THE USE OF SIMULATION TO EVALUATE OPTIMISATION-GENERATED MASTER SURGERY SCHEDULES

MSc Thesis Engineering & Policy Analysis

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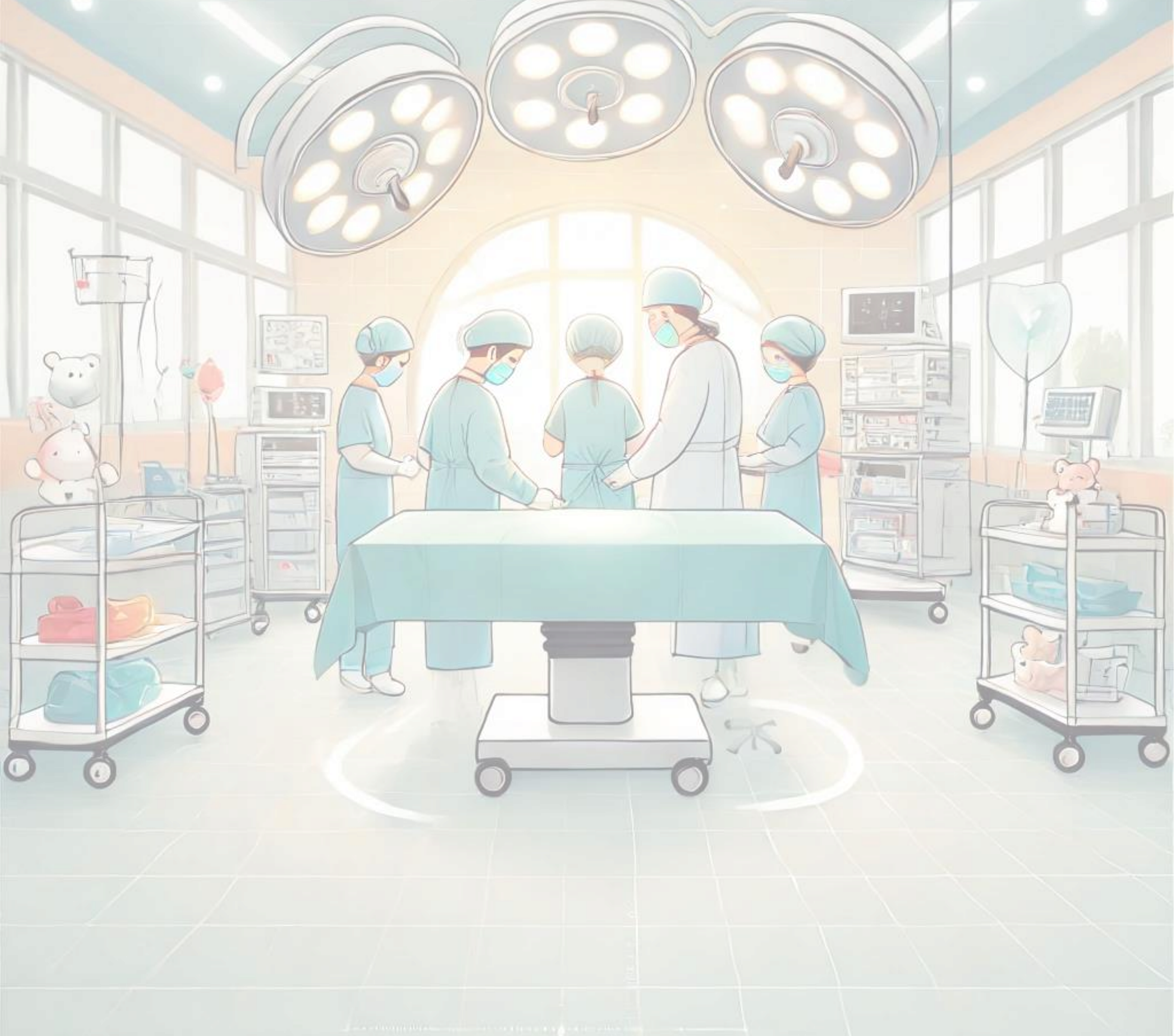

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BY

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EXECUTIVE SUMMARY

During the COVID-19 pandemic, many elective surgeries had to be rescheduled as resources such as beds and ventilators were reallocated, causing significant delays in patient care. To avoid such disruptions in the future effective resource management and planning approaches for elective surgery are essential. Optimisation is a commonly used method to enhance elective operating theatre scheduling, it is a technique used for mathematical modeling. It can integrate various criteria to maximise benefits and minimise costs within specified constraints. However, optimisation alone often falls short in addressing the complexities and required flexibility of operating theatre scheduling. This is where simulation can build upon these limitations. Simulation techniques can model system behaviour by replicating real-world processes, introduce uncertainty, and evaluate responses to different policies, helping to identify bottlenecks and improve system efficiency. Sequencing optimisation and simulation can test theoretically sound solutions under real-world uncertainties and complexities. This leads to the following research question:

"How can Discrete Event Simulation evaluate optimisation-generated Master Surgery Schedules for operating theatres?"

The research question focuses on a Master Surgery Schedule, which coordinates different surgical specialities, sharing OTs and pre- and post-surgery resources. While this approach increases resource utilisation, it also adds complexity by needing to accommodate the varying requirements of each speciality. The research aims to evaluate different Master Surgery Schedule using Discrete Event Simulation to contribute to the optimisation model.

Overall, the use of the Discrete Event Simulation model provided detailed insights into the performance of various schedules. Testing these schedules under different types of uncertainty demonstrated their robustness, as the behaviour remained consistent across scenarios. By comparing the schedules side by side, the simulation model effectively evaluated their effectiveness, ensuring the intended purposes were served and identifying areas for improvement.

The research specifically considers Discrete Event Simulation as this method can queue patients for different resources and have them move throughout the system based on decision rules. It is also a standard applied method for modelling healthcare systems. Both Discrete Event Simulation and optimisation are standard methods for improving OT scheduling. Even sequencing the methods has been proven to contribute to OT scheduling. However, applying this approach to a Master Surgery Schedule is new and introduces additional complexity related to the shared OTs and pre- and post-surgery resources.

To explore this research question, a case study was conducted at Sophia Children's Hospital in Rotterdam. Previous research developed the Master Surgery Schedule using an optimization model, resulting in four different schedules. These schedules either balanced ward leveling and operating theatre utilization equally or prioritized ward leveling. They also varied in computational requirements, as the model updated the bed availability either every 15 minutes or every hour. This research categorizes 18 different surgical departments into 50 groups based on their surgery duration and length of stay, assigning time slots to these groups in the schedules.

This research uses these groupings to fit different distributions for the input variables of length of stay and surgery duration. Five different types of distributions were tested for each group, and the best-fitting distribution was assigned. Additionally, previous research provides a schedule for ward capacity and establishes decision rules for patient management. In collaboration with the hospital, the probability of Intensive Care assignment and the various decision rules were validated.

The sensitivity analysis revealed a slight overestimation of surgery duration compared to the test data, but this did not significantly impact outcomes. The model is more vulnerable to ward capacity and length of stay, which were then selected for scenario analysis. The schedule prioritising ward levelling and checking availability every 15 minutes outperformed others, effectively addressing ward unavailability, the primary bottleneck. However, increasing capacity improves the number of successful surgeries but also leads to more cancellations due to operating theatre unavailability and increased overtime occurrences. This highlighted a trade-off between operating theatre utilisation and other Key Performance Indicators.

The sensitivity analysis revealed a slight overestimation of surgery duration compared to the test data, but this did not significantly impact the overall outcomes. The model was found to be more sensitive to ward capacity and length of stay, which were then selected for scenario analysis. Among the different schedules, the one prioritizing ward leveling and checking bed availability every 15 minutes outperformed the others, effectively addressing ward unavailability, which was identified as the primary bottleneck. However, while increasing ward capacity improved the number of successful surgeries, it also resulted in more cancellations due to operating theatre unavailability and increased overtime occurrences. This finding highlighted a trade-off between operating theatre utilization and other Key Performance Indicators.

In line with the literature, the research reveals that striving for increased operating theatre utilisation puts excessive pressure on other resources. Ward unavailability is identified as the main reason for surgery cancellations, indicating that wards require even greater focus. An increase in ward capacity had the best outcomes during the scenario analysis, showing that this is the biggest bottleneck in the system.

The simulation model identified new parameters for the optimisation model and highlighted weaknesses in the system to be improved upon. Future research should explore ward capacity in greater detail and develop better methods for sharing resources across different operating theatres and wards to reduce the differences in utilisation. Additionally, further research could investigate other causes of surgery cancellations and refine the definitions of surgery groups.

ABBREVIATIONS

DES	Discrete Event Simulation
ICK	Intensive Care Kinderen (Children)
KPI	Key Performance Indicator
MCU	Medium Care Unit
MSS	Master Surgery Schedule
OT	Operating Theatre

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1 INTRODUCTION

In March 2020, the Netherlands found itself in one of the most severe healthcare crises in recent history, with the start of the COVID-19 pandemic. However, the healthcare sector faced significant challenges before the crisis, including substantial staff shortages (Kalkhoven & Van Der Aalst, 2018). Regrettably, the aftermath of the pandemic has persisted, with the government projecting a shortage of 137.000 employees by 2032 in the health and welfare sector (Ministerie van Volksgezondheid, Welzijn en Sport, 2024). These shortages are particularly concerning considering that this sector already employs 1.4 million individuals in the Netherlands (Dashboard Arbeidsmarkt Zorg En Welzijn (AZW), n.d.). The lack of personnel is causing the quality and accessibility of healthcare to be under a lot of pressure (Ministerie van Volksgezondheid, Welzijn en Sport, 2024). By the end of 2021, 305.000 fewer operations were performed than initially expected, resulting in the loss of 320.000 healthy life years (RIVM, n.d.).

Aside from the sheer scale of personnel involved in Dutch healthcare, the government's financial commitment is also substantial. Prior to the pandemic, government spending on the healthcare sector amounted to 6.5% of the Dutch GDP, totalling €80.9 billion (CBS, 2020). Of this allocation, €29 billion went to hospital care and medical speciality care (Ministerie van Volksgezondheid, Welzijn en Sport., 2022). In 2024, the government has allocated over €103 billion for the healthcare sector (Ministerie van Volksgezondheid, Welzijn en Sport, 2023), representing the most significant expense in the Dutch governmental budget (Ministerie van Algemene Zaken, 2023).

Effective planning can save money by allowing for (human) resources to be allocated more efficiently (Stanimirović & Brinovec, 2023). Various planning frameworks have been utilised to attain optimal outcomes within the healthcare industry. The principal objective of healthcare planning and management is to provide the best care while minimising expenses (Wang & Demeulemeester, 2023). One approach is to use optimisation to generate more efficient schedules, considering several performance indicators. Another could be a simulation, testing different interventions under uncertainties and seeing how they perform.

The following paragraph first explains how this research is relevant within the mater Engineer and Policy Analysis. The paragraphs after dive into the complexity of creating efficient hospital OT schedules and into both optimization and simulation approaches for operating theatre scheduling, addressing the abilities of these methodologies to account for these complexities and improve overall efficiency.

1.1 CONNECTION TO ENGINEERING AND POLICY ANALYSIS

The following section focuses on how this thesis aligns with the context of the Master 'Engineering and Policy Analysis'. Addressing challenges within the healthcare system is inherent to the Engineering and Policy Analysis program. As outlined, the societal impact of this sector is evident; in addition, the systems present many different complexities. The implementations of change can be complicated by the interdependencies between different entities and departments (Brailsford, 2007). The challenges in implementing change are attributed to the intricate interdependencies between various departments, highlighting the need for careful consideration, especially when employing operations research to drive improvements.

The Engineering and Policy Analysis Master's program emphasises technological and societal challenges involving stakeholders and relevant parties (MSc Engineering and Policy Analysis, 2024). This project uses an analytic approach and modelling techniques that are part of the Engineering and Policy Analysis program to see how new interventions can improve relevant Key Performance Indicators (KPIs) by studying the interaction of different entities, thus perfectly aligning with the key points of the program.

1.2 COMPLEXITY OF IMPROVEMENTS IN HOSPLITAL OPERATING THEATRE SCHEDULING

The COVID pandemic brought to light some critical issues in hospital OT scheduling policies. Several elective surgeries had to be rescheduled during the pandemic because resources, such as beds and ventilators, had to be allocated elsewhere. Causing significant operational delays, leading to the loss of numerous healthy life years in the Dutch populations. This is an example of how changes in scheduling and extreme cancellations can result in severe and far-reaching consequences. Additionally, the financial constraints within the sector mean that management missteps can lead to misallocated funds, depriving life-saving initiatives of essential support.

Efficient OT scheduling is considered very complex due to the healthcare system's interconnected components, which involve different participants and specialties over time and across various locations; Kuziemsky (2016) refers to this as the nonlinear nature of the healthcare sector. The system of a healthcare setting consists of people, processes, and resources which are interdependent, requiring each part to adapt flexibly to disruptions (Tien & Goldschmidt-Clermont, 2009). Understanding how these components respond to changes and how they depend on each other is crucial for effective OT scheduling (Robone et al., 2011). It is not only beneficial to look at these components separately but even more to look beyond the individual behaviour of the parts and study how the system interacts as a whole (Boon et al., 2007).

These complexities require scheduling methodologies that can integrate various criteria to enhance the efficiency of scheduling and provide a structured approach. One of the techniques that can achieve this is mathematical optimisation. Optimisation techniques can help create more efficient schedules that better allocate resources, minimize delays, reduce bottlenecks, and improve overall system outcomes. The following section will explore the use optimisation generated scheduling for operating theatres.

1.2.1 OPTIMISATION OF HOSPITAL OPERATING THEATRE SCHEDULING

Optimization can be a powerful tool for improving the scheduling of hospital operating theatres. These models integrate multiple criteria to maximize benefits and minimize costs or resource usage within specific limits (Crown et al., 2018). Mathematical optimization models aim to enhance the overall performance of the system while considering key indicators and constraints (Reddy & Scheinker, 2020*)*. Constraints could include budget limitations or resource availability, such as the availability of operating theatres (Crown et al., 2018).

While optimisation models aim to maximise the number of surgeries and patient throughput, resource scarcity often gets in the way of creating optimal utilisation (Oliveira et al., 2022). Insufficient resources often result in patients being held up, leading to delays and backups at each stage of the process, consequently prolonging overall processing times (Abedini et al., 2017). Considering the impact on downstream resources, such as (intensive care unit) beds, adds another layer of complexity to creating efficient operating theatre schedules (Abedini et al., 2017). This complexity increases even further when the demands of different departments are factored in. Mathematical optimisation cannot fully capture the inherent complexities of the efficient OT scheduling (Jun et al., 1999). Integrating all the complexities into the model reduces the likelihood of effective implementation, as the computational challenges in achieving an optimal solution increase (Asghari et al., 2022). Factors such as methodology, data quality, and underlying assumptions must be carefully considered and pose significant challenges for successful implementation (Crown et al., 2018). Consequently, the number of effectively implemented optimization-generated solutions that provide sustainable improvements in operating theatre scheduling remains limited (Xie et al., 2022).

Therefore, it is crucial to consider strategies that address these challenges and account for the complexity of the system to successfully implement optimised scheduling for OTs. The flowing section on simulation will explore the application of simulation modelling in the complex OT scheduling setting and the specific use of discrete event simulation to test and evaluate various interventions for OT scheduling. It gives an insight in how simulation can account for the complexity within the healthcare sector.

1.2.2 Simulation Modeling for Operating Theatre Scheduling

Simulation modeling is a about creating an virtual environment that represents a real word system in order to make adjustment and see how the system responds (Smith et al., 2020). It can improve efficient resource allocation, managing wait times and patient flows, and optimising bed occupancy and scheduling (Almagooshi, 2015). Simulation aids in understanding the intricate behaviour of healthcare systems which is crucial for decision-makers (Traoré et al., 2019). When the system is understood, informed adjustments can be made to enhance efficiency.

When considering potential changes, it is essential to consider as much complexity as possible to anticipate various outcomes better and increase the likelihood of success. Simulation is a valuable tool in this regard, enabling testing changes across diverse environments to comprehensively assess their potential impact before implementation (Forsberg et al., 2011). Simulation modelling enables the exploration of various parameters and experimentation with policies without the fear of real-world consequences (Forsberg et al., 2011). It offers immediate insights into the results of proposed changes (Forsberg et al., 2011), empowering management to adjust parameters and explore ways to improve outcomes.

Simulation modelling provides estimated outcomes and helps reveal unintended consequences (Smith et al., 2020). By enabling a virtual environment of the hospital processes where different scenarios can be evaluated, simulation modelling helps to identify the bottlenecks and improve the system's efficiency by testing and comparing multiple policies in an environment where failures do not have consequences. The strength of simulation lies in its capability to consider greater complexity and accommodate diverse stakeholder interests (Almagooshi, 2015). It leads to notable enhancements such as increased patient satisfaction, improved quality of care, cost reduction, and enhanced patient flows (Feili, 2013).

On of the methods to mirror the complexities of the real-world system is Discrete Event Simulation (DES). DES is a powerful tool widely applied within the healthcare sector (Zhang, 2018). Section 3.2 delves into the inherent characteristics of DES, elaborating on why it was selected as the simulation methodology for this thesis and its application.

Despite the potential of simulation to provide insights, the adoption rates of proposed solutions for hospital scheduling remain remarkably low, primarily due to implementers' hesitancy to trust the validity of these solutions (Harper et al., 2022). Indicating the need for further improvements to enhance trust and confidence in simulation-generated results.

1.3 KNOWLEDGE GAP

Given the complexities of OTs scheduling and the need for improved efficiency this research looks into how optimisation and simulation contribute to this domain. The previous sections have highlighted that both optimisation and simulation print the potential of improving healthcare policy. Numerous optimisation studies have explored the potential benefits of the method, yielding theoretically sound results. However, the complexity of OT scheduling contains inherent uncertainties due to downstream resources and interdepartmental dependencies, which are hard to include in optimisation modelling. The application of these optimisation models often overlooks the dynamic complexities and variable nature, limiting their practical adaptability and, thus effectiveness of the schedules.

Before implementing these theoretically sound scheduling solutions, more detail needs to be considered to take into account these complexities, and test for different uncertainties with the system. This leads to the following problem statement: Optimisation enhances OT scheduling but fails to account for its complexities and uncertainties, highlighting the necessity for a deeper exploration of these theoretically sound solutions.

Simulation presents a viable remedy to these issues, offering a tool capable of replicating the real-world effects of optimised schedules amidst OT operations' intricate and fluctuating demands. Simulation has the ability to model complex systems; this approach enables the detailed modelling of entity interactions and event flows over time.

By integrating optimisation techniques and simulation, decision-makers can leverage the strengths of both approaches. Optimisation seeks the ideal solution, whereas simulation rigorously evaluates the performance in practical scenarios, identifying unforeseen variables that must be considered. This sequenced approach allows for the thorough assessment and refinement of solutions prior to their actual implementation. While integrating these methodologies appears promising, it may also unveil new challenges. Therefore, this thesis is dedicated to exploring the following pivotal research question:

"How can Discrete Event Simulation evaluate optimisation-generated Master Surgery Schedules for operating theatres?"

The research question mainly focuses on a Master Surgery Schedule (MSS); this type of schedule means it is planned across multiple different surgical specialties. These specialities share resources but also require different arrangements that need consideration. This thesis will use the term operating theatres (OT) to refer to the rooms in a hospital where surgeries are performed. Although the literature often uses 'Operating theatres' and 'Operating Room' interchangeably, this thesis will consistently use OT to avoid confusion with other terms.

1.4 STRUCTURE

This thesis is built up of seven chapters. The first chapter introduces the problem and defines the knowledge gap this thesis will attempt to bridge. Chapter 2 presents a literature review covering the complexity of using simulation and optimisation for OT scheduling and what can be learned from previous research. Chapter 3 describes the research design, defining the different sub-questions that will aid in answering the main research questions and elaborating on the method used in this thesis.

Chapter 4 further elaborates on the case of using the simulation model, including the key performance indicators and the definition of the model parameters. Chapter 5 discusses the setup of the simulation model, including the validation and the verification step. Chapter 6 outlines the experiments and scenario analysis performed on the schedules under evaluation. Chapter 7 addresses the main research question by answering the in Chapter 3 defined sub-question and using these answers to build up to the conclusion. Lasty chapter 8 will comment on the academic contribution provided by the study, the studies limitations and the recommendations for further research.

The model developed during the research for the case study can be accessed using: https://github.com/LunavanV/Thesis

2 LITERATURE REVIEW

The previous chapter laid the groundwork for this thesis by diving into the complexity of the problem, defining the knowledge gap, and the following research question. This chapter presents a literature review on similar research and what can be incorporated from previous experiences. First, 2.1 Introduces how the data for the thesis was gathered while 2.2 further elaborates on the type of papers that were used. Using this information, section 2.3 and 2.4. use the literature to confirm the knowledge gap and outline the challenges in applying simulation and optimisation for OT scheduling. Section 2.5 dives into what can be learned from previous research about building a simulation model for testing OT scheduling.

2.1 METHOD OF LITERATURE REVIEW

The literature review for this chapter has been split up into two parts, each with its own search string. It first focuses on identifying comparable research to further elaborate on the knowledge gap of Chapter 1 showing what has been done before and to which domain this research would contribute. Secondly, it focuses on what can be learned from previous research to answer the research question successfully. This is approached using peer-reviewed articles from Scopus, employing the following methodology. Both searches were refined to include articles published within the last 20 years (2004-2024); this limit was chosen due to the intensive research performed in the domain and wanting only to include recent, relevant improvements. Table 1 outlines the search strings used. After defining a fitting string, papers were then selected based on their titles or through an initial scan of the abstract. The flow of the paper selection for either string is further elaborated by PRISMA in Figure 1, the blue figures represent the flow of string one, and the green figures represent the flow of string two.

TABLE 1: SEARCH STRING RESULTS

	SEARCH TERM SCOPUS
1.	(optimis* OR optimis*) AND ("Discrete Event Simulation" OR des) AND ((operating AND theatre) OR (operation AND room) OR (surger* OR surgic*)) AND schedul*
2.	("Discrete Event Simulation" OR des) AND ((operating AND theatre) OR (operation AND room) OR (surger* OR surgic*)) AND schedul*

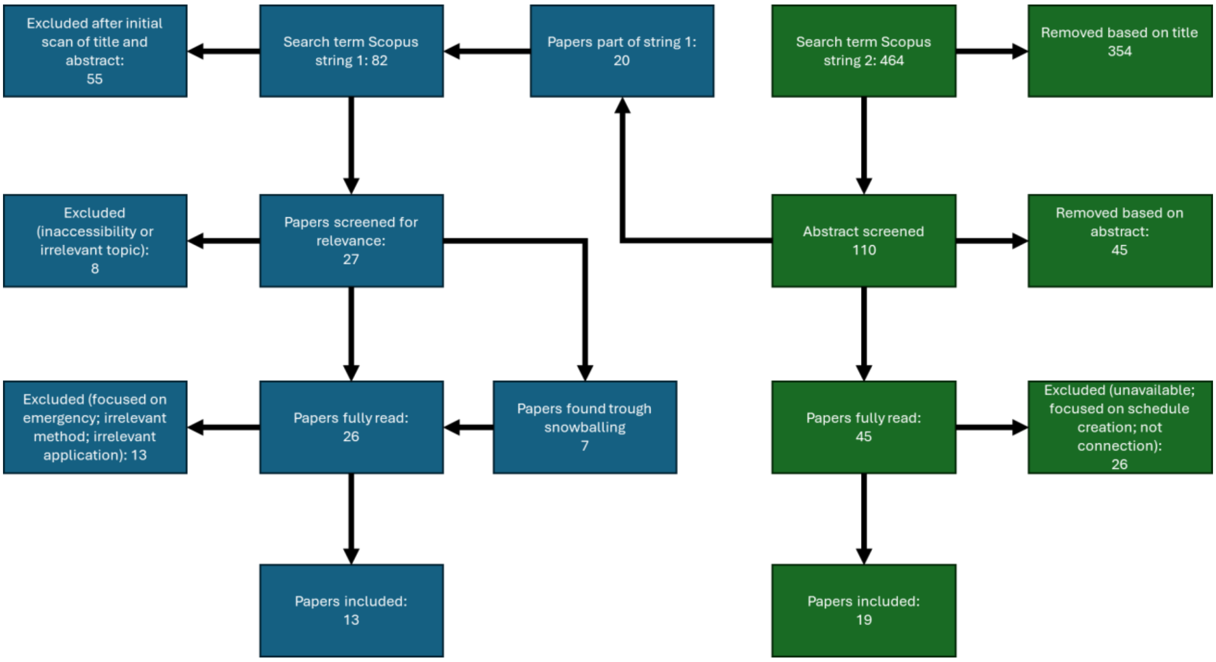


FIGURE 1: PRISMA SCOPUS SEARCH

2.2 GENERAL INFORMATION ABOUT LITERATURE

This research consists of a diverse range of studies. The first string focuses on research that provides information on sequencing optimisation and simulation, such as Discrete Event simulation, in a healthcare setting. It gives examples of healthcare problems and information about where the current research is still lacking. The second string focuses on research that aims to improve hospital room operations using discrete event simulation and research that builds discrete event simulation models of hospital settings. These techniques support decision-making, handling uncertainty, and evaluating the impact of different scheduling policies. Additionally, they discuss the input parameters and common testing and validation methods to ensure accuracy and reliability.

Most studies are published in peer-reviewed journals, ensuring the high quality and credibility of the findings. The research is internationally distributed, giving different settings for the research for general applicability. To provide a little more context on what type of information is included, a research table is presented in Table 2. It gives an overview of the type of data that is included in each part of the literature review.

TABLE 2: SUMMARY LITERATURE REVIEW DATA

	String 1 + snowballing	*String 2*
Total number of studies	13	19
Publishing year	2010-2022	2005-2023
Research focus	- Surgery scheduling and resource management using various optimisation techniques - Integrated approaches for operating theatre and intensive care unit management - Stochastic optimisation and simulation for healthcare scheduling - Patient flow optimisation in elective surgeries - Bed-occupancy simulation in critical care units	- Operating theatre efficiency and utilisation - Simulation modelling for decision support - Handling uncertainty and variability - Scheduling policies
Common keywords	Scheduling; OT; Simulation, Optimisation, Resource allocation; Ant colony optimisation; Mixed integer programming; Discrete event simulation	Discrete Event Simulation; Operating Room Scheduling; Simulation; Optimisation; Scheduling; Healthcare Management; Capacity Utilisation
Methodologies	- Simulation studies - Optimisation studies - Integrated approach studies - Stochastic optimisation - Survey studies - Review studies	- Discrete event simulation - Scenario analysis - Validating simulation models - Distributions
Country of research (some originate from more than one country)	Tunisia; China; Iran (2); Germany; Canada (2); Netherlands; France; Italy (3); UK (2); USA (2)	Australia; France (2); Tunisia; USA (7); Hong Kong; UK (2); Belgium; Sweden; Canada (2); Taiwan; Italy (2)
Publication type	Journal articles (10); conference paper; conference proceedings; book chapter	Journal articles (13); conference paper (2); conference proceedings (3); book chapter

The goal of the first search string was to have a broad focus, to explore research that has taken similar approaches and to identify the limitations across the field. This can be seen by the broad research focus and range of methodologies shown in Table 2. The search information helps better understand the different gaps in the literature and the domain to which this thesis will contribute. Table 3 gives an overview of all the papers selected from the search string that is used to write a section 2.3 and 2.4. It gives an overview of the techniques these papers apply, the interesting takeaways for this research. The last paragraphs talks about the limitations or differences that need to be considered when using the information and conclusions from that paper. These sections aim to explain what has been found in these papers and the currently available information about applying DES to evaluate optimisation-generated scheduling.

TABLE 3: RESOURCE TABLE, FIRST STRING

Source	Technique	Information/conclusions	The usefulness of the article	relevant limitations or differences from the focus of this research
Xiao and Yoogalingam (2022)	simulation optimisation and DES	The use of open scheduling, allocating a mix of surgeries to available operating theatre slots, improves OT utilisation. Simulation optimisation can consider many different aspects while accounting for the uncertainty. Highlight the complexity brought by changing the duration of surgery and how the scheduling of surgery is considered complex due to this and other uncertainties. Proposes using open slots in a schedule for emergent surgeries or same-day rescheduling.	The article highlights the complexity of considering scheduling in healthcare. It is an example of how operational research can aid in this complexity and what potential contributions are. However, the conclusions focus on scheduling policy rather than schedule testing.	Does not consider post-operative resource availability. Considers the extra uncertainty brought by emergent arrivals.
Hamid et al. (2018)	mathematical optimisation and DES	The sequencing of DES after optimisation leads to the optimal number of ICU beds to support operative recovery. The study illustrates the potential for optimisation techniques for scheduling to enhance OT performance and utilisation significantly.	The article provides an example of using a mathematical model to schedule surgeries. The optimisation model was updated based on the simulation model recommendation. It showed that optimisation generated scheduling is better than human scheduling.	Focus on a singular department limits the applicability across the broader MSS. The objective is to minimise waiting time and the maximum completion time. Considers the extra uncertainty brought by emergent arrivals.
Rachuba et al. (2022)	optimisation and simulation	Developed a framework for scheduling to streamline patient scheduling decisions. The human planning decisions are tested in the simulation. They consider the effects of different rules on the utilisation of intensive care and OT, overtime, cancellations and the number of patients fully treated. Mimic human planning decisions to consider their effectiveness. Compares the use of optimisation and simulation.	An example of useful KPIs for evaluating the effectiveness of policy. They consider the acceptable risk, as there are clear trade-offs to be made when evaluating policy.	Research focuses solely on operating theatre and intensive care unit availability and is not integrated with the hospital-wide MSS. Does not address dynamic responses to changes in capacity or other hospital-wide resources
Debats et al. (2021)	DES	Established surgical planning guidelines that prioritise surgical and post-anaesthesia care unit resources. The goal is not only to increase the number of planned surgeries but also to smoothen the workload for both surgical staff and nursing staff in the Post Anesthesia Care Unit. Integrating both OT utilisation, OT resources and postoperative resources into the schedule improves hospital operations.	Looking at the problem with a more holistic view and also considering factors such as resources helps to manage the flow more efficiently. Decreasing the variability in the bed demand improves the workload. However, to get a complete picture, the entire patient flow should be considered, including all the required resources throughout the entire patient flow.	Neglects to consider variations in the length of patient stays. Does not consider the outflow of patients to departments other than the Post Anesthesia Care Unit
Antonelli et al. (2018)	simulation	This study utilised data from ward logs and questionnaires completed by hospital staff to develop a simulation model aimed at reducing waiting lists and hospital length of stay while optimising hospital capacity utilisation. The model provides a comprehensive analysis of patient flow. The research also proposes to consider a redesign of the activities as it can improve the potential delays and waiting times before surgery.	When looking at the complete patient flow to investigate the improvement in the waiting list, waiting time and bed utilisation, a compromise between bed utilisation and waiting times comes to light.	The system is very sensitive to the variability in the length of stay and does not allow for buffers in the system.

Davoudkhani et al. (2019)	simulation-based optimisation	The use of a mathematical model to set up a schedule and then using different rules, such as longest duration or shorter duration first, to attach a surgery to a schedule slot reduces the total waiting time and improves OT utilisation. They considered the different rules and the base case schedule as different scenarios, which were then compared.	The study considers the complexity of non-identical operating rooms for elective patients and how to most effectively schedule these.	The focus is on assigning patients to slots from the waiting list, not focused on the effect on other resources of the system.
Xiang et al. (2015)	Ant Colony Optimisation	Using Anto Colon Optimisation to solve the surgery scheduling problem and comparing them using DES can help to efficiently determine surgery duration and allocate resources such as personnel facilities, taking into consideration staff qualification. The use of Ant Colony Optimisation improves the scheduling within acceptable calculation times. The study also considers a surgent speciality and level of experience, resulting in different expected surgery durations.	Considers the effect and advantage of shared resources between different departments. It also considers there is more to surgery than simply the availability of the OT and the surgeon. The use of open scheduling makes surgery scheduling more complex. For the uncertain variable of surgery duration, there can be more to consider than the average surgery time of the surgery in question.	The type of optimisation is different from what this literature review generally refers to. Considers the extra uncertainty brought by emergent arrivals.
Saadouli et al. (2015)	Optimisation and DES	This research combines the use of optimisation to generate schedules and test them using simulation. This tackles the scheduling challenge taking into account uncertainties (such as surgery duration, recovery times and resource capacity).	Provides an example of how DES can aid in the evaluation of different optimisation generated schedules. The paper also mentions simulations limitation to only be able to consider a limited number of variables, which is where optimisation can prove useful. It highlights the importance of considering the stochastic nature of the input variables.	The research is department-specific, suggesting that extending the application to other disciplines or a multiservice system (MSS) might present additional challenges.
Griffiths et al. (2010)	scenario analysis using DES	This research minimises elective surgery cancellation by levelling the bed occupancy. And considers the trade-offs that are to be made between the utilisation of resources and the cost of resources. Effective management of ward utilisation requires a combined approach to bed capacity, improving patient scheduling and optimising discharge procedures. Scenario testing is proven to be a valuable insight when testing the combination of different interventions. Focussing on bed-blocking emerges as the best strategy for reducing occupancy levels and cancellation rates. However, chaining practices of staff can be beneficial as well.	Mentions that the unavailability of beds is often a reason for the cancellation of elective surgery. To improve efficiency, the focus needs to be on more than one of the elements, including, but not limited to, the number of beds, scheduling methodology and patient flow.	-
Abedini et al. (2017)	Optimisation and DES	When improving the MSS it is important to consider blockings between the OT and downstream resources. Using optimisation, these blockings can be reduced, and their effectiveness should be tested under variation using simulation.	An Example of improving a MSS using optimisation and testing changes in healthcare using simulation. The complexity in MSS scheduling is often caused by other resources, and unavailability of these resources causing blocking in these flows.	Only consider uncertainty in input variables and not scenario analysis of system uncertainty. Resources in the system are shared with emergency cases.

Cappanera et al. (2014)	optimisation simulation	Compares different scheduling policies, each prioritising different areas of interest. The study reveals the causal mechanism that, under certain circumstances, makes certain balancing criteria perform better than others.	The main takeaway focuses on the trade-offs that are to be made when considering effective healthcare policy. However reasonable trade-offs are most likely possible to be found. Aiming for high utilisation of the wards should not be the priority as these are often underestimated, causing overbooking.	No clear solution in terms of efficiency, balancing and robustness. The optimisation does not consider the actual hospital dimension, and many hospital resources are left out.
Guerriero & Guido (2010)	Literature review on operational research	Operational research, including simulation and optimisation, focuses on increasing the number of patients, increasing satisfaction of all involved, maximising resource utilisation, reducing cancellations and reducing delays.	Efficient use of resources improves most system KPIs. Explains that literature highlights trade-offs between the different KPIs in order to find acceptable levels on all fronts, including weighing costs. Most of the literature does not deal with all system constraints simultaneously.	-
Erdogan et al. (2011)	Analysis of surgery scheduling	Little time has been spent on considering rules for schedule deviations. More attention should be spent on the waiting lists and uncertainty cancellations. Additionally, other resources than OT should also be considered. Uncertainty in demand is a subject that has minimally been subjected to research.	There are a lot of factors, no-shows, cancelations and additional cases that cause deviations in surgical schedules, which are often not considered in the creation of elective surgery schedules. Additionally, the consideration of post-surgery resources is important. Uncertainty in patient inflow is important to consider; surgeries can be cancelled for numerous reasons, which causes resources to go to waste.	-

The goal of the second string was to explore what can be learned from previously produced healthcare simulations. Looking specifically into common practices for input data, model validation, sensitivity analysis and scenario testing in healthcare. The selection of papers was chosen to contribute to these subjects as these are of interest for the writing of the rest of the thesis. The papers of string two were used to write the rest of the literature review, specifically section 0. Unlike the first part, where the research table was employed to briefly state the practices of the different research, for the second part, the narrative is led by the exploration of these research practices, so the decision was made to forgo a research table. By presenting this information in a narrative format, the literature review aims to provide a clear understanding of common practices and what can be learned from these for the rest of the thesis. The exploration of the second string provided information on how to handle some of the systems complexity, common practices for input data for a DES, validating a DES model and scenario testing in a DES model

2.3 THE TRADE-OFF BETWEEN OT UTILISATION AND OTHER RESOURCES

One of the key insights derived from the analysis of the research papers in Table 3 is the trade-off between striving for full utilisation of the OT and the resulting pressure on other resources, which could then become bottlenecks. While an MSS often improves the OT utilisation it also increases the complexities by sharing the system's resources.

Efficient utilisation of resources minimises delays, costs and excessive waiting times (Guerriero & Guido, 2010). Balancing these resources is considered even more complex when employing an MSS where specialities share resources. MSS is considered an open schedule which mixes different specialities; the advantage of using such a schedule is an increase in the utilisation of the OT (Xiao and Yoogalingam, 2022). According to Abedini et al. (2017), efficient scheduling prioritises OT utilisation and ensures a smooth flow of patients through all hospital flows, eliminating bottlenecks. Fully utilising the capacity of the OT leads to efficient utilisation of system capacity and reduces waiting lists (Antonelli et al., 2018). However, OT capacity might not always be the primary bottleneck in scheduling problems. The increase in the utilisation of OTs increases the pressure on post-surgery resources, resulting in a trade-off between how many extra surgeries can be planned without overutilisation of other resources (Debats et al., 2021). Misaligned scheduling occurs when there is a mismatch between demand and the availability of resources, leading to inefficiencies (Erdogan et al., 2011). Even more, when the strain on these post-surgery resources increases, such as increased bed utilisation, this can lead to shortages when unexpected extreme lengths of stay occur.

Few efforts have been made to integrate post-surgery resource limitation into optimisation models focused on increasing OT utilisation (Erdogan et al., 2011). Capacity and resource constraints, admission limitations, and medical staff preferences constitute the primary constraints, creating a trade-off between OT time, patient waiting list, and surgical and post-surgical resources (Guerriero & Guido, 2010).

To conclude, using a MSS brings advantages for the utilisation of the OT. However, this increases the complexities of the shared resources. As highlighted in section 1.2 optimisation cannot fully take into account these detailed complexities of the interdependent department resources, which is where simulation might come in. The next paragraph will consider how simulation can be used as a tool for guiding decision makers about scheduling changes.

2.4 SIMULATION AS A DECISION SUPPORT SYSTEM FOR OPTIMISATION-GENERATED SCHEDULING

The use of simulation for testing optimisation-generated solutions in the healthcare sector emerges as an interesting strategy to navigate and enhance the complex landscape of healthcare improvement. Many researchers have already looked into applying these operational research methodologies in the healthcare sector, employing various techniques to refine scheduling processes and evaluate the efficacy of interventions.

Evaluating an optimisation model for surgical scheduling using a DES model offers valuable insights into enhancing surgical scheduling efficiency (Davoudkhani et al., 2019). Optimisation can generate a scheduling framework that can enhance the efficiency of both operating theatres and intensive care units. Simulation can then be used for effective resource management, such as ward beds, which requires a combination of strategies, including adjusting bed numbers, refining patient scheduling, and optimising discharge processes (Griffiths et al., 2010). It has been shown that sequencing these methods by applying simulation tools, such as DES, after optimisation can lead to valuable insights for decision-makers (Hamid et al., 2018). A simulation model can enhance the operational efficiency of a framework (Rachuba et al., 2022).

Both Saadouli et al. (2015) and Hamid et al. (2018) effectively use DES to validate optimisation-generated schedules. They show that optimisation accounts for a wide range of parameters, therefore reducing costs and enhancing operation efficiency. Optimisation thus addresses the limitations of simulation of only being able to address a limited number of variables, enabling the incorporation of diverse parameter variabilities (Saadouli et al., 2015). The dual approach also enables testing real-life scenarios, leading to recommendations for the optimal number of intensive care unit beds to support post-operative recovery. The studies illustrate the potential for optimisation techniques for scheduling to enhance OT performance and utilisation significantly. However, neither of their approaches considered the complexity a MSS introduced. Considering more departments and a complete patient flow can create a more comprehensive approach (Debats et al., 2021).

One use of simulation modelling is scenario testing, which involves exposing the system to potential future settings and exploring how the environment responds, allowing evaluation of possible changes while exploring how they would respond in different potential futures (Sciomachen et al., 2005). Several studies have explored the use of scenario testing to evaluate specific policies. Griffiths et al. (2010) employed various "what-if" scenarios, concluding that effective bed management requires a combination of strategies. The scenario testing made possible by DES offered valuable insights into the potential outcomes of different combinations of interventions.

As highlighted by the studies, exploring optimisation and simulation techniques for scheduling within healthcare demonstrates considerable advancements in this domain. Optimisation can strive to create more efficient schedules, and simulation can consider how these new schedules affect the system and perform in different future scenarios. However, this has not yet been explored when considering the additional complexity of a MSS. Key issues that arise in such a setting include managing capacity constraints across various departments, handling the unpredictable durations of surgeries, and dealing with fluctuations in resource availability.

2.5 ADVANCEMENT AND CHALLENGES IN USING DISCRETE EVENT SIMULATION FOR HEALTHCARE SCHEDULING

The upcoming section of the chapter delves deeper into the application of simulation for testing surgical schedules, with a particular emphasis on DES. DES is recognised as a standard method for addressing planning challenges in healthcare management, as DES offers a dynamic environment to test and refine scheduling strategies (Sciomachen et al., 2005). The paragraph talks about what can be learned from the literature about the input variables for the system, model validation and scenario testing.

Another major challenge they highlight is stakeholder buy-in, which is the notion that managers are often averse to risk and might oppose new tools to prevent disruptions. Cox (2019) adds to this that the design and execution of a schedule are often very different. Managers might not recognise how schedules and departments are intertwined, impacting each other's ability to execute correctly. Addressing these differences required assessing bottlenecks and room for improvement. Simulation is a great tool to aid in this process; after creating a valid representation of reality, changing parameters can provide great insight into how bottlenecks can be addressed, thus decreasing the gap between management planning and reality.

2.5.1 The Use of Distributions for Input Data

To create accurate representations of reality, accurate parameters are required. Simulation models heavily rely on the accurate representation of input variables through statistical distributions, a point emphasised across multiple of the included studies to assess their impact on hospital operations and cost efficiency.

In their exploration of improving a surgical schedule and utilising DES to test the application of such a schedule, Chabouh et al. (2021) tested various scheduling policies. They highlight the importance of considering the variability in patient arrival and surgery conditions to reflect real-world uncertainties and not leave out any complexities. However, they also highlight that it is equally important to consider factors that can be simplified while keeping the core dynamics. They advocate for using machine learning software to set up input variables such as length of stay and surgery duration.

Wang and Dexter (2022), on the other hand, state that using this kind of application will only increase complexity, which is not compensated equally by the decrease in predictive errors. Their application of DES for schedule implementation evaluated the impact of enhanced predictive accuracy on labour productivity without increasing the allocated times for surgeries. Their study examined the assumption that increased computational complexity from machine learning reduces predictive errors proportionally. Wang and Dexter (2022) found that the improvements in prediction accuracy, while statistically significant, resulted in only negligible enhancements in productivity when the allocated times were not adjusted.

The study by Fairley et al. (2018) at Lucile Packard Children's Hospital Stanford also implemented machine learning to optimise surgical schedules, specifically to reduce congestion in the post-anaesthesia care unit. They found they could use machine learning to develop models to sequence operations effectively, minimising post-anaesthesia care unit-related delays without compromising OT utilisation. However, the approach's reliance on detailed patient records for their algorithms points to a significant barrier.

Monnickendam and De Asmundis (2018) illustrate how the distribution of procedure times significantly affects OT utilisation and the economic evaluation of hospital procedures. Their study demonstrates that not accounting for the full range of variability in procedure times can lead to underestimating resource consumption and procedure costs, particularly for procedures with longer and more variable durations.

Both Zeng et al. (2014) and Johnston et al. (2009) find the best fit for their event estimations, including surgery duration, in the gamma distribution. In contrast, Persson et al. (2017) find their best fit for surgery duration in the log-normal distribution. Determining a good fit is crucial in a simulation's ability to mimic real-world operations.

To validate these models and ensure their practical relevance, statistical tests such as the chi-squared test for goodness of fit are commonly used, which Johnston et al. (2009) apply to affirm the alignment of their simulation models with observed data at a 95% confidence level. Chabouh et al. (2021) additionally employ the Kolmogorov–Smirnov test. Choosing and validating good statistical distributions in simulation models enhances the accuracy of predicting operational impacts and ensures that the scheduling solutions are robust and applicable across different surgical settings.

2.5.2 Model Validation and Sensitivity Analysis of Healthcare Simulation Models

Validation in simulation modelling involves testing if the model faithfully represents the actual system it aims to emulate (Yuen & Wu, 2017). This process typically employs real-world data to compare the model's outcomes against actual operational data. Huschka et al. (2007) built a DES model to improve the OT and recovery bed utilisation. They used existing data on the utilisation to validate the simulation model in a base case scenario. Additionally, the accuracy and relevance of the simulation can be enhanced through collaboration with hospital staff (Persson et al., 2017). In their study, Gül et al. (2011) applied these principles by comparing the outcomes from their DES models, such as the number of surgeries and expected overtime, against the real data from a baseline schedule of outpatient procedures. Using real patient data and expert feedback ensures that the model accurately reflects the operational realities of the surgical centre. Their primary objective was to optimise scheduling under the uncertainty of procedure durations to minimise patient waiting times and reduce OT overtime. The DES model is used to test various scheduling heuristics.

Sensitivity analysis plays a pivotal role in model validation by determining how changes in input parameters affect outputs, thereby assessing the robustness of the model. Bam et al. (2017) utilised this technique to explore efficient resource allocation within hospitals, particularly focusing on operating theatres and hospital beds. They assessed impacts on critical performance indicators by varying key parameters such as surgery duration, length of stay and bed availability. This way, they can understand how this changes their KPIs and how robust the model is. Similarly, Marcon and Dexter (2006) emphasised the importance of sensitivity analysis to see how the adjustment of the model changes the outcomes for the model. By altering resource allocations and prioritizations, they demonstrated the model's sensitivity to operational settings, particularly how the presence of nurses throughout the day significantly influences outcomes. These studies underscore that sensitivity analysis not only tests model validity but also informs necessary adjustments to enhance system efficiency and responsiveness.

2.5.3 Scenario Testing in Healthcare Simulation Models

Scenario testing is a pivotal component of applying DES. It enables operational enhancements by varying parameters such as resources or procedures to assess their impact on KPIs (Johnston et al., 2009). Banditori et al. (2013) discuss the complexities of Master Surgical Scheduling, focusing on balancing resources such as OTs and post-surgical beds to enhance both the efficiency and robustness of schedules. In their scenario analysis, they consider different OT utilisation ranges and perform 30 simulation runs; they conclude that it is best not to aim for full utilisation for both beds and OTs as it does not leave much room for flexibility. Azari-Rad et al. (2014) also utilised DES to evaluate different surgical scheduling policies. They demonstrated how such policies could significantly reduce surgical cancellations by prioritising surgeries based on expected length of stay and adjusting bed availability. This not only tested the robustness of the system but also the adaptability to changes. Furthermore, Rifi et al. (2022) introduced uncertainty into their model during their scenarios. By varying the uncertainty in the duration of activities and patient arrival times, vulnerabilities in the system can be revealed and potential bottlenecks pinpointed. By identifying where bottlenecks are located in different circumstances, they can also highlight potential points of intervention (Marmor et al., 2013).

2.5.4 Conclusions

The papers that are part of the second research string, discussed in this paragraph, were focused on the general application of simulation in a healthcare setting. They talk about aspects that need to be considered when building a DES model. None of these papers consider the additional of using an optimisation model to setup the policy to be tested in the DES. The information from these papers that are valuable to this research is about common methods and approaches. First of all the papers highlight that using using traditional distributions for modelling input variables is more efficient than using advanced machine learning. These distributions accurately represent the variability in surgery durations and can be rigorously tested for fit using statistical tests such as the chi-squared or the Kolmogorov–Smirnov test, a standard practice in the domain.

Furthermore, these simulation models benefit from validation against real-world data and the application of sensitivity analysis to assess how parameter changes affect model outcomes. Such validation is crucial for ensuring the models' practical relevance and reliability. Notably, the literature advises against targeting full resource utilisation within scheduling models. This approach helps prevent potential bottlenecks and issues related to exceeding capacity. The methods for data input and model validation will be further explored in Chapter three, providing detail on how these techniques will be employed effectively in this research.

3 RESEARCH DESIGN

The following chapter outlines the approach that is used in the thesis. Initially, it will identify and define a series of sub-questions. These sub-questions are designed to support and facilitate an answer to the main research question:

"How can Discrete Event Simulation be used to evaluate an optimisation-generated Master Surgery Schedule for operating theatres?"

The chapter then concentrates on the rationale behind selecting DES as an analytical tool. It details the reasons behind this choice and describes how DES can be specifically applied within the context of this thesis to explore and evaluate optimisation-generated MSS in operating theatres.

3.1 SUB-QUESTIONS

This research is split up into four sub-questions. Each guides a stage of the research.

1. What are the key considerations and performance indicators for setting up a Discrete Event Simulation model to evaluate an optimisation-generated Master Surgery Schedule?

When setting up a simulation model to test an optimisation-generated MSS, it is crucial to determine what the model should focus on and how it influences the outcome. This is the goal for answering the first research question. The literature review in Chapter 2 has begun this process by examining similar research and experiences for using DES in healthcare scheduling. This review highlights the features that need to be considered when constructing a simulation model for a MSS and standard practices in the domain. Chapter 4 discusses how these lessons are incorporated into our simulation model, detailing the specific considerations and KPIs that can be utilised in this research. Additionally, the assumptions for the model setup and the decisions made in the model are validated by an expert from the hospital..

2. What type of uncertainties does the discrete simulation model need to take into account when evaluating Master Surgery Schedules?

Once the model is set up, it is important to see how it performs under different types of uncertainty to see how robust the MSS is. The research will explore two different types of uncertainty: model uncertainty and system uncertainty. The first is uncertainty in the input variables, Chapter 4 defines the setup of the model, including the assumptions and decisions about the input variables (Bai & Jin, 2015). During the validation phase, the simulation model's sensitivity to this uncertainty is further tested and explored so the conclusions can be considered during the experimentation phase. This phase tests for the second type of uncertainty, system uncertainty, which is about the uncertainties posed by the system under evaluation (Kuzmin, 2014). The future is unknown, and a good solution would be as robust as possible; the goal of this research would be to evaluate the different schedules under these uncertainties and see which schedule performs better or worse and how their behaviour might change.

This research question aims to identify the uncertainties that the DES model needs to consider. The objective is to ensure that the MSS remains effective despite unexpected events. Chapter 2 has already outlined different examples of similar research and their approach to applying DES to simulating schedules. Here, it was found that common practices in varying parameters are the length of stay, surgery beds and surgery duration. Additionally, the research provides examples of how to formulate these input variables and validate the model when applying simulation models in healthcare. Here, several lessons can be learned that can be taken into account. Chapter 5 explains the different scenarios of uncertainty that can be used to test the scheduling.

3. How do the identified uncertainties impact the performance of the Master Surgery schedule?

The last research question will continue with the identified uncertainties and aim to set up different scenarios under which the schedules will be tested. Exposing the system to these different uncertainties allows the modeller to make conclusions about the robustness of the schedules and compare them across different potential scenarios. Studying the behaviour of the model under each of these scenarios will provide extra insight into the effectiveness of all schedules. Using this information to answer this question will aid in answering the main research question about the contributions of using simulation for testing optimisation generation MSS.

3.2 DISCRETE EVENT SIMULATION

This research aims to explore the application of DES in evaluating optimisation-generated MSS. By delving into considerations for setting up simulation models, understanding uncertainties, analysing simulation experiment findings, and examining simulation insights for decision-making, this study seeks to provide valuable insights into the effectiveness and practical implications of optimisation-driven scheduling strategies. The subsequent sections delve into the methodology behind DES, providing insights into the rationale, advantages, and relevance to the research objectives.

Simulation manifests in various forms; however, this paper will concentrate on DES. DES is known to help healthcare decision-makers assess the effectiveness of implementing new policies, is used as a forecasting tool to analyse the impact of changes in flows or resource allocation and is used to understand complex systems better (Jacobson et al., 2013). It can capture the dynamic behaviour of such systems and interactions among individuals, populations, and environments. These systems operate stably, involving components, planned tasks, queues, and decision rules (Brailsford & Hilton, 2000). It allows users to test policies and system changes without changing the original system (Jacobson et al., 2013), which is the application that will be used in this thesis.

The aim is to compare various policies to find how to effectively implement the most efficient ones (Zhang, 2018). According to Brailsford & Hilton (2000), DES has often been applied to a tactical or operational level. By providing insights into management alternatives, it empowers administrators and analysts to enhance system performance, reconfigure existing systems, or plan new ones while maintaining continuity (Jacobson et al., 2013).

In DES, state changes happen at each step, with the state staying constant between steps. DES represents the systems as an interconnected network featuring quests and activities. Behaviour is determined by characteristics assigned to each individual. (Brailsford & Hilton, 2000)

However, it is essential to acknowledge that DES models offer simplified depictions of reality, similar to the abstractions found in other modelling techniques (Zhang, 2018). DES is not an optimisation tool but provides estimates of potential outcomes when implementing specific policies (Jacobson et al., 2013). Optimisation techniques such as linear programming are often limited when applied in complex systems. They can often not study the details of day-to-day operations (Jacobson et al., 2013), which is where DES can come in. Its flexibility, adeptness in handling variability and uncertainty, and utilisation of graphical interfaces make it the preferred method for modelling healthcare systems (Brailsford & Hilton, 2000). Integrating Discrete-Event Simulation (DES) when evaluating changes in healthcare systems can expand perspectives and facilitate a deeper understanding of interdependencies. By providing a more comprehensive view, DES enables users to make informed decisions, ensuring a more realistic assessment of the potential impacts (Zhang, 2018).

3.2.1 Challenges in Using Discrete Event Simulation

Sadly, barely any of the uses of DES in healthcare result in the actual implementation of the solutions (Hassanzadeh et al., 2023). Applying DES in healthcare has some limitations; firstly, DES models are subject to complexity, often expensive to develop, experience long running times and require a lot of data as input (Brailsford & Hilton, 2000). Another issue with applying DES for health care applications is generalizability; when using local data, the policies are often limited to the application of that specific case (Zhang, 2018). Testing an intervention in a simulation at one hospital does not necessarily imply that it will be applicable or beneficial to other hospitals. When creating a DES model, often different assumptions need to be made about system behaviour which might oversimplify the system, not taking into account some of the dynamics and uncertainty (Qiao & Wang, 2021). These limits highlight that there are some challenges in applying DES and that there might be more steps to take before implementing a solution. However, this does not mean that the results are not valuable in learning more about a system and how to improve it further.

3.2.2 How Will Discrete Event Simulation Be Used in This Thesis

Using simulation in healthcare is seen as a widely researched topic. Liu et al. (2020) define 22 different research areas in healthcare using DES, with most showing increasing trends in the amount of research being performed. However, most research is focused on improving the emergency department (Vázquez-Serrano et al., 2021). This thesis, however, will focus on the application of scheduling elective procedures and how to utilise the available resources best.

The research question focuses on testing an optimisation-generated MSS using DES. This way, other effects or improvements can be considered when applying the new scheduling method. By testing the MSS under different scenarios, it could provide feedback on how best to make the scheduling more robust.

The previous section mentions that an important characteristic of DES is the use of queuing and decision rules. The schedule determines when the entities will enter the simulation, but then different queues will be part of different elements of the system. The decision rules will determine when the entities are moved to another space or out of the system, creating more space for new entities and shortening the queues. This characteristic is why DES was chosen as a modelling technique since the goal is to investigate the length of time patients are waiting for resources, queues, and move patients throughout the system based on predefined procedures, decision rules.

3.2.3 The DES Packages Used in This Thesis

Many different packages are available for setting up a DES model, one of which is the package Salabim. At the end of 2016, Salabim was developed to improve existing packages by offering a powerful animation tool and simplifying the process of enabling entities to hold, activate, passivate, and stand by (Van der Ham, 2024). Salabim comes in two versions: a 'yield' version and a 'yieldless' version. The version used in this thesis is the ‘yieldless’ version released in March 2024. While the ‘yieldless’ version does not run on all hardware, it is considered more intuitive (Van der Ham, 2024).

3.3 THEORETICAL DISTRIBUTIONS FOR INPUT DATA

Section 2.5 already mentioned that using theoretical distributions for input data is considered common practice for uncertain variables such as the length of stay and surgery duration. This thesis will also employ this method by fitting distributions for the length of stay and surgery durations used in the simulation model. Considering uncertainty in these variables' duration is an important aspect of simulation modelling in healthcare scheduling. The selection of appropriate distributions is guided by the book "Simulation modelling and analysis" (Law, 2014), was used. This book presents a methodical approach for identifying suitable distributions for a given dataset. It advocates for the use of theoretical distributions as preferable to empirical distributions or the direct use of data values in simulations.

Chapter 6 of the book (Law, 2014) discusses twelve distinct distributions, each with specific applications and characteristics suited for various analytical scenarios. By examining the descriptions of these distributions and common applications of these distributions, the selection has been narrowed down to six potentially suitable distributions. Table 4 provides an overview of these distributions and their explanations, as outlined in chapter 6 of the book (Law, 2014). Chapter 4 will delve into the different model inputs to find which distributions fit well with the available data.

TABLE 4: SELECTED DISTRIBUTIONS

Distribution	*Possible application*
Gamma	Time to complete some task, e.g., customer service or machine repair
Weibull	Time to complete some task, time to failure of a piece of equipment; used as an application rough model without data.
Log-Normal	Time to perform some task [density takes on shapes similar to gamma(a, b) and Weibull(a, b) densities for a > 1, but can have a large "spike" close to x = 0 that is often useful]; quantities that are the product of a large number of other quantities (by virtue of central limit theorem); used as a rough model in the absence of data
Log-Logistic	Time to perform some task
Pearson type V	Time to perform some task (density takes on shapes similar to lognormal, but can have a larger "spike" close to x = 0)

To see which distributions fit best, different tests are performed to compare the distributions to the original data. The literature review of section 2.5 identifies using the Chi-Squared and Kolmogorov-Smirnov tests to assess the distributions as a common practice. The chi-square test compares the histogram with the fitted density or mass function, the KS-test compares the empirical distribution with the distribution function of the hypothesised distribution (Law, 2014). The KS test is applicable for any sample size and does not necessitate data binning, thereby preserving information and avoiding issues related to interval specification. Conversely, the Chi-square test is more suitable for categorical data. Given that this research does not require distinctions based on categories within the different distributions, the KS test is the most appropriate choice.

If this does not provide enough insight, another evaluation method is to visually examine using a QQ-Plot. These plots are used to compare the sample quantiles on the Y-axis as the real values are plotted on the X-axis. A 45-degree line can be drawn as a guide; the closer the data points are to this line, the more linear the data points are, and the better the distribution fit (Kafadar & Spiegelman, 1986). So, together, the KS test and the QQ plots should help decide which distribution is the best fit for the input data. First, with the statistical test, and if that does not provide a significant fit, a visual inspection of the QQ-Plot will aid in choosing the best fit.

3.4 MODEL VALIDATION

Validation is about showing that the model that has been created is an accurate representation of the system (Yuen & Wu, 2017). A model can only be used as a tool for aiding decision-makers if a model is considered valid (Law, 2014). A standard practice in validating a simulation model is comparing the model output to real-life data. However, this is not always possible either due to the unavailability of data or the uncertainty in the system (Kleijnen, 1995).

"All models are wrong, but some are useful."

- Professor George E.P. Box

The goal of the simulation model is to compare the performance of different schedules and determine what simulation can offer additionally when evaluating the different MSS. This goal is kept in mind when validating the model; to use the model in the future, this application needs also be considered as the model might not be helpful for other purposes (Law, 2014).

The previous section talked about how the input variables setup by distribution are assessed for their goodness of fit by using tests and visual inspection. These can also be validated using cross-validation, which is about comparing the outcomes of the model using the distribution with the outcomes of the model when the raw data was used (Yates et al., 2023). Another form of validation is to perform a sensitivity analysis. Sensitivity analysis involves identifying which variables significantly impact the model's output when altered. This helps determine which variables have the largest effect on the model. Additionally, it assesses whether the model's behaviour changes according to expectations (Law, 2014).

Another version of data input involves decision rules, as discussed in section 3.2, making entities move through the system based on several predefined rules. The decision flows, and assumptions within the DES model can be validated through expert input from a stakeholder. Expert validation, or face validation, is considered a standard operational validation technique and a minimum level of validation is necessary (Olsen & Raunak, 2019). An expert is someone whose experience with the system's environment is relevant to the subject (Krueger et al., 2012). For this research, an expert opinion was used to validate the different decision flows for the patient that were used as the model input. For the case used in this research, the expert is a paediatric Anaesthesiologist at the Sophia Childres Hospital in Rotterdam.

So, this research used expert validation, cross-validation and sensitivity analysis and considered lessons learned from the literature to validate the model, including the assumptions and the approach.

3.5 APPROVAL BY THE HUMAN RESEARCH ETHICS COMMITTEE

To build the simulation model past data is needed about surgery events, including the duration of the surgery, length of stay and surgery name. The data used in this model was already anonymised. The ethics committee of the TU Delft has approved the use of this data, the study is in compliance with the ethical and data management standards by the TU Delft. The letter of approval can be found in Appendix A.

3.6 THE USE OF ADDITIONAL TOOLS

The first tool that was used as an aid in this thesis is AI. For the writing of this thesis, there are several aspects in which Chat GPT was used as a tool. First, chat GTP was used to understand the packages, including Salabim, better. The user could easily find the commands that best fit the defined goal by uploading the package's description into the AI tool. Additionally, Chat GPT was used to clean up the code and as inspiration for further improvement, making it more efficient and reliable. For the writing of the thesis, the AI tool was mostly used on an inspirational level, an aid for ordering the information and improving the sentences so it more clearly stated the goal as intended.

The second tool is the use of Grammarly. This program was used for spelling and grammar corrections throughout the thesis.

4 MODEL FORMULATION

This chapter focuses on the optimisation model, the MSS, and how it is used as input for the simulation model in this thesis. It will also outline a detailed explanation of the setup of the simulation model and the input data. The entire simulation model can be found on https://github.com/LunavanV/Thesis

First, the case is introduced by outlining the optimisation model and the known information. This includes defining the KPIs, a conceptualisation of the system and the model flow. Next, all the input variables are explained one by one, and an overview of all the model's assumptions is provided. Finally, the type of output generated by the model is described and explained.

4.1 CASE INTRODUCTION

The optimisation-generated schedule that will be used for the case in this thesis was created by Vos (2022). A mathematical optimisation model creates a schedule template for the operating theatres of the Sophia Children's Hospital in Rotterdam, utilising four years of surgical data from 2018 to 2022, three years for training and one for testing. The model optimises operating theatre utilisation and levelling bed occupancy across various wards. This is achieved by considering factors such as OT availability, speciality needs, and patient group scheduling.

Vos categorises surgeries into groups within each speciality based on the expected length of stay and surgery durations. Appendix C details what the characteristics of each group look like. For each day and each operating theatre, a certain speciality is assigned, and from which groups they can perform surgery. Each of these groups has about 2 to 128 different types of surgeries that can be assigned to a corresponding slot.

Vos developed an optimisation model which designed four different OT schedules. The simulation model will evaluate the performance of these schedules against the KPIs (defined in 4.1.2). Detailed definitions of each schedule are provided in Table 5, while the schedules themselves are presented in Appendix B. The first parameter either equally prioritises increased OT utilisation and the levelling of the ward capacity or prioritises levelling the wards. The second parameter determines how often per hour the optimisation model updates and checks ward availability, impacting computational efficiency. The more times the availability is checked, the more variables are part of the model, which means it takes more time to get to a solution.

TABLE 5: MSS CHARACTERISTICS

Schedule	*OT Utilisation vs Ward levelling*	*Ward availability check*
A	Equal priority	Every hour
B	Equal priority	Every time block (15 min)
C	Priority on ward levelling	Every hour
D	Priority on ward levelling	Every time block (15 min)

4.1.1 INPUT DATA

The simulation model uses the same data as input as the optimisation model did. The data consists of 18 082 patient entries, including their surgery durations, the type of surgery, the length of hospital stay, and under which speciality that surgery was performed. How this data will be used as input variables will be explained further in section 4.3.

The simulation model also incorporates information provided by the hospital, including decision rules about which ward a patient is assigned to during their stay, see section 4.3.4 for the flow. Additionally, in collaboration with the hospital and using data from a previous thesis, the capacities for all the wards were determined, see section 4.3.5.

4.1.2 Key Performance Indicators

Based on the previous thesis and discussion, several KPIs were identified. These were chosen as they provide information about the scheduled performance. Table 6 displays an overview of these KPIs. The first, utilisation of wards, is about how much of the availability capacity of the wards is used. Following are the number of cancelled surgeries; here, a distinction is made between surgeries cancelled due to the unavailability of the wards and the unavailability of the OT; other reasons for surgery cancellation are out of the scope of the simulation model. Similar to ward utilisation, there is a KPI for OT utilisation: an OT is opened from 8:00 in the morning until 15:30. This variable is calculated using the hours of surgery performed each day compared to the total time the OT is opened; overtime will cause overutilisation. Overtime is also a separate KPI, calculating the number of times an OT goes into overtime and the length of this overtime. The hospital allows the OTs to work overtime for 25% of the OTs for a maximum of 45 minutes, including cleaning time.

Table 6: Model KPIs

KPI	Unit
Utilisation of wards	% of the ward capacity that is used
Surgeries cancelled due to OT unavailability	# of Surgeries
Surgeries cancelled due to ward unavailability	# of Surgeries
OT utilisation	% of the time OT is used
OT overtime (per OT)	# of days OT goes into overtime
Length of overtime	Minutes an OT goes into overtime

4.1.3 Conceptualisation

Figure 2 provides an overview of the entire system, illustrating the relationship between the optimisation model from previous research and the simulation model used in this thesis. In the prior research, surgery groups were created based on surgery duration and patient length of stay. Each surgery was assigned to a specific group, and a discrete probability distribution was chosen for each group, serving as input for the optimisation model. This model then produced four different schedules, as explained at the beginning of this section.

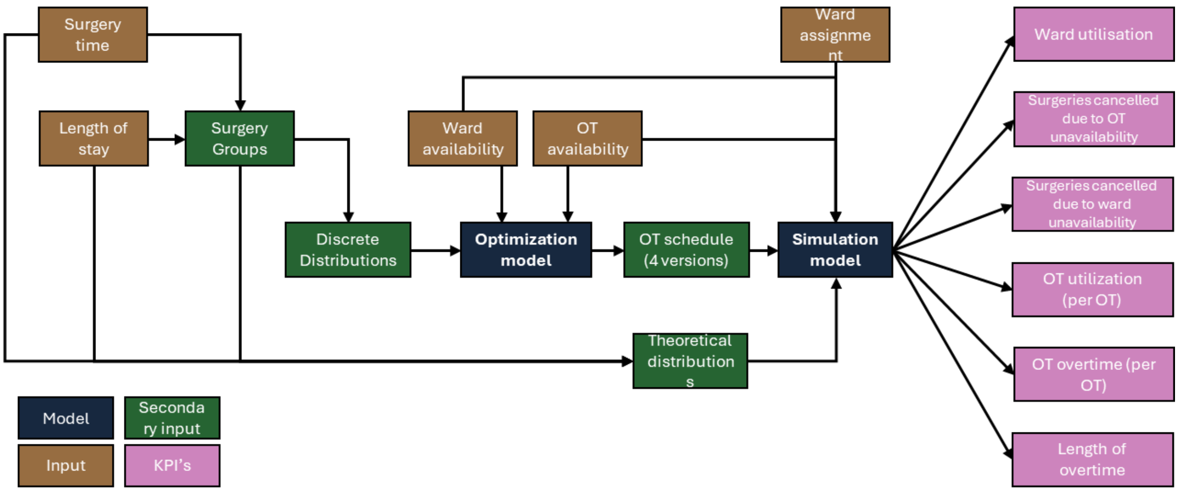


Figure 2: System conceptualisation

In Figure 2, if data is used to set up input data for the next step, it is called secondary input. Since the distributions were set up using input data for surgery time or length of stay, they are considered secondary input. Additionally, the OT schedules, used as input data for the simulation model based on the optimisation model output, are also identified as secondary input because they serve as input for the simulation model but are set up using the provided data.

The simulation model uses the same surgery groups and input data as the optimisation to fit theoretical distributions rather than discrete distributions, section 4.3 explains how these are set up. The distributions for length of stay and surgery duration, the schedules generated for the optimisation model and the availability of the wards and operating theatre all serve as input for the simulation model. On the right side of the figure, the various KPIs used to compare the results are displayed, providing a clear framework for evaluating the effectiveness of the different schedules.

4.2 MODEL FLOW

Figure 3 provides an of the total model flow. Specifically, the model will take the schedule and assign each surgery grouping slot a surgery duration, length of stay, and a fitting ward, and determine if the patient will be moved to the Intensive Care Unit, called 'Intensive Care Kinderen' (ICK), post-surgery. Sixty minutes before surgery, the entity (the patient) is created in the model and enters a queue for a specific ward. The maximum waiting time for a patient to get a ward depends on the average duration of their surgery. The time until the OT closes is calculated, and the average time for a surgery from that surgery group is subtracted and considered the maximum waiting time. If a bed becomes available but there is not enough time left before the OT closes to complete the surgery, the patient leaves. However, in the simulation model, the patient's information is recorded under "cancelled surgery due to ward unavailability”. The simulation model checks every time step of one minute if a bed on the ward has become available; this would happen if another patient leaves and releases the resource back to the system. In reality, the surgery would be rescheduled.

This requirement for average surgery duration to fit in the time left can be quite strict, or sometimes quite loose, since the ranges within surgery groups vary quite a bit, see Appendix C. However, the actual surgery duration would not be known, and in reality, an estimation would have to be made as well. Given the information available for the simulation model, this is the best estimation possible.

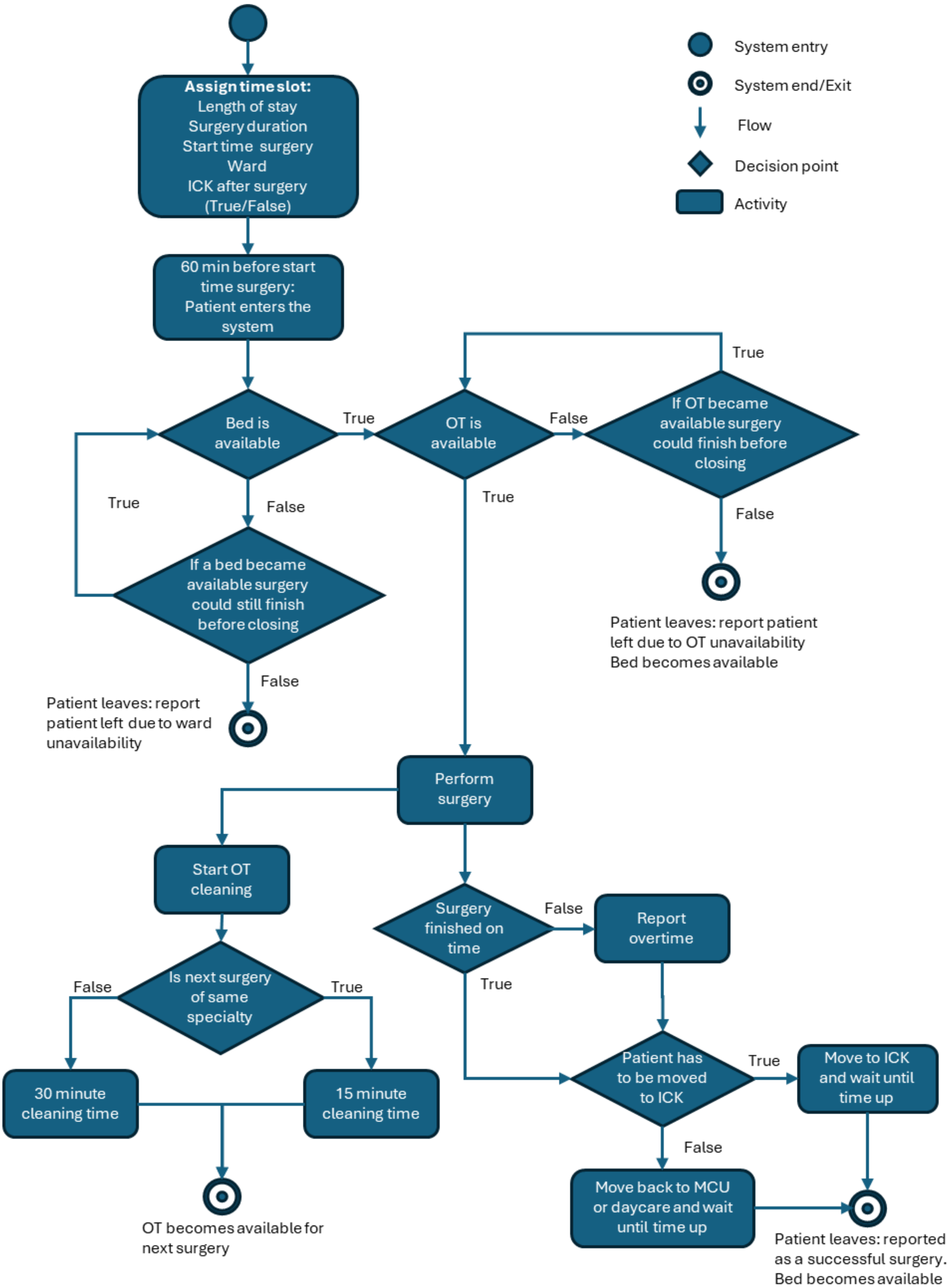


FIGURE 3: MODEL FLOW

When a patient has been assigned a bed, OT still needs to become available. Since the patient arrives 60 minutes before surgery, the patient almost always has to wait for this. However, suppose the patient needs to wait longer than the designated start time, the patient can wait maximum until it is estimated, using the average surgery duration, that the patient will no longer finish in time. The model checks every time step, which is a minute, if the OT has become available. Available means that the previous surgery has finished and the OT has been cleaned. If this maximum waiting time has passed and the OT has not become available, the surgery will be cancelled. If this happens in reality, the surgery would be rescheduled; however, in the simulation model, the patient's information will be stored under "cancelled surgery due to OT unavailability". If the surgery is estimated to finish on time, it will proceed.

After the surgery is completed, the patient will be moved to either the daycare unit, a MCU or an ICK, as predetermined based on length of stay and the probability of the ICK assignment, and after that has passed, the bed will become available again, and the patient leaves the system.

After each surgery, the OT needs to be cleaned. If the next surgery is of the same speciality, the cleaning takes 15 minutes. If a different speciality performs the next surgery, the cleaning takes 30 minutes.

4.3 MODEL PARAMETERS AND VARIABLES

The following section will discuss the simulation model's various input variables and parameters. First, it will explain how the distributions used for surgery duration and length of stay are established. This will be followed by a description of how a ward is assigned to a patient and how ward availability is determined in the model.

4.3.1 DISCRETE VS THEORETICAL DISTRIBUTIONS

For the optimisation model, discrete random variables were established for the input variables such as length of stay and surgery duration. Probability distributions were created to determine the likelihood of a surgery lasting a certain number of time blocks or a patient staying for a specific duration, based on their surgery group. These distributions were derived from historical hospital data by calculating the frequency of different surgery durations and lengths of stay to obtain probabilities. One disadvantage of using discrete probability distributions is that they are not uniquely identified by their mean and variance; different distributions can share the same mean and variance (Montgomery & Runger, 2010). The discrete probability distributions provide a more straightforward approach for modelling input variables.

As mentioned in section 2.5.1 theoretical distributions, such as the gamma and log-normal distribution, are more commonly used to describe the surgery duration, taking into account rare but critical extreme values. These distributions, as detailed in Table 4 in section 3.3, are frequently associated with estimating the time required for a task. They can generate a full spectrum of possible outcomes, including extreme values, presenting the data more compactly. Additionally, they capture the nuanced characteristics of the underlying distribution by smoothing out the data (Law, 2014).

4.3.2 DURATION SURGERY

The following sections will define a theoretical distribution for surgery duration that can be used as input for the simulation model. To evaluate the suitability of various empirical distributions, initial analysis involves creating a histogram to visualise the general shape of the distribution and a boxplot to identify any extreme outliers. Following this preliminary analysis, more precise fitting methods such as QQ plots, and the Kolmogorov-Smirnov test are employed to assess the adequacy of each distribution.

4.3.2.1 TOTAL DATASET EXPLORATION FOR SURGERY DURATION

The dataset comprises more than 18 000 data points. Figure 4 illustrates these data points in both a histogram and a boxplot. Based on these it can be seen that the data is quite centred around the 100 minutes. The boxplot does show some extreme outliers in these data points. The only adjustment that is made is removing negative data points since having a negative surgery duration is not logical.

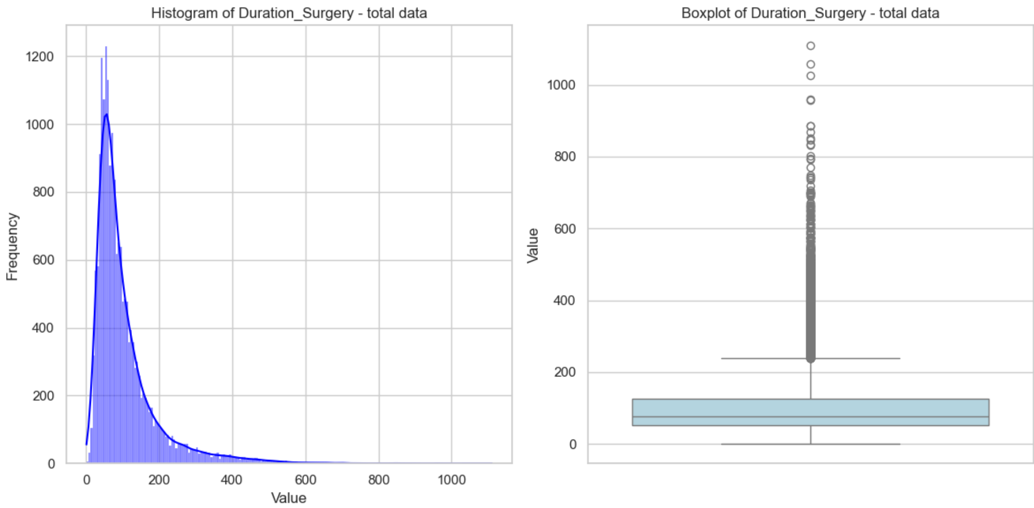


FIGURE 4: BOXPLOT AND HISTOGRAM OF THE TOTAL DATASET

The dataset is divided into training and testing data to validate the model later. The training comprises three years of the dataset, 14 178 data points, and the testing covers one year, 4 402 data points. Figure 5 present histograms and boxplots for the training data of surgery duration and Figure 6 present histograms and boxplots for the test data of surgery duration. The figures show similar shapes, differing mainly in frequency. However, the training data has some additional extreme cases compared to the testing data.

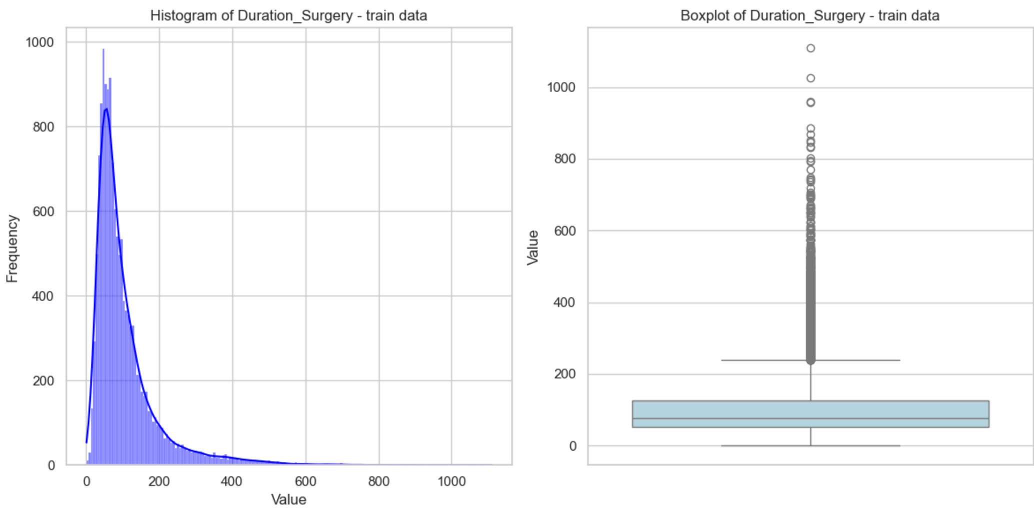


FIGURE 5: BOXPLOT AND HISTOGRAM TRAINING DATA SURGERY DURATION

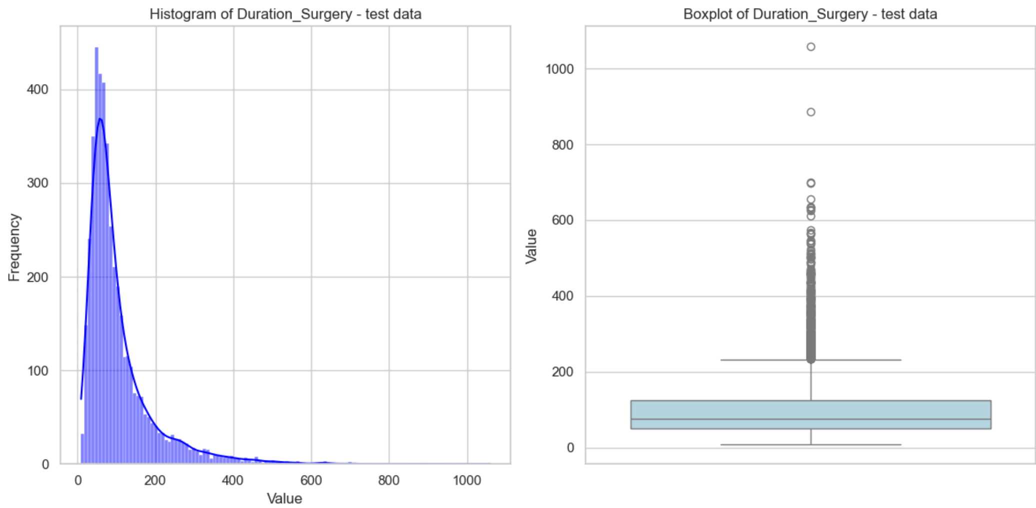


FIGURE 6: BOXPLOT AND HISTOGRAM TESTING DATA SURGERY DURATION

Figure 7 presents the QQ plots for each of the six chosen distributions, providing a visual method to compare the theoretical quantiles of the distributions against the dataset. Table 7 offers an overview of the Kolmogorov-Smirnov (KS) test results assessing the goodness of fit.

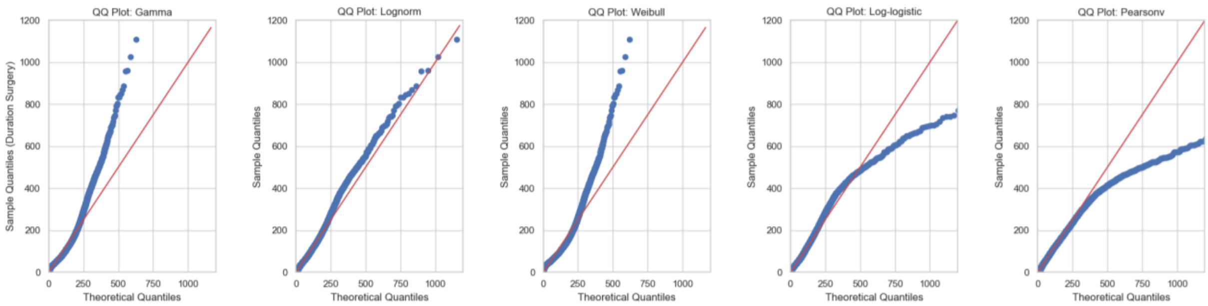


FIGURE 7: QQ-PLOTS FOR THE CHOSEN DISTRIBUTIONS

TABLE 7: RESULTS OF STATISTICAL TESTS

Distributions	*KS statistic*	*KS P-value*
Gamma	0,0866	$5{,}2618\cdot10^{-87}$
Log-Normal	0,0407	$6{,}9340\cdot10^{-15}$
Weibull	0,0930	$3{,}1260\cdot10^{-101}$
Log-Logistic	0,0316	$9{,}1441\cdot10^{-7}$
Pearson type V	0,0309	$3{,}3117\cdot10^{-6}$

Based on the QQ plots in Figure 7 , it would seem that the lognormal distribution might be a good fit for the overall data. However, considering the P-values of Table 7 it would seem none of the distributions are a proper fit. This could be explained by the data distribution, which is unclear from the QQ plots. Table 8 reveals that the majority of the data points are under 200 minutes. Interestingly, the final 10% of the data spans a range five times wider than the preceding 90%.

TABLE 8: DISTRIBUTION OF THE DATA SURGERY DURATION

RANGE IN MINUTES	**NR OF SURGERY DATA POINTS**
0-200	12660
200-400	1220
400-600	249
600-800	38
800-1000	9
1000<	2
TOTAL	**14 178**

Considering the extensive spread of the total dataset, it might be more effective to analyse the data by specific groupings. Group-specific differences might impact the model's behaviour, so it is essential to account for these differences in the input data to ensure a more accurate analysis. The following section will detail the assignment of distributions per grouping.

4.3.2.2 PER GROUP ASSIGNMENT OF DISTRIBUTIONS FOR SURGERY DURATION

This section will explore the possibility of segmenting the dataset into the predefined surgery groups to determine if distinct distributions can be defined separately for each group. All of the histograms and boxplots of these groupings are shown in Appendix D. Additionally, the second part of Appendix C also shows the sample size for each of the groupings.

When considering whether a data set is significant, using a significance level of 0,05 is standard practice. If the p-value is above 0,05, there is evidence to expect the observed data not to differ too much from the distributed data (Law, 2014). Table 9 Provides an overview detailing the number of groups out of 50 for which the p-value of the KS-test was statistically significant at various levels of significance.

TABLE 9: SIGNIFICANT NUMBER OF TEST RESULTS PER DISTRIBUTION

Distributions	*Significant KS P-value (α = 0,05)*	*Significant KS P-value (α = 0,01)*
Gamma	36	39
Weibull	21	31
Log-Normal	35	41
Log-Logistic	45	47
Pearson type V	33	37

When looking more closely into the distribution, it can be found that only four groupings cannot fit in any of the distributions according KS-test with a significance level of 0,05. The KS-test has a p-value below the significance level of 0,05 for all of the fitted distributions.

The next step would be to see which distributions fit best based on the QQ plots for the remaining groupings. Figure 8 shows an example of one of these groupings, group 43; the closer the dots are to the red line, the better the distribution fits. So, for this group, the Weibull distribution (top middle graph) is chosen; here, the data points are closest to the 45-dree guideline. For the other groupings that were not yet assigned a distribution, these graphs and their chosen distributions are provided in Appendix D, additionally the P-value of the KS test is also provided for all of the assigned distributions.

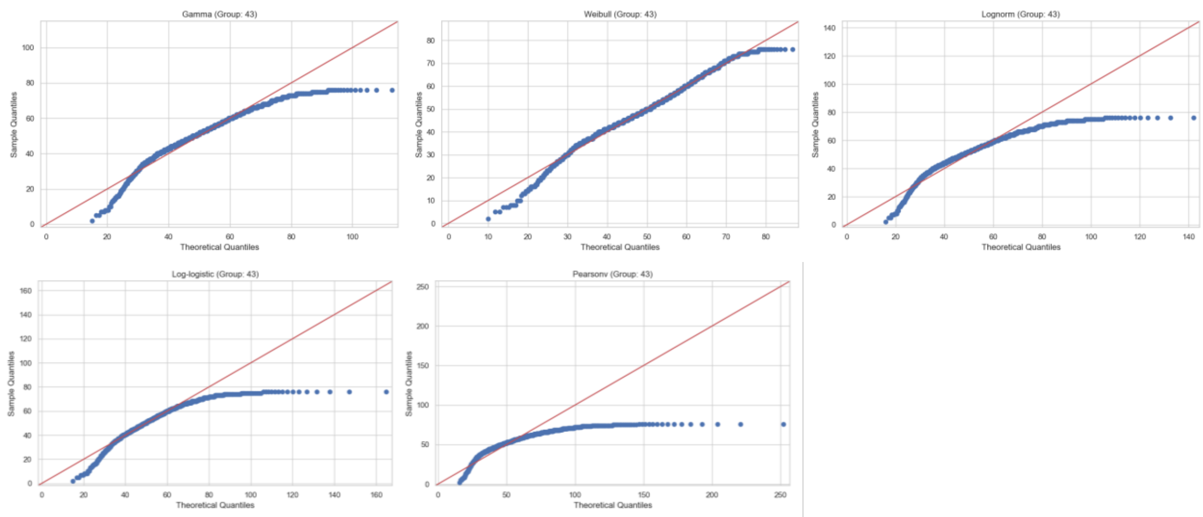


FIGURE 8: EXAMPLE GROUP QQ PLOT, GROUP 43

Table 10 provides an overview of how many groupings are chosen for each distribution, either by visual inspection or assignment based on the KS test. Interestingly, most groupings are assigned a log-logistic or a Pearson type V distribution, while the literature highlighted the Gamma or the Log-Normal distributions as best fitting for data such as surgery duration.

TABLE 10: NUMBER OF GROUPS PER DISTRIBUTION, SURGERY DURATION

Distributions	*Number of groups*
Gamma	5
Weibull	3
Log-Normal	3
Log-Logistic	24
Pearson type V	15

4.3.3 LENGTH OF STAY

The following input variable for the model is the length of stay. It was considered that this variable might also be influenced by surgery duration. If this were the case, a multiple linear regression model could be a suitable analytical approach, allowing the inclusion of both group and surgery duration as independent variables. Multiple linear regression facilitates examining relationships between a dependent variable and multiple independent variables. As outlined by Montgomery & Runger (2010), employing this type of model involves setting hypotheses: the null hypothesis states there is no significant relationship between the dependent and independent variables, while the alternative hypothesis suggests a significant relationship exists.

However, the correlation between surgery duration and length of stay needed to be assessed to determine if this approach would be appropriate. The total dataset exhibited a correlation of only 0,4 between these variables. When examining individual groups, most showed even lower correlations. This weak correlation indicated that a multiple linear regression model might not be suitable for this data. The scatterplot in Figure 9 visually demonstrates the relationship between surgery duration and length of stay of the training data, visualising the weak correlation between these variables. Since the relationship between these variables was not considered strong, it was decided also to fit the distributions for the Length of Stay variable.

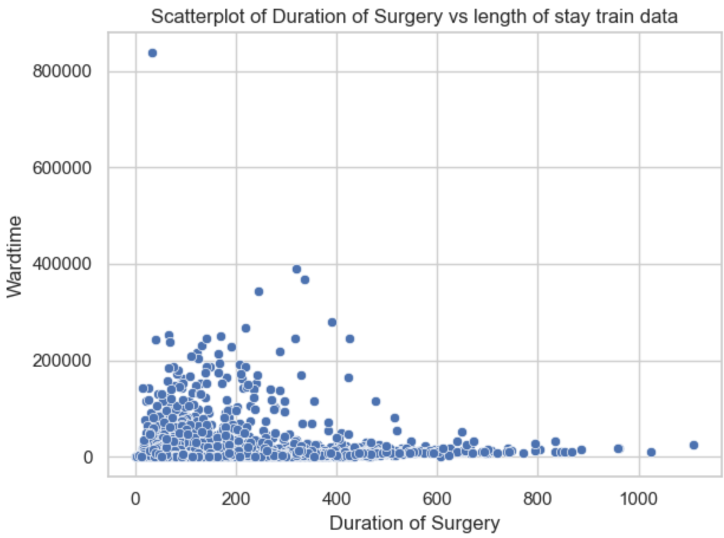


FIGURE 9: SCATTER PLOT SURGERY DURATION AND LENGTH OF STAY

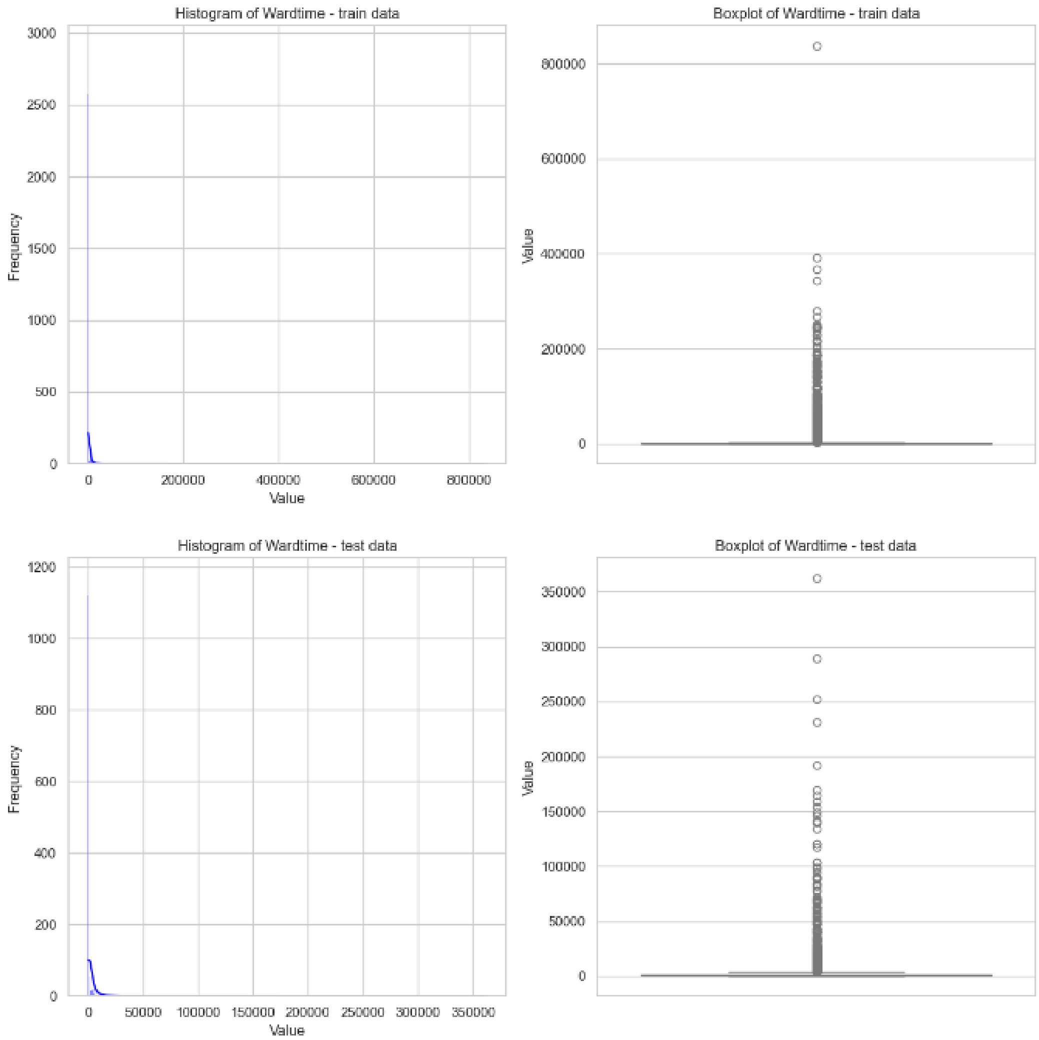


FIGURE 10: HISTOGRAM AND BOXPLOT LENGTH OF STAY TRAINING DATA (LEFT) AND TEST DATA (RIGHT)

Figure 10 shows the histograms and the boxplots for the total length of stay, which immediately reveals many extreme outliers in the dataset. For more specific insight into the data, Appendix E gives an overview of the histograms and boxplots per grouping.

To provide better insight into the total dataset, Figure 11 displays the QQ plots for the distributions defined in Table 4, and Table 11 provides an overview of the statistical tests. To enhance visualisation, outliers have been excluded from the QQ plots in Figure 11. The statistical tests in Table 11 indicate that none of the distributions fit the data properly, as all p-values for the KS-test are below the chosen significance level of 0,05. This is then confirmed by the plots of Figure 11 where it can be seen that the data occurrences are not even close to the 45-degree line, meaning that the distribution does not fit the data.

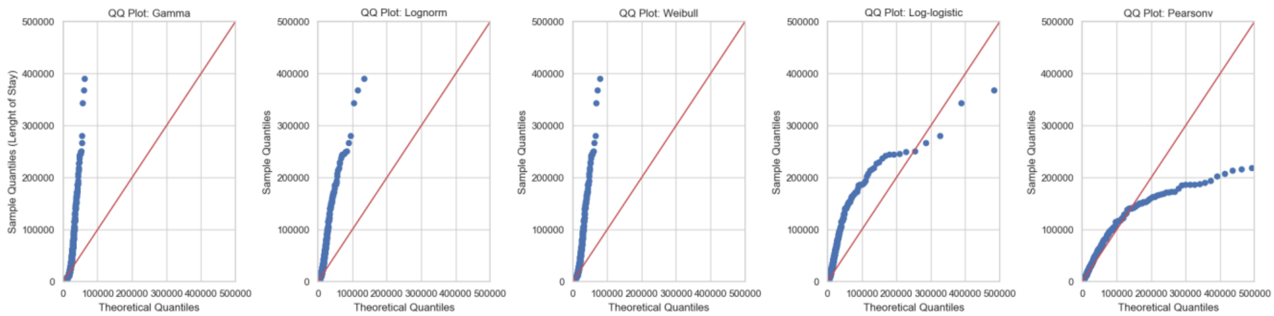


FIGURE 11: QQ-PLOTS FOR THE CHOSEN DISTRIBUTIONS

TABLE 11: RESULTS OF STATISTICAL TESTS

Distributions	*KS statistic*	*KS P-value*
Gamma	0,2343	0,00
Log-Normal	0,1836	0,00
Weibull	0,1980	0,00
Log-Logistic	0,1435	$2{,}4907 \cdot 10^{-249}$
Pearson type V	0,1399	$2{,}0686 \cdot 10^{-236}$

Table 8 shows that the data is also very centred on the lowest variables. As length of stay varies between 0 and 80 000, but 50% of the values are lower than 500.

TABLE 12: DISTRIBUTION OF THE DATA LENGTH OF STAY

RANGE IN MINUTES	NR OF SURGERY DATA POINTS
0-500	6992
500-1000	1635
1000-1500	527
1500-2000	1754
2000-3000	295
3000-4000	797
4000-5000	450
5000-10000	805
10000-15000	345
15000-20000	91
20000-30000	155
30000+	332
TOTAL	**14 178**

Because the differences in groups would, similar to the length of stay variable, impact the model behaviour and the total dataset does not seem to provide proper fitting, the variable is also split up in the surgery groups. Table 13 presents the test results for each distribution.

TABLE 13: OUTCOMES DISTRIBUTION TEST LENGTH OF STAY

Distributions	*Significant KS P-value (α = 0,05)*	*Significant KS P-value (α = 0,01)*
Gamma	3	3
Log-Normal	7	9
Weibull	3	5
Log-Logistic	13	17
Pearson type V	6	9

When looking more closely into the distribution, it can be found that only 37 groupings cannot fit in any of the distributions according to the KS-test with a significance level of 0,05. When lowering the significance level, to 0,01, 4 more groupings are able to find a fitting distribution. Similarly, as done with the groupings for surgery duration, the next step is to see which distribution fit best based on the QQ plots for these last groups that did not score sufficiently on the KS-test. Based on visual inspection, each of these groupings is assigned distributions; both the QQ plots and parameters for the chosen distributions are provided in Appendix E. However, since so many of them do not fit any grouping based on the KS-test also when choosing a best fit based on visual inspection there are some doubts on whether the distributions can give a good representation of the length of stay.

TABLE 14: NUMBER OF GROUPS PER DISTRIBUTION, LENGTH OF STAY

Distributions	*Number of groups*
Gamma	7
Weibull	9
Log-Normal	14
Log-Logistic	15
Pearson type V	5

Table 10 gives an overview of how many groupings are assigned to each distribution. Again it is interesting to see that the distributions highlighted by the literature as fitting for this type of data does not get the highest number of distributions assigned.

4.3.4 WARD ASSIGNMENT

The model needs strict rules to decide which bed a patient needs to be assigned. These rules were set up using the information available in previous research and validated by an expert from the hospital. The assignment of wards is divided into three stages. The total flow of the conceptual model is provided in Figure 3. The first stage occurs before surgery, where a patient is assigned a bed in either the medium care unit or the daycare ward. The second stage takes place after surgery. Suppose the patient was initially assigned to the medium care unit. In that case, there is a probability that the patient was also assigned to an intensive care unit and has to be moved after surgery to intensive care. The third and final stage concerns patients initially assigned to the daycare unit. It is possible that the patient's ward time runs long, and they may need to stay overnight and are subsequently moved to a medium care unit.

4.3.4.1 STAGE 1: BED ASSIGNMENT UPON ARRIVAL

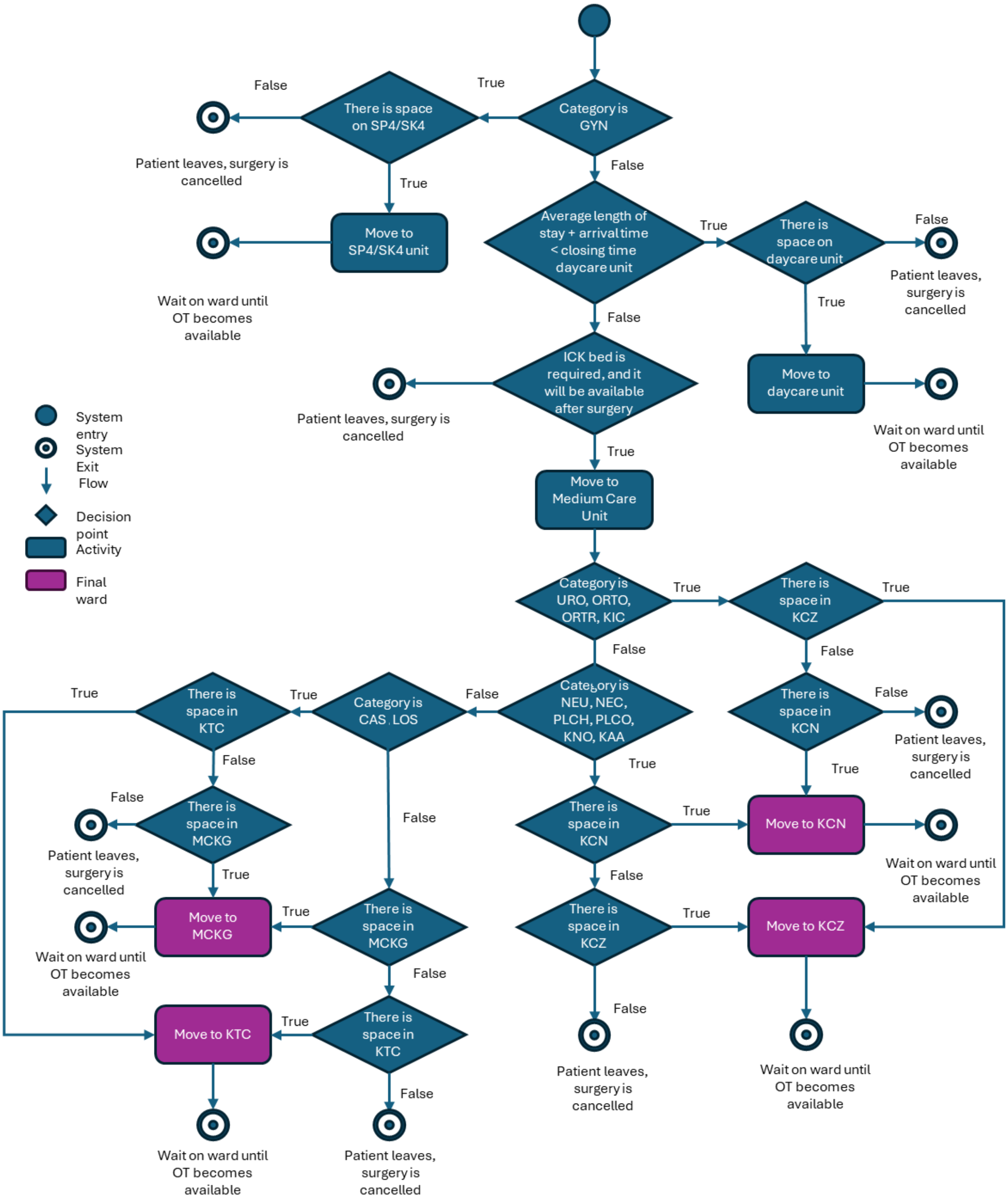


FIGURE 12: STAGE 1, ASSIGNING A BED ON ARRIVAL

Figure 12 Illustrates the bed assignment flow for patients upon their arrival at the hospital. Patients from the gynaecology speciality are always placed in the SK4 or SPN 4 ward. If it is known that a patient will have a short stay after their surgery, they are assigned to the daycare unit and will be discharged the same day. If they require a longer stay, the patient is assigned to a medium care unit. The specific medium care unit to which a patient is assigned depends on the speciality associated with their surgery (for the speciality full names, see Appendix C).

For some medium care units, beds can be interchangeable if needed. For instance, a patient can be moved to an alternate unit if one unit is full. This is the case for the pairs of units on the left, between KTC and MCKG, and on the right, between KCZ and KCN. If no beds are available in either of these units, the patient will be discharged, and the surgery will be rescheduled.

Some medium-care unit patients might have to be moved to the ICK after surgery. It needs to be checked if a bed is going to be available for this patient after the surgery. If not, the surgery can't continue and is cancelled.

4.3.4.2 STAGE 2: ICK ASSIGNMENT AFTER SURGERY

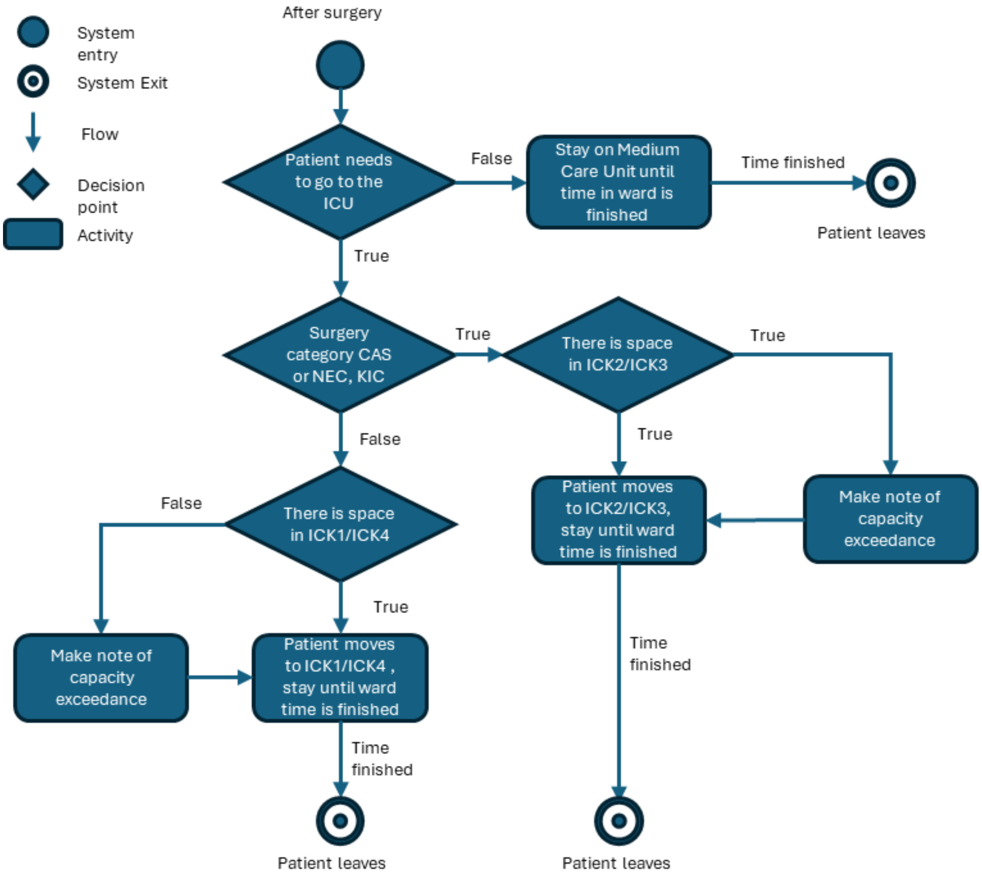


FIGURE 13: STAGE 2, ASSIGNING AN ICK AFTER SURGERY

Figure 13 illustrates the process of the patient post-surgery. Patients not assigned an ICK bed remain in their designated medium care unit until their stay is completed. For patients assigned an ICK bed, this assignment is determined before surgery, but the actual transfer occurs after surgery.

There are two types of ICK: patients can be vented, ICK 2 and ICK 3, and patients cannot, ICK1 and ICK 4. Whether patients need to be vented after surgery is determined by the surgeon and the patient's status. However, this is subjective, so in the model, assumptions are made about this. Here, it is assumed that patients operated on by the Cardiac (CAS) or Neurology (NEU) speciality are moved to the vented ICKs if they need to be transferred to the ICK. All other patients are moved to the unvented, lower-care ICKs. The availability of these beds should have been checked before surgery, but if, due to any unforeseen circumstances, no bed is available, the ICK is forced to exceed its capacity

4.3.4.3 STAGE 3: MCU ASSIGNMENT AFTER SURGERY

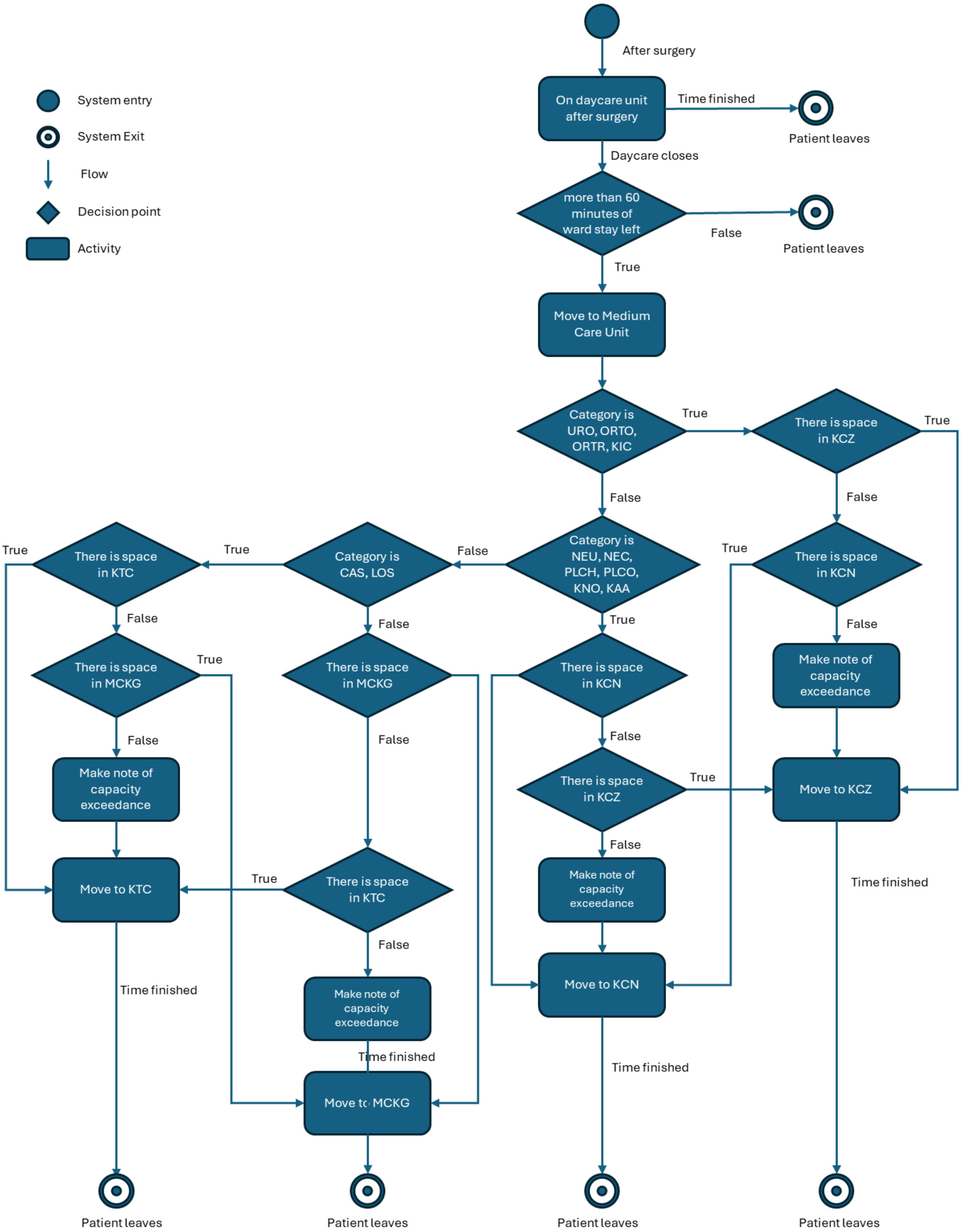


FIGURE 14: STAGE 3, ASSIGNING A MCU AFTER BEING PLACED ON DAYCARE

Figure 14 illustrates the patient flow for those assigned to a daycare unit. Patients can leave without issue if they complete their stay before the daycare unit closes. However, if the patient needs to remain in the hospital after the daycare unit is closed, they must be moved. A boundary level of 60 minutes is used to determine the course of action. If patients have less than 60 minutes remaining, they are discharged early. If more than 60 minutes are left, the patient is transferred to a medium care unit. The process for assigning the medium care unit is the same as the pre-surgery assignment shown in Figure 12. The difference is that now, the assignment is not the final step of the flow. After being assigned to a medium care unit, the patient remains there until their ward time is completed, after which they are discharged from the hospital. Additionally, suppose the patient has to be moved to a medium care unit but none can handle that specific patient's requirements. In that case, one of the units has to exceed its capacity and take up a bed that was not initially designated for an elective surgery patient.

4.3.4.4 ASSIGNING THE INTENSIVE CARE BED

The previous section mentioned that in stage 2, there is a possibility of a patient being transferred to the ICK. However, the surgeon decides which patient is moved before surgery, as they request the ICK bed when scheduling the surgery. In collaboration with the hospital, it was determined which surgeries often get assigned an ICK bed after surgery. Some procedures had a probability greater than 95% of being assigned an ICK bed; some had an approximate 30% probability, while others had a 0% probability. Based on the frequency of each surgery occurring during the four years and the share of surgeries that are (sometimes) assigned an ICK bed in the total group frequency, the probability of the patient being transferred to the ICK after surgery is determined. The model then uses a binomial distribution with the given probability.

4.3.5 WARD AVAILABILITY

After a patient has been assigned a ward, it still needs to be checked to see if a ward is available. The availability of the ward is dependent on the ward's capacity for surgical patients. However, the number of beds available for these patients varies, depending on the inflow of other patients and the resources available. In collaboration with the hospital, Kelly Vos set up averages for each of the wards; however, these averages were not rounded. Using the available bed usage over time, it could be seen that, on average, fewer beds were actually used compared to the capacity. So in the simulation model, these averages will be rounded down. Table 15 gives an overview of the unrounded capacity. Every ward is open 24 hours a day, seven days a week, except for the daycare unit, which is only open on working days from 7:00 until 18:00. For some wards, the availability varies during the different shifts of the schedule. Additionally, the KCN unit has extra availability on the shift from 7:00 until 16:00 on Tuesdays and Fridays.

TABLE 15: WARD AVAILABILITY

Ward	Time	Weekday	Weekend
ICK1/ICK4	00:00-23:59	4,5	3
iCK2/ICK3	00:00-23:59	4	4
KCZ	07:00 – 16:00	10	8,5
	16:00 – 23:00	9,5	8
	23:00 – 07:00	9	8
KTC	07:00 – 23:00	4,5	3
	23:00 – 07:00	4	3
MCKG	07:00 – 23:00	3,5	2,5
	23:00 – 07:00	3	2,5
SK4/SP4	07:00 – 16:00	4	3,3
	16:00 – 07:00	3,9	2,2
KCN	07:00 – 16:00	10	8,5
	16:00 – 23:00	9,5	8
	23:00 – 07:00	9	8
KCN	07:00 – 16:00	8,5 (10,5 on Tue and Fri)	5
	16:00 – 23:00	8	4,5
	23:00 – 07:00	7,5	4,5
Daycare	07:00 – 10:00	8,5	CLOSED
	10:00 – 14:00	9	
	14:00 – 18:00	5,5	

4.4 MODEL ASSUMPTIONS

Table 16 provides an overview of all the assumptions incorporated into the model. It also explains each assumption's rationale and the foundation for its inclusion. In instances where previous sections have addressed these subjects, the relevant sections are referenced within the table, or the last column of the table includes supporting evidence from the literature for certain assumptions.

TABLE 16: MODEL ASSUMPTIONS

ASSUMPTION	EXPLANATION	SUPPORT FOR ASSUMPTION
Patients arrive on time.	This model does not consider a patient arriving too late for their surgery.	
Patients don't cancel surgeries.	In reality the lack of availability is not the only reason for a surgery to get cancelled. For example patient could fail to show up, or their health is not fitting to go through surgery. However, in this model, the only form of cancellation considered is due to the lack of availability of the OT or the wards.	
As soon as a patient arrives, the surgery can start.	Since the patient is asked to be there an hour in advance the pre-surgery procedure can start before a bed has been assigned. So, even though a bed might be assigned later, the procedure can start as soon as the bed is assigned and the OT is available.	Validated by hospital expert.
Patients are in the hospital for one surgery.	Even though patients, in reality, might need multiple surgeries since the surgeries are considered electives, they are also seen as separate from one another since they need to be planned differently.	
The capacity for elective surgery patients is independent of that of other patients in the hospital.	The resources in all specialties are specifically for patients in the hospital for elective surgery. In reality, the availability is influenced by the stream of other patients, including emergency surgery.	(Cappanera et al., 2014) Section 4.3.5
A surgery is cancelled if, on average, a surgery can't finish on time anymore.	In the system, as soon as a patient arrives, it ques for a bed on a specific ward. And surgery can only start as soon as the bed has become available. However, the maximum waiting time is determined based on the closing of the OT and the average length of the surgery that needs to be performed. If, on average, a surgery will cause overtime, the patient is sent home.	
The assignment of the wards is set using the expert-validated flow	For the assignment of a bed, decision flows are set and validated by an expert from the hospital	Section 4.3.4
Patients have to go to the ICK after surgery based on the probability	Before the patient is assigned a regular ward, the probability is used to determine if a patient requires an ICK bed after surgery	Section 4.3.4.4
The operating theatres have a capacity of 1 when opened	There are ten operating theatres and MRI on the schedule. They open at 8 in the morning and close at 15:30 (or when they go into overtime at 16:15). Each can handle one patient at a time	(Vos, 2022)
Cleaning takes 15 minutes or 30 minutes for different specialties	When surgery is finished, and the same type of speciality needs to use that same OT, there must be 15 minutes between each surgery. When there are different specialties, there needs to be 30 minutes between each surgery because more changes need to be made.	(Vos, 2022)
There is a 25% occurrence of overtime allowed	25% of the OTs are allowed to go into overtime with a maximum of 45 minutes.	(Vos, 2022)
The length of stay and surgery duration is determined by the distribution set for each grouping.	Common practice is to use distribution to set the input variables.	See section 2.3.1
The NICU is left out.	In the input model, no distinction is available on the patient's age, so it cannot be determined if a patient needs to go to the NICU. So, these are left out, and all patients are placed in the regular ICK if required.	
The year does not have any holidays.	On holidays, the hospital performs no elective surgery; however, this is not considered.	

4.5 MODEL OUTPUT

The following section gives an output example of the system. The mode output presented is not based on any of the schedules that will be evaluated. The schedule used to set up these plots is generated by the optimisation model but is not part of the evaluation of this thesis. These plots only serve as an example to explain what the visualisation of the model output means. This section outlines the different forms of model output and how each KPI is reflected.

The first KPI is the utilisation of the wards, which measures the percentage of total capacity used. Figure 15 illustrates the overall ward capacity utilisation in the system across the 28-day cycle while

Figure 16 provides a breakdown of utilisation per ward. The utilisation is the percentage of time the ward is used, so if the utilisation is 1, 100% of the capacity is used. When it is higher than 1, there is overutilisation, and for lower than 1, underutilisation. In Figure 15 the different boxplots represent the different wards throughout the hospital, while in Figure 16 the x-axis represents the different wards in the hospital.

This visualisation illustrates how the utilisation differs between the different wards or cycle days. It enables the ability to find wards with an increased utilisation compared to others or whether the utilisation is levelled throughout the entire cycle.

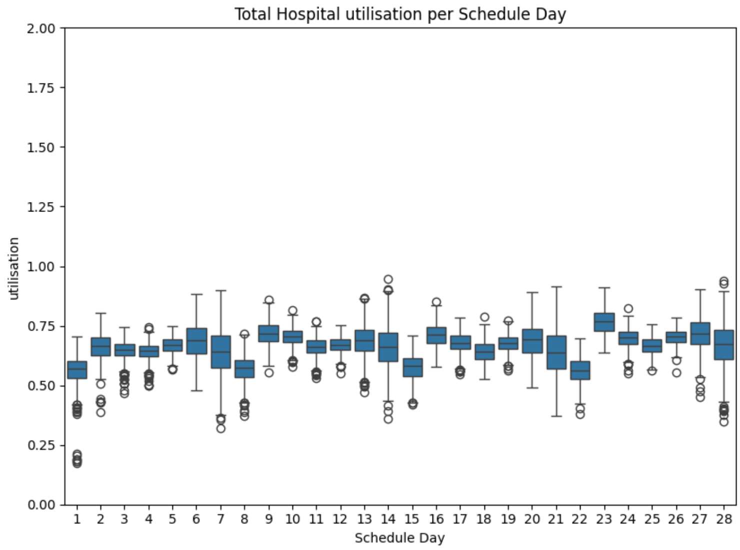


FIGURE 15: EXAMPLE VISUALISATION OF TOTAL WARD UTILISATION

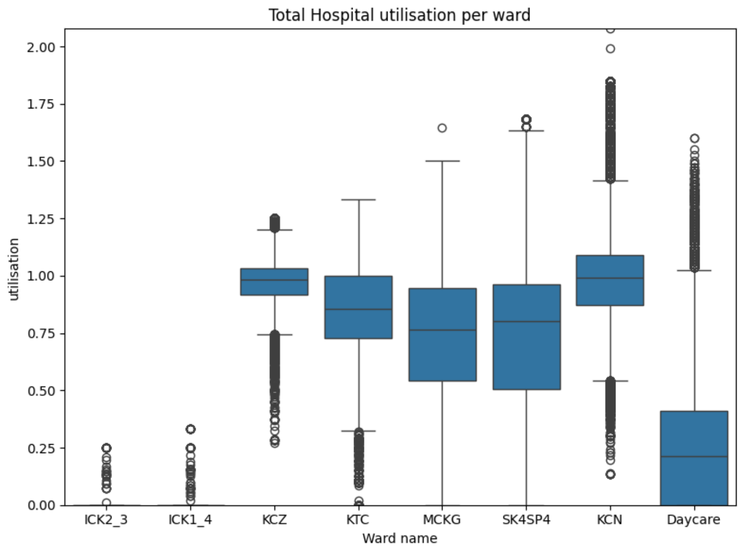


FIGURE 16: EXAMPLE VISUALISATION WARD UTILISATION PER WARD

The following KPI focuses on the utilisation of the OTs, measuring the percentage of available time occupied by surgeries. In the same manner as the wards, the utilisation of the OT is presented to analyse the efficiency of surgical scheduling. Figure 17 illustrates the OT capacity used across the 28-day cycle; the x-axis here represents the day of each cycle, providing insight into the fluctuations of the OT utilisation of the entire hospital.

Figure 18 offers a breakdown of OT utilisation per individual theatre. The number on the x-axis represents the different OTs. The boxplot per OT enables comparison of the different schedules for all of the OTs. These visualisations help identify which OTs experience more extreme utilisation than others and can show across schedules if there are overscheduled or under-scheduled days.

There is no data for days 6, 7, 13, 14,20, 21, 27 and 28 as there are weekend days and no elective procedures are performed on weekends.

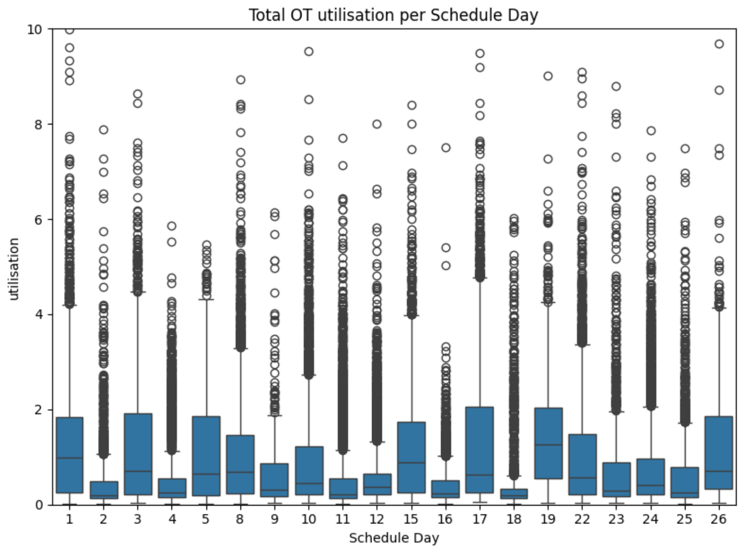


FIGURE 17: EXAMPLE VISUALISATION OF TOTAL OT UTILISATION

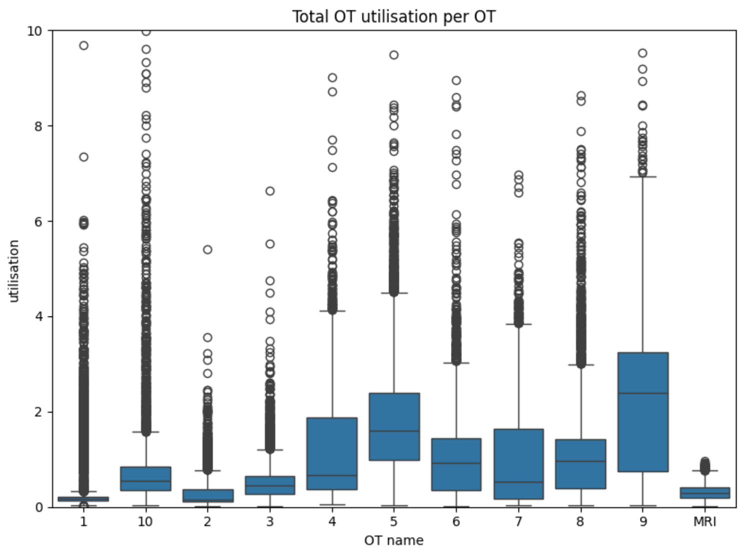


FIGURE 18: EXAMPLE VISUALISATION OF OT UTILISATION PER OT

The following KPI with a visual output is the overtime of the OTs. Figure 19 illustrates the total hospital overtime. The figure on the left shows the percentage of days each OT has overtime during the cycle. For instance, a value of 20 means that 4 out of 20 days experience overtime.

The figure on the right depicts the number of overtime occurrences for different durations. The y-axis shows the percentage of surgery days with overtime, and the x-axis shows the length of overtime. For example, the first bin indicates that about 0,8% of all surgeries experience a 15-minute overtime. The red line at 45 minutes marks the acceptable threshold for the hospital, which allows for 45 minutes of overtime (including cleaning time) for 25% of the OTs. This visualisation helps assess the acceptability of overtime occurrences.

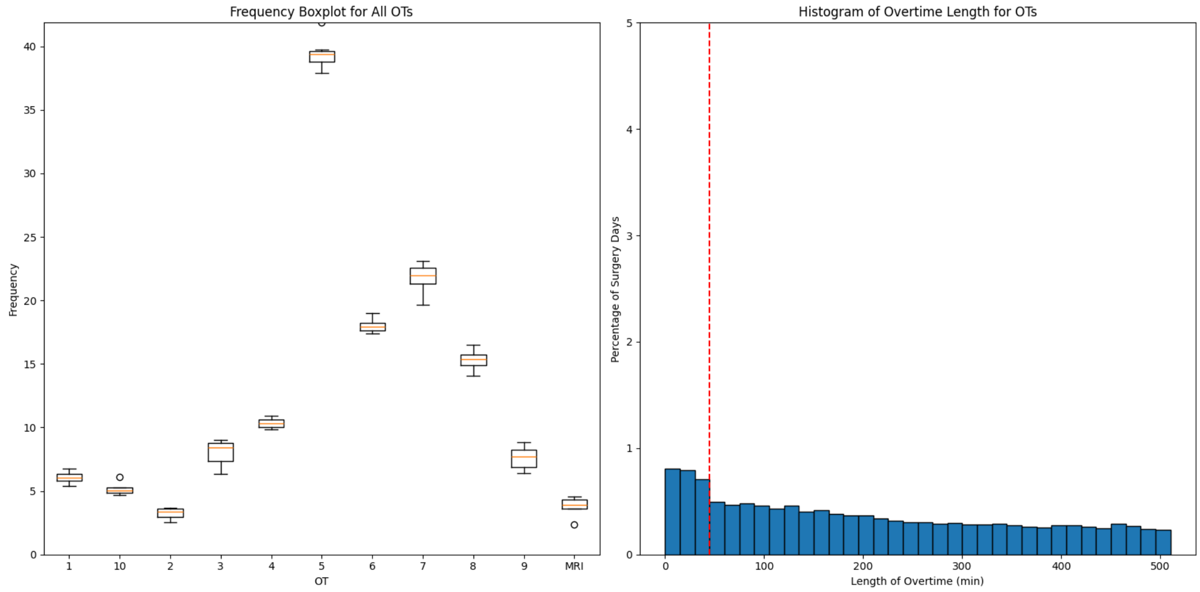


FIGURE 19: TOTAL OVERTIME VISUALISATION

Figure 20 provides a more detailed overview of the overtime as it provides the overtime per OT. The first and last visualisations are similar to that of the total overtime. The second figure gives the length of overtime for each occurrence per scheduled day. They provide an insight that if the cycle day experiences overtime the average overtime per cycle can be considered long or short. Because even if an OT experiences low occurrences of overtime, these occurrences might still be longer.

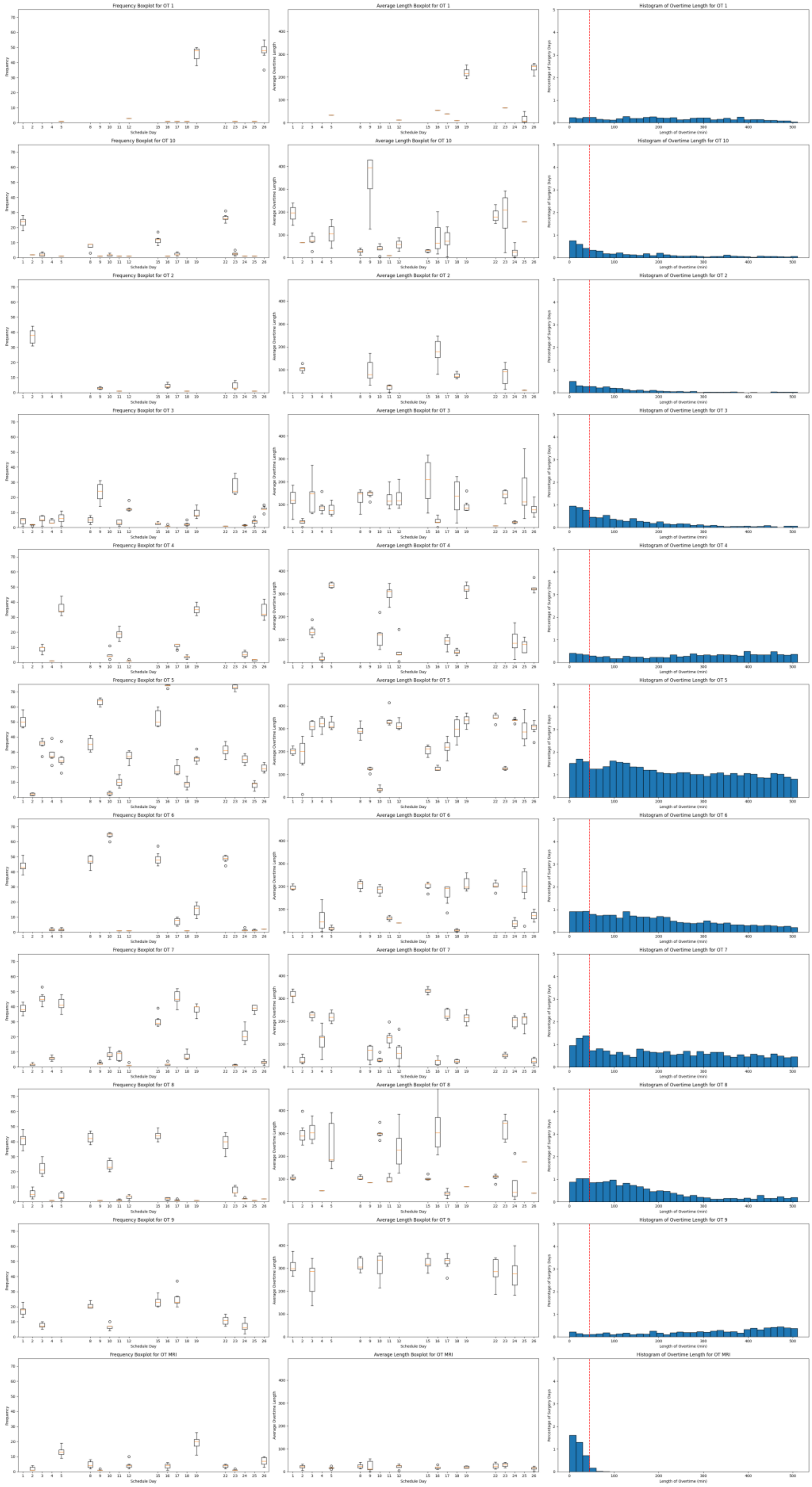


FIGURE 20: EXAMPLE OUTPUT OVERTIME

The last two KPIs that have to be defined are the number of surgeries cancelled due to the unavailability of the OT or the unavailability of the ward. As explained earlier, a surgery is cancelled after a maximum number of waiting time has passed and a bed or OT has not yet become available. This waiting is calculated using the average time of the surgery, cleaning time and time left in the day when the patient arrives. Table 17 and Table 18 give these overviews per ward and OT; the last column is the percentage of the times a surgery had to be cancelled because that specific ward or OT was unavailable and caused the cancellation. It gives an insight into which OTs or wards cause the most surgeries to be cancelled. The standard deviation shows whether this varies across the different runs.

TABLE 17: EXAMPLE OVERVIEW SURGERIES CANCELLED DUE TO OT UNAVAILABILITY

OT	AVERAGE	STANDARD DEVIATION	PERCENTAGE
1	0	0	0
2	18,43	6,02	36,24
3	40,00	6,70	44,86
4	393,86	9,16	83,84
5	766,43	44,93	2018,53
6	247,43	12,07	145,67
7	230,71	16,56	274,20
8	24,71	4,13	17,06
9	279,86	11,83	139,84
10	13,43	6,21	38,53
MRI	1,43	1,05	1,10

TABLE 18: EXAMPLE OVERVIEW SURGERIES CANCELLED DUE TO WARD UNAVAILABILITY

WARD	AVERAGE	STANDARD DEVIATION	PERCENTAGE
Daycare	0	0	0
ICK1_4	0	0	0
ICK2_3	0	0	0
SK4SP4	42,71	17,22	296,49
KCN	4322,14	121,78	14830,41
KCZ	7608,29	200,37	40147,92
KTC	540,00	18,76	352,00
MCKG	3351,71	72,29	5226,49

Lastly, Table 19 gives an overall summary of the simulation results, providing the number of attempted surgeries and how many were successful, cancelled or caused over time. Additionally, sometimes a ward is forced to exceed its capacity because surgery has already happened; this is also shown in Table 19. Lastly, a value for the average utilisation of all the OTs and wards in the hospital is presented. It gives an overview of the overall performance of the model. It aids in comparing some of the different KPIs as they are presented in a summarised format next to one another.

TABLE 19: SUMMARY MODEL OUTPUT

Run	*Successful Surgeries*	*Cancelled Surgeries (OT Unavailability)*	*Cancelled Surgeries (Ward Unavailability)*	*Overtime Occurrences*	*Total number of surgeries*	*Times a ward had to exceed capacity*	*Average OT utilisation*	*Average ward utilisation*
1	13725	2030	15667	2145	31434	860	0,93	0,66
2	13096	1914	16407	2162	31434	905	0,93	0,67
3	13655	2035	15728	2106	31434	871	0,94	0,66
4	13974	2182	15264	2259	31434	843	0,95	0,65
5	13603	2034	15778	2146	31434	841	0,93	0,66
6	13278	1955	16183	2142	31434	896	0,92	0,67
7	13425	1964	16027	2190	31434	876	0,92	0,66

5 SIMULATION MODEL SETUP

The upcoming chapter details the setup of the simulation, including determining the simulation length and the number of replications. After which, the chapter will focus on verifying the model and finally validating the model. It is important to note that during these steps, the model's output is not based on any of the schedules that will be tested in the experimentation phase. The scheduled version being used is known to maximise operating theatre usage but does not adequately account for levelling bed occupancy. The optimisation model also created this schedule but was not proposed as one of the solutions. This approach was chosen to more rigorously test the model, exposing it to extremes in patient flows without yet taking into consideration the levelling of the wards. This method allows for a thorough assessment of the model's functionality.

5.1 SIMULATION RUNS AND RUNNING LENGTH

When running a simulation model, a decision needs to be made about how many times the model needs to run and for how long a period the model needs to run. The model works with a four-week schedule, so when deciding on the length, it is considered how many times this schedule should be repeated. The outcomes of several combinations of run lengths and repetitions are compared to determine the correct number of runs. For this, the model was first run for 1, 2, 3, 6 or 10 years with either 1, 3, 5, 10 or 20 repeats. The model then seemed to stabilise between 5 and 10 repeats, so another run was done for 6,7,8 and 9 repeats to provide additional detail.

After inspecting this bundle of runs, the correct number of repetitions is identified when outcome variations stabilise (Lorscheid et al., 2011). This point where the variation in the outcomes seemed to stabilise was found when the model was run for seven repetitions, each spanning six years. Increasing the number of runs or the duration beyond this point did not result in significant changes in the outcomes.

5.2 MODEL VERIFICATION

Verification is about discovering whether the model is designed as intended and proof that the model is validly debugged (Law, 2014). That is what this section intends demonstrate. The previous sections have outlined the intent of the model and the type of decision that needs to be made. The next parts will discuss how this translates into the model. Each section outlines a part of the model and how it does what the previous sections have outlined.

5.2.1 ASSIGNING SURGERY DURATION AND LENGTH OF STAY

The initial step of the model involves assigning patients and their respective characteristics to each surgery slot. Every day, the model reviews the scheduled surgeries for each OT and uses the chosen distributions for each surgery type, as explained in section 4.3, to determine the surgery duration and length of stay. This assignment process includes setting a start time for each surgery; the subsequent expected arrival time for the patient is 60 minutes in advance. For the first surgery of the day, the start time is set to the opening of the OT at 8:00 in the morning. For surgeries later in the day, this depends on the previous scheduled surgeries.

Additionally, the model calculates when the OT will be available again by determining the expected ending time. It adds the average surgery duration for that specific surgery group and the necessary cleaning time. The cleaning time is 15 minutes for surgeries within the same speciality and 30 minutes for surgeries from different specialities. This estimation can then be used to determine the scheduled start time for the next surgery. The patient's arrival time is set to 60 minutes before the expected start time of their surgery. This ensures that if the surgery takes less time than expected, the next patient will already be in the hospital, and the surgery can start earlier. However, if a surgery exceeds the expected duration, the next patient will have to wait longer than the predetermined 60 minutes, and a bed will be occupied for longer.

All this information is utilised to initialise the generation of patients accurately. At the start of each day, patients are generated and assigned to wait until their actual start time arrives before proceeding with further actions. This detailed scheduling and assignment process ensures that each entity has all the necessary information to model the patient flow accurately. This process aligns with the expected setup for the model and, considering several assumptions is correct compared to realistic procedures.

To verify that all of this is done correctly, the schedule information of the generation of the first two days for the MRI, first OT and second OT is shown in Table 20. The table shows the line of information that the entity is given. Additionally it can be seen that the generation and starting time is done correctly. During the second day, the MRI has multiple elements in the schedule, as can be seen in schedule A in Appendix B. The duration of the first scheduled MRI surgery is at minute 480 (which represents 8:00 when the OT opens), and the average time in an MRI is 51 minutes, so the next surgery is planned 51 minutes later, plus a cleaning time of 15 minutes. As can be seen, the next start time is at 546, which is 66 minutes later. So, this is correctly assigned.

TABLE 20: EXAMPLE OF PATIENT INFORMATION GENERATION

Day	OT	Category	Group	Surgery duration	Length of stay	Start time	arrival time	Average Length of stay	Average duration surgery
1	MRI	-	-	-	-	-	-	-	-
1	1	GYN	2	79	88	480	420	3190	81
1	2	LOS	1	272	59	480	420	346	63
2	MRI	RON	1	58	33	480	420	269	51
2	MRI	RON	1	57	56	546	486	269	51
2	MRI	RON	1	39	38	612	552	269	51
2	MRI	RON	1	44	46	678	618	269	51
2	MRI	RON	1	53	49	744	684	269	51
2	MRI	RON	1	80	36	810	750	269	51
2	1	GYN	2	63	60	480	420	3190	81
2	2	KNO	1	113	29	480	420	289	36
2	2	KNO	2	50	37	531	471	720	67
2	2	KNO	1	425	22	613	553	289	36
2	2	KNO	3	92	107	664	604	448	127

5.2.2 PATIENT FLOW

The second part of the model is the patient's flow after being generated. As mentioned in the previous section, the first thing the patient does is wait until the process can start, until the arrival time is initiated, using the ‘hold’ function built into Salabim. When that hold has passed, and the model is at the current time, the patient starts by requesting a bed. However, which ward the patient is assigned depends on the surgery speciality and availability. Figure 21 Shows an example of different specialities requesting a bed and the KCN unit. Every time a bed is assigned, the availability is lowered by one. However, for the last one, the availability is zero, so the KCZ unit is assigned. This is an example of the application explained in the flow of Figure 12.

```
The KCZ availabilty is 9, while the KCN availablity is 2
The KCN was chosen for category KNO
The KCZ availabilty is 8, while the KCN availablity is 1
The KCN was chosen for category PLCO
The KCZ availabilty is 9, while the KCN availablity is 0
The KCZ was chosen for category KNO
```

FIGURE 21: WARD SELECTION FOR CATEGORIES BELONGING TO KCZ

However, if neither ward is available, the patient waits for the ward that becomes available first, this wait is limited by the maximum waiting time, which is determined by calculating the time until the OT closes and the average time of the surgery plus cleaning time. This means that if it is already, on average, expected that the surgery will take too long, the surgery won't start, and it is cancelled and reported due to ward unavailability.

```
Time now: 865.0
Arrival time: 680
Start time surgery: 740
Average surgery: 50
Maximum waiting time: 185.0
Ward: ['MCKG', 'KTC']
```

FIGURE 22: EXAMPLE WARD UNAVAILABILITY

Figure 22 shows an example of a surgery that was cancelled due to the unavailability of the ward. It can be seen that the patient was assigned to ward MCKG; however, they could use KTC if that one became available earlier. The patient arrived 60 minutes before the start time of the surgery. So the maximum allowed waiting was the time until closing which is at 15:30 (930 minutes) minus the average duration of that surgery and the cleaning time of 15 minutes. It is also possible that the patient is assigned a bed on time but did have to wait for the bed to become available; this is shown in Figure 23. When a patient has to wait for a ward to become available, it is always assigned a backup ward, as can be seen in the figure. The patient's maximum waiting time would have been 134 minutes, a bed seemed to have become available in 55 minutes so the patient could continue.

```
The patient has been assigned a bed on ['KCN', 'KCZ']
The time now is 803.0
The patient arrived at 748
Patient maximum waiting time would have been 134.0
The patient has been assigned a bed on ['MCKG', 'KTC']
The time now is 836.0
The patient arrived at 615
Patient maximum waiting time would have been 265.0
```

FIGURE 23: EXAMPLE OF A PATIENT THAT HAD TO WAIT, BUT THE BED DID BECOME AVAILABLE IN TIME

If a patient requires to go to an ICK after surgery, this is already determined ahead of time, and one of these beds needs to be available after the surgery finishes. Figure 24 shows an example of a surgery being cancelled because there is assumed to be no space on the ICK after the surgery is finished. So, the patient has to go to the ICK, which has no venting option. However, the next bed will only be available in 3 hours and 48 minutes. Even though the patient still has to wait 60 minutes until it surgery starts and the surgery will take 71 minutes, there still will be no bed for this patient after surgery, so the patient is sent home.

```
The time now is 530.0
Start time surgery: 590
Average surgery duration: 71
Ward: ICK1_4
Times next bed becomes available in: 228.0
```

FIGURE 24: EXAMPLE ICK BED UNAVAILABLE

Assuming the patient gest assigned a ward before the maximum allowed waiting time has passed, and if necessary, an ICK is available for the patient after surgery, the patient enters the next queue for the OT. Again, here, a maximum waiting time is used based on the same criteria as the closing time of the OT. If the OT does not become available before the maximum waiting has passed, the patient is sent home. In the context of the model, the patient's flow is done and is documented under surgery cancelled due to OT unavailability. One of the model outputs is a data frame that includes all the surgeries that have been cancelled due to the unavailability of an operating theatre. Table 21 shows a snippet of this table for a certain run. Here, it can be seen for several surgeries that the patient has a planned start time and arrives 60 minutes before that time. The maximum waiting time is then determined by calculating the time until the OT closes and subtracting the average and, with that expected, surgery duration. The patient waits for the OT to become available, but none do, so the patient leaves after the time has passed.

TABLE 21: EXAMPLE OUTPUT SURGERIES CANCELLED DUE TO OT UNAVAILABILITY

category	group	OT	Planned start time	Arrival time patient	Average duration surgery	Maximum waiting time	Time patient left
KNO	3	2	669	609	127	194	803
ORTO	4	10	480	420	221	230	709
PLCO	3	6	605	545	161	19	769
KAA	3	6	654	594	159	18	771
URO	5	5	687	627	178	125	752

However, it is also possible that a patient does have to wait, but there is no need to cancel the surgery because the OT becomes available in time. Figure 25 shows an example of a patient whose surgery should have started at 10:05; however, the OT was unavailable then, so the surgery started with a 5-minute delay. The patient could have waited for 3 hours and 29 minutes; however, this was unnecessary.

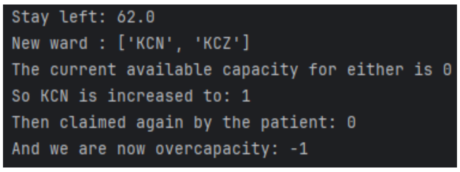
```
The patient has been assigned a OT 6
The time now is 610.0
The surgery should have started at 605
Patient maximum waiting time would have been 209.0
```

FIGURE 25: AN EXAMPLE OF A DELAYED PATIENT WHOSE SURGERY WAS NOT CANCELLED

If the OT does become available in time, the resource is claimed, and the surgery is started. Except for the OTs where surgery of a different speciality was performed before, in this case, the OT is held for an extra 15 minutes of cleaning time before the surgery can start; the start time is then reported as the time after those 15 minutes. Starting the surgery means the patient ‘holds’ for the surgery duration pulled from the distribution.

After the surgery duration has passed, the entity waits an additional 15 minutes for cleaning before the resource of OT is released. If the surgery is finished after the OT's closing time, including cleaning time, the surgery is reported as a surgery that went into overtime.

After surgery, it is possible that a patient assigned to the daycare unit has to be moved to the MCU because the daycare unit is closing. The model uses a 60-minute boundary; if the patient has more than 60 minutes to go, the patient is moved to the MCU. Based on the characteristics of the surgery, the patient is transferred. However, if no space is available on any fitting wards, the ward is forced to exceed capacitation. This means the capacity is temporarily increased and, after that, decreased immediately only to allow the patient to claim a bed. The model then notes this as an occurrence of exceeding capacity. The patient remains on this ward until the time is finished. Figure 26 shows an example of a ward being forced to exceed capacity. The patient has over an hour left while the daycare is closing. However, the KCN and the backup ward both do not have the capacity. However, the package used can’t force a resource use above its capacity, so KCN is increased so the resource can be claimed but is again lowered to achieve the exceeding of the capacity.



```
Stay left: 62.0
New ward : ['KCN', 'KCZ']
The current available capacity for either is 0
So KCN is increased to: 1
Then claimed again by the patient: 0
And we are now overcapacity: -1
```

FIGURE 26: PATIENT HAS TO BE MOVED, BUT THERE IS NO AVAILABILITY ONWARD

Similarly, this is done for the patients who must be moved to ICK after surgery. It is checked before surgery if the assigned ICK is available; however, due to unforeseen delays, it is possible that the ICK is unavailable. The ICK is also forced to exceed its capacity since the patient has already had the surgery.

The patient is counted as a successfully finished surgery if nothing goes wrong. This detailed tracking and management ensure the model can accurately simulate the hospital's operations and provide insights into improving efficiency and patient care quality. These stages are critical for validating that the model performs as expected, accurately representing the scheduling, patient generation, and patient flow processes within a hospital environment. Based on the information and examples shown in this section, it can be seen that the model achieves the flow that was set out during the formulation.

5.3 MODEL VALIDATION

The following section discusses several validation tests performed in order to validate the model. First, cross-validation was conducted to test the model behaviour when run with the training compared to the behaviour when the raw testing data was used to validate the model's input. This was followed by a sensitivity analysis where a range of variables are changed to extreme values to see if the model behaves as expected.

5.3.1 CROSS-VALIDATION

Cross-validation is the first type of validation performed on the model, a validation of the defined input distribution. In Chapter 4, different distributions were determined for the dataset. Before that, the dataset was split into training data and testing data. Cross-validation is about comparing the model's output using the defined distribution against the model's outcomes when using the testing data (Yates et al., 2023). This means the input for the model will be real data, combinations of the real surgery duration and following the ward time of the patient.

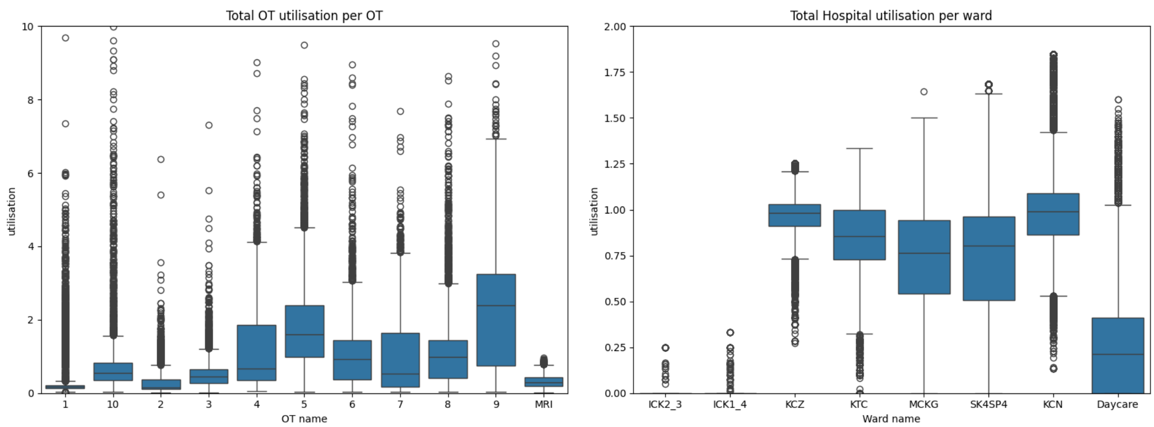


FIGURE 27: AVERAGE OT(LEFT) AND WARD (RIGHT) UTILISATION DISTRIBUTION DATA

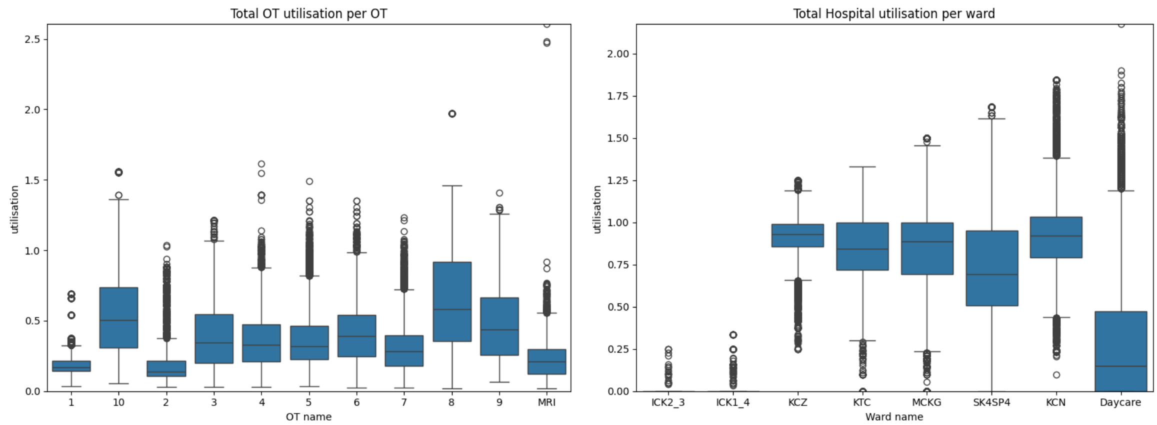


FIGURE 28: AVERAGE OT AND WARD UTILISATION REAL-DATA

TABLE 22: SUMMARY MODEL OUTPUT COMPARISON OF REAL AND DISTRIBUTED DATA

	Mean distributed data	*Standard deviation distributed data*	*Mean real data*	*Standard deviation real data*
Successful Surgeries	13537	294,02	15538	350,29
Cancelled Surgeries (OT Unavailability)	2016	86,86	36	7,23
Cancelled Surgeries (Ward Unavailability)	15865	375,92	15845	350,24
Overtime Occurrences	2164	48,71	648	17,78
Total number of surgeries	31434	0,00	31434	0,00
Times a ward had to exceed capacity	870	24,52	2148	21,42
Average OT utilisation	0,93	0,0082	0,35	0,0033
Average ward utilisation	0,66	0,0053	0,65	0,0057

Table 22 presents an overview of all summarised variables from the model. The comparison reveals critical discrepancies between the results obtained using the distributed data and those from the testing data. Firstly Table 22 shows that the number of overtime occurrences and cancelled surgeries are considerably higher when using the distribution data, while the number of successful surgeries is considerably lower. Interestingly, the times the ward had to exceed its capacity were lower when using the distributed data.

Additionally, the plots in Figure 27 and Figure 28 illustrate that for the real data, the utilisation rates of the OTs seem to lower so much that the scale of the graph had to be changed. Table 22 shows that while using the distributed data, the OT utilisation is over two times as high. This overall trend suggests that the real data contains shorter surgery durations compared to those produced by the fitted distributions. A lower value for this parameter would decrease OT utilisation. It would also cause fewer surgeries to be cancelled due to OT unavailability. Using less extreme values for these parameters would also reduce the overtime occurrences. Interestingly, is the increase in the number of times a ward had to exceed its capacity, the wards are forced into exceeding capacity more when the surgery duration is shorter. However, this can be caused by an overall increase in the number of surgeries performed.

For the length of stay variable, it seems that they are quite similar. The ward utilisation is almost the same and the number of surgeries cancelled due to ward unavailability is as well. Both runs would suggest no full utilisation of the wards but do have a high cancellation rate due to ward unavailability. However, when considering the utilisation per ward, it can be seen that the average is brought down by the ICKs and the Daycare unit who experience relatively low utilisation.

So, there seems to be an overestimation in the parameters for the distributions for surgery duration, showing more extremes than the underlying data does. Upon re-examining the differences between the plots of the tested and training data (comparing Figure 5 and Figure 6), it could be said that more extreme data points are included in the training data compared to the testing data for surgery duration. This could result in longer surgery durations in the distributed data. For the purpose of this model this does not necessarily propose a problem since the objective is to compare different schedules all using the same inputs. However, it is worth noting that the surgery durations might be slightly overestimated.

5.3.2 Validation Through Sensitivity Analysis

The following section shares the results of a validation through sensitivity analysis. The goal is to drastically change the input variables and asses the model's response. Each section first explains which variable will be changed and the hypothesised behaviour. Subsequently, the relevant outputs are displayed and determined whether the observed changes align with the expectations.

5.3.2.1 Sensitivity Analysis Capacity

During the sensitivity analysis for the ward capacity, the capacity for each of the wards is adjusted to 10%, 50%, 200% and 1000% of the original capacity. This adjustment involves multiplying the original capacity by the chosen factor and rounding the result to an integer. Lowering the capacity to 10% would cause some capacities to be reduced to zero.

It is to be expected that when the ward capacity decreases, the number of surgeries cancelled due to the lack of capacity will increase. Additionally, the utilisation of each ward is expected to increase, potentially reaching or exceeding full capacity, as ICKs or MCUs might be pushed towards exceeding their capacity. The number of surgeries cancelled due to OT unavailability will decrease as fewer surgeries will progress to the stage of waiting for OT due to prior patient discharge caused by bed unavailability. Both are directly related to a decrease in the expected overtime.

On the other hand, when the capacity is increased significantly, fewer surgeries are cancelled due to capacity constraints, and the utilisation would decrease. However, this will increase the number of surgeries cancelled due to OT unavailability since more surgeries will secure a bed and request the OT to be available.

Table 23: Summary table sensitivity analysis ward capacity

Capacity	*Successful Surgeries*	*Cancelled Surgeries (OT Unavailability)*	*Cancelled Surgeries (Ward Unavailability)*	*Overtime Occurrences*	*Total number of surgeries*	*Times a ward had to exceed capacity*	*OT utilisation*	*Ward utilisation*
10%	1241	0	30192	269	31434	0	0,92	2,34
50%	7664	634	23128	1338	31434	931	0,82	0,77
100%	13537	2016	15865	2164	31434	870	0,93	0,66
200%	23461	6560	1388	3657	31434	237	1,18	0,49
1000%	24195	7213	0	3683	31434	0	1,19	0,10

Table 23 shows that at 10% capacity, all cancelled surgeries were due to ward unavailability. This extreme limitation also led to a minimal number of successful surgeries and a low number of overtime occurrences. However, the latter is most likely caused by the increased number of cancelled surgeries. The behaviour for the run for 50% of the capacity is similar; slightly fewer surgeries are cancelled due to ward unavailability, leading to a few surgeries being cancelled due to OT unavailability and increasing overtime occurrence.

Doubling the capacity to 200% further improved the number of successful surgeries and drastically reduced the cancellations due to ward unavailability. The increase in the number of successful surgeries, when increasing to 1000%, is even higher. No surgeries are cancelled due to ward unavailability. However, with fewer patients being sent home due to the lack of bed availability, more are sent home due to OT unavailability. However, interestingly, the increase in cancellations due to OT unavailability is not as large as the decrease in cancellations due to ward unavailability, which might suggest ward capacity be a bigger bottleneck than surgery duration.

Table 23 also confirms that with the increase in capacity, a decrease in utilisation of the ward can also be noted. Additionally, 50% capacity shows lower OT utilisation, and with the increase in capacity, this utilisation seems to grow along. With over utilisation rates being reached at a 100% capacity.

The interesting behaviour is the increase in the number of times a ward is exceeding its capacity when going from 10% to 50%. While the capacity increases, so does this number, while we would expect more beds to be available, having less need to exceed capacity. However, this is most likely caused due to more surgeries being performed, increasing the number of occurrences that patients have to be moved after surgery. Since the capacity is already low and probably near full utilisation, the patients who must be moved will almost always cause a ward to exceed its capacity.

The sensitivity analysis reveals that increasing ward capacity significantly reduces cancellations due to ward unavailability and increases the number of successful surgeries. However, it also leads to a rise in cancellations due to OT unavailability and increases overtime occurrences. Balancing ward capacity with OT availability is crucial for optimising overall hospital performance and minimising cancellations and overtime.

5.3.2.2 SENSITIVITY ANALYSIS LENGTH OF STAY

For the sensitivity analysis of the variable length of stay, the total time a patient spends in the hospital surrounding the surgery is adjusted. First, the length of stay is lowered to 10% and 50% of the time drawn from the distribution; second, this time is increased to 200% and 1000% of the time drawn from the distribution. When lowering to 10% and 50%, the patient's surgery duration might be longer than the length of stay. However, then the patient would be released straight away after surgery.

When lowering the length of stay, there is an increased turnover of the number of beds, decreasing the utilisation rate of the wards as patients will occupy the bed for shorter durations. This likely reduced the number of surgeries cancelled due to the lack of bed availability. However, similarly to the increased availability, the number of patients requesting an OT will increase, increasing the number of surgeries cancelled due to OT unavailability and OT utilisation.

Conversely, when the length of stay is greatly increased, fewer surgeries can be performed since an increased number of patients will already have been sent home due to a lack of bed availability. Ward utilisation rates will rise, potentially reaching or exceeding capacity limits. Additionally, similarly to the increase of capacity, fewer patients will reach the stage of waiting for the OT due to the extended occupancy of a smaller number of patients, reducing OT utilisation and a number of surgeries cancelled due to OT unavailability.

TABