily. Lastly, investigating how our methodology could be adapted to enhance flexibility in highly active departments such as EDs or ICUs, which exhibit a higher number of equipment and cross-flows, would be worthwhile. Exploring these avenues would contribute to advancing the understanding and application of flexible layout design methodologies, not only in healthcare settings but also in other industries that share standard resources, such as coworking spaces.

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## Bibliography

- Abbasi, E., Ahmadi, S. H., Naderi, S., and Vahdani, F. A. (2017). Modelling of layout design and selection of appropriate design with a case study. *International Journal of Industrial and Systems Engineering*, 25(2):251–264.
- Amaral, A. R. (2012). The corridor allocation problem. *Computers and Operations Research*, 39(12):3325–3330.
- Arnolds, I. and Nickel, S. (2015). Layout planning problems in health care. *International Series in Operations Research and Management Science*, 232:109–152.
- Arnolds, I. V. and Nickel, S. (2013). Multi-period layout planning for hospital wards. *Socio-economic Planning Sciences*, 47(3):220–237.
- Assem, M., Ouda, B. K., and Wahed, M. A. (2012). Improving operating theatre design using facilities layout planning. *2012 Cairo International Biomedical Engineering Conference, Cibec 2012*, pages 109–113.
- Bate, P. and Robert, G. (2006). Experience-based design: From redesigning the system around the patient to co-designing services with the patient. *Quality and Safety in Health Care*, 15(5):307–310.
- Becker, F. and Parsons, K. S. (2007). Hospital facilities and the role of evidence-based design. *Journal of Facilities Management*, 5(4):263–274.
- Bekker, R., Koole, G., and Roubos, D. (2017). Flexible bed allocations for hospital wards. *Health Care Management Science*, 20(4):453–466.
- Benitez, G. B., Da Silveira, G. J., and Fogliatto, F. S. (2019). Layout planning in healthcare facilities: A systematic review. *Health Environments Research and Design Journal*, 12(3):31–44.
- Boucherie, R. J., Hans, E. W., and Hartmann, T. (2012). Health care logistics and space: Accounting for the physical build environment. *Proceedings - Winter Simulation Conference*, page 6465222.
- Butler, T. W., Karwan, K. R., Sweigart, J., and Reeves, G. (1992). An integrative model-based approach to hospital layout. *Iie Transactions*, 24(2):144–152.
- Chraibi, A., Kharraja, S., Osman, I. H., and Elbeqqali, O. (2013). A mixed integer programming formulation for solving operating theatre layout problem:

- A multi-goal approach. *Proceedings of 2013 International Conference on Industrial Engineering and Systems Management, Ieee - Iesm 2013*, page 6761401.
- Chraibi, A., Kharraja, S., Osman, I. H., and Elbeqqali, O. (2014). A multi-objective mixed-integer programming model for a multi-section operating theatre facility layout. *Icores 2014 - Proceedings of the 3rd International Conference on Operations Research and Enterprise Systems*, pages 196–204.
- Chraibi, A., Kharraja, S., Osman, I. H., and Elbeqqali, O. (2015). Multi-agent system for solving dynamic operating theater facility layout problem. *Ifac-papersonline*, 28(3):1146–1151.
- Chraibi, A., Kharraja, S., Osman, I. H., and Elbeqqali, O. (2016). A particle swarm algorithm for solving the multi-objective operating theater layout problem. *Ifac-papersonline*, 49(12):1169–1174.
- Chung, J. and Tanchoco, J. M. (2010). The double row layout problem. *International Journal of Production Research*, 48(3):709–727.
- Cornuéjols, G., Nemhauser, G., and Wolsey, L. (1983). The uncapacitated facility location problem. Technical report, Cornell University Operations Research and Industrial Engineering.
- Cubukcuoglu, C., Nourian, P., Sariyildiz, I. S., and Tasgetiren, M. F. (2020). A discrete event simulation procedure for validating programs of requirements: The case of hospital space planning. *Software*, 12:100539.
- Cubukcuoglu, C., Nourian, P., Sariyildiz, I. S., and Tasgetiren, M. F. (2022). Optimal design of new hospitals: A computational workflow for stacking, zoning, and routing. *Automation in Construction*, 134:104102.
- Cubukcuoglu, C., Nourian, P., Tasgetiren, M. F., Sariyildiz, I. S., and Azadi, S. (2021). Hospital layout design renovation as a quadratic assignment problem with geodesic distances. *Journal of Building Engineering*, 44:102952.
- Danish Ministry of Health (2021). The danish super hospital programme. <https://sum.dk/Media/0/2/TheDanishSuperHospitalProgramme2021.pdf>.
- Davidovici, I. (2021). Hospital-as-city. the healthcare architecture of herzog & de meuron. In Jasper, A., editor, *gta papers. Social Distance*, volume No. 5, pages 118–131. gta, ETH Zurich, Zurich.

- de Bruin, A. M., Bekker, R., van Zanten, L., and Koole, G. M. (2010). Dimensioning hospital wards using the erlang loss model. *Annals of Operations Research*, 178(1):23–43.
- De Neufville, R., Lee, Y. S., and Scholtes, S. (2008). Flexibility in hospital infrastructure design. In *IEEE Conference on Infrastructure Systems*, pages 8–10. Rotterdam, Netherlands.
- Delon, G. L. (1970). A methodology for total hospital design. *Health Services Research*, 5(3):210–223.
- Delon, G. L. and Smalley, H. E. (1970). A stochastic model for inter-departmental traffic. *Health Services Research*, 5(3):196–209.
- Drira, A., Pierreval, H., and Hajri-Gabouj, S. (2007). Facility layout problems: A survey. *Annual Reviews in Control*, 31(2):255–267.
- El Kady, A., Sami, S. A., and Eldeib, A. M. (2017). A two stage heuristics for improvement of existing multi floor healthcare facility layout. *Acm International Conference Proceeding Series*, 128534:97–101.
- Elshafei, A. N. (1977). Hospital layout as a quadratic assignment problem. *Operational Research Quarterly*, 28(1):167–179.
- Feng, X. and Su, Q. (2015). An applied case of quadratic assignment problem in hospital department layout. *2015 12th International Conference on Service Systems and Service Management, Icassm 2015*, page 7170278.
- Garey, M. R. and Johnson, D. S. (1979). *Computers and intractability. A guide to the theory of NP-completeness*. Freeman.
- Gendreau, M. and Potvin, J. Y. (2014). Tabu search. *Search Methodologies: Introductory Tutorials in Optimization and Decision Support Techniques, Second Edition*, pages 243–264.
- Glover, F. (1986). Future paths for integer programming and links to artificial intelligence. *Computers and Operations Research*, 13(5):533–549.
- Hahn, P. M. and Krarup, J. (2001). A hospital facility layout problem finally solved. *Journal of Intelligent Manufacturing*, 12(5-6):487–496.
- Haji, M., Wang, L., Wong, Y., and Darabi, H. (2006). Renovation of mercy family health center. *Ifac Proceedings Volumes (ifac-papersonline)*, 12(1).

- Hall, R. (2012). Bed assignment and bed management. *International Series in Operations Research and Management Science*, 168:177–200.
- Harini, S., Subbiah, M., and Srinivasan, M. R. (2018). Fitting length of stay in hospitals using transformed distributions. *Communications in Statistics Case Studies Data Analysis and Applications*, 4(1):1–8.
- He, L., Chalil Madathil, S., Oberoi, A., Servis, G., and Khasawneh, M. T. (2019). A systematic review of research design and modeling techniques in inpatient bed management. *Computers and Industrial Engineering*, 127:451–466.
- Helber, S., Böhme, D., Oucherif, F., Lagershausen, S., and Kasper, S. (2016). A hierarchical facility layout planning approach for large and complex hospitals. *Flexible Services and Manufacturing Journal*, 28(1-2):5–29.
- Heragu, S. S. (2022). *Facilities Design, Fifth Edition*. CRC Press.
- Herzog & De Meuron (2014). New north zealand hospital. <https://www.herzogdemeuron.com/projects/416-new-north-zealand-hospital/>.
- Hicks, C., McGovern, T., Prior, G., and Smith, I. (2015). Applying lean principles to the design of healthcare facilities. *International Journal of Production Economics*, 170:677–686.
- Holm, L. B., Luras, H., and Dahl, F. A. (2013). Improving hospital bed utilisation through simulation and optimisation with application to a 40% increase in patient volume in a norwegian general hospital. *International Journal of Medical Informatics*, 82(2):80–89.
- Holst, M. (2015). Optimal hospital layout design. *Ph.d.-serien for Det Teknisk-Naturvidenskabelige Fakultet, Aalborg Universitet*.
- Huo, J., Liu, J., and Gao, H. (2021). An nsga-ii algorithm with adaptive local search for a new double-row model solution to a multi-floor hospital facility layout problem. *Applied Sciences (switzerland)*, 11(4):1–21.
- Ibrahim, A. (2012). A framework for genetic algorithm application in hospital facility layout design. *IUP Journal of Operations Management*, 11(4):16.
- Jamali, N., Leung, R. K., and Verderber, S. (2020). A review of computerized hospital layout modelling techniques and their ethical implications. *Frontiers of Architectural Research*, 9(3):498–513.
- Johnson, D. S. (1974). Fast algorithm for bin packing. *Journal of Computer and System Sciences*, 8(3):272–314.

- Juan, A. A., Faulin, J., Grasman, S. E., Rabe, M., and Figueira, G. (2015). A review of simheuristics: Extending metaheuristics to deal with stochastic combinatorial optimization problems. *Operations Research Perspectives*, 2:62–72.
- Kao, E. P. C. and Tung, G. G. (1981). Bed allocation in a public health care delivery system. *Management Science*, 27(5):507–520.
- Kritchanchai, D. and Hoeur, S. (2018). Simulation modeling for facility allocation of outpatient department. *International Journal of Healthcare Management*, 11(3):193–201.
- Lee, Y. H. and Rismanchian, F. (2018). Optimizing hospital facility layout planning through process mining of clinical pathways. *Annals of Optimization Theory and Practice*, 1(1):1–9.
- Liang, L. Y. and Chao, W. C. (2008). The strategies of tabu search technique for facility layout optimization. *Automation in Construction*, 17(6):657–669.
- Lin, Q. L., Liu, H. C., Wang, D. J., and Liu, L. (2015). Integrating systematic layout planning with fuzzy constraint theory to design and optimize the facility layout for operating theatre in hospitals. *Journal of Intelligent Manufacturing*, 26(1):87–95.
- Ma, Y., Zuo, X., Huang, X., Gu, F., Wang, C., and Zhao, X. (2016). A moea/d based approach for hospital department layout design. *2016 Ieee Congress on Evolutionary Computation, Cec 2016*, page 7743872.
- Marazzi, A., Paccaud, F., Ruffieux, C., and Beguin, C. (1998). Fitting the distributions of length of stay by parametric models. *Medical Care*, 36(6):915–927.
- Michalek, J. J., Choudhary, R., and Papalambros, P. Y. (2002). Architectural layout design optimization. *Engineering Optimization*, 34(5):461–484.
- Motaghi, M., Hamzenejad, A., Riyahi, L., and SOHEILI, K. M. (2011). Optimization of hospital layout through the application of heuristic techniques (diamond algorithm) in shafa hospital (2009). *International Journal of Management and Business Research*.
- Munavalli, J. R., Rao, S. V., Srinivasan, A., and Van Merode, F. (2022). Dynamic layout design optimization to improve patient flow in outpatient clinics using genetic algorithms. *Algorithms*, 15(3):85.

- Nickel, S. and Tenfelde, D. (2000). Planning and organisation in the hospital. *Operations Research Proceedings 1999*, pages 548–553.
- Rashid, M. (2015). Research on nursing unit layouts: An integrative review. *Facilities*, 33(9-10):631–695.
- Rismanchian, F. and Lee, Y. H. (2017). Process miningbased method of designing and optimizing the layouts of emergency departments in hospitals. *Health Environments Research and Design Journal*, 10(4):105–120.
- Rizk-Allah, R. M., Slowik, A., Darwish, A., and Hassanien, A. E. (2021). Orthogonal latin squares-based firefly optimization algorithm for industrial quadratic assignment tasks. *Neural Computing and Applications*, 33(23):16675–16696.
- Robinson, S. (2014). *Simulation: The Practice of Model Development and Use, 2nd edition*. Bloomsbury Publishing.
- Sasanfar, S., Bagherpour, M., and Moatari-Kazerouni, A. (2021). Improving emergency departments: Simulation-based optimization of patients waiting time and staff allocation in an iranian hospital. *International Journal of Healthcare Management*, 14(4):1449–1456.
- Silva, R. M., Resende, M. G., Pardalos, P. M., Mateus, G. R., and De Tomi, G. (2013). Grasp with path-relinking for facility layout. *Springer Proceedings in Mathematics and Statistics*, 59:175–190.
- Tongur, V., Hacibeyoglu, M., and Ulker, E. (2020). Solving a big-scaled hospital facility layout problem with meta-heuristics algorithms. *Engineering Science and Technology, an International Journal*, 23(4):951–959.
- Utley, M. and Worthington, D. (2012). Capacity planning. *International Series in Operations Research and Management Science*, 168:11–30.
- van Essen, J. T., van Houdenhoven, M., and Hurink, J. L. (2014). Clustering clinical departments for wards to achieve a prespecified blocking probability. *Or Spectrum*, 37(1):243–271.
- Wang, T., Guinet, A., and Besombes, B. (2009). A sizing tool for allocation planning of hospital bed resources. *Studies in Computational Intelligence*, 189:113–125.
- Wang, T. K., Yang, T., Yang, C. Y., and Chan, F. T. (2015). Lean principles and

- simulation optimization for emergency department layout design. *Industrial Management and Data Systems*, 115(4):678–699.
- Whitehead, B. and Eldars, M. (1965). The planning of single-storey layouts. *Building Science*, 1(1):127–139.
- Wurzer, G. (2012). In-process agent simulation for early stages of hospital planning. *Ifac Proceedings Volumes*, 45(2):358–363.
- Yeh, I. C. (2006). Architectural layout optimization using annealed neural network. *Automation in Construction*, 15(4):531–539.
- Zhou, L., Geng, N., Jiang, Z., and Wang, X. (2018). Multi-objective capacity allocation of hospital wards combining revenue and equity. *Omega (united Kingdom)*, 81:220–233.
- Zuo, X., Li, B., Huang, X., Zhou, M. C., Cheng, C., Zhao, X., and Liu, Z. (2019). Optimizing hospital emergency department layout via multiobjective tabu search. *Ieee Transactions on Automation Science and Engineering*, 16(3):1137–1147.

## Appendix 4.A Classification of recent HLP approaches

Table 4.8: Classification of recent HLP approaches

	Objective	Base	Solving
<i>Theoretical layout of imaginary hospital</i>			
Whitehead and Eldars (1965)	Minimise 'Travel Cost'	SLP	Best insertion heuristic allocation of the units with simulation evaluation
Delon (1970)	Minimise Construction Cost	SLP	CORELAP software for iteratively inserting department, CRAFT software for performing swaps
Hahn and Krarup (2001)	Minimise Transportation Cost	QAP	Exact
<i>Positioning departments in a hospital</i>			
Elshafei (1977)	Minimise Transportation Cost	QAP	Construction heuristic, iterative improvement procedure
Butler et al. (1992)	Minimise Transportation Cost & goodness of the positioning	QAP	Two phases with simulation performance measurement
Nickel and Tenfelde (2000)	Minimise Transportation Cost	QAP	Multi-criteria with branch and bound, and stochastic
Haji et al. (2006)	Minimise Transportation Cost	FF	MIP simplification and solver
Motaghi et al. (2011)	Maximise Closeness	SLP	
Feng and Su (2015)	Minimise Transportation Cost	QAP	MIP simplification and solver
Abbasi et al. (2017)	Minimise Transportation Cost and Maximise Closeness	FF	MIP simplification and solver
<i>Positioning departments in a hospital with several levels</i>			
Yeh (2006)	Maximise Closeness	QAP	Annealed neural network
Liang and Chao (2008)	Minimise Transportation Cost	QAP	TABU Search
Ibrahim (2012)	Minimise Transportation Cost	-	Genetic Algorithm
Silva et al. (2013)	Minimise Transportation Cost	QAP	GRASP with path-relinking
Arnolds and Nickel (2015)	Maximise Closeness	GTA	Also presented an iterative simulation-Optimisation solving of a QAP
El Kady et al. (2017)	Minimise Transportation Cost and Maximise Closeness	SLP	
Tongur et al. (2020)	Minimise Transportation Cost and Maximise Closeness	QAP	Migrating Bird Optimization, Tabu search, Simulated annealing
Cubukcuoglu et al. (2021)	Minimise Transportation Cost	QAP	Iterative Local Search
Huo et al. (2021)	Minimise Transportation Cost and Maximise Closeness	DRLP	NSGA-II Algorithm with Adaptive Local Search
Cubukcuoglu et al. (2022)	Maximise Closeness	SLP	Hierarchical 3 Stages

## Section 4.A: Classification of recent HLP approaches

<i>Positioning activities in OT</i>				
Assem et al. (2012)	Maximise Closeness	GTA	Heuristic	
Chraibi et al. (2013)	Minimise Transportation Cost and Maximise Closeness	FF	MIP simplification and solver	
Lin et al. (2015)	Maximise Closeness	SLP		
Chraibi et al. (2016)	Minimise Transportation Cost and Maximise Closeness	FF	Particle swarm algorithm	
<i>Positioning activities in a ED</i>				
Ma et al. (2016)	Minimise Transportation Cost	QAP	Construction heuristic, iterative improvement procedure	
Rismanchian and Lee (2017)	Goal Programming: 5 Goals	-	Process Mining	
Lee and Rismanchian (2018)	Maximise Closeness	QAP	Process Mining	
Zuo et al. (2019)	Minimise Transportation Cost and Maximise Closeness	SLP	Multi-objective Tabu Search	
<i>Positioning departments in a hospital with several buildings</i>				
Holst (2015)	Maximise Closeness	QAP	Genetic Algorithm	
Helber et al. (2016)	Minimise Transportation and Adaptation Cost and Maximise Closeness	QAP	Multi-objective Evolutionary Algorithm Based on Decomposition	
Rizk-Allah et al. (2021)	Minimise Transportation Cost	QAP	Firefly Algorithm - Mutually Orthogonal Latin Squares	
<i>Positioning wards with variable demands</i>				
Arnolds and Nickel (2013)	Minimise construction and operation cost, maximise demand satisfaction	-	5 models to handle demand variation in a robust or flexible way	
Chraibi et al. (2015)	Minimise Transportation Cost	QAP	Multi-Agent Architecture	

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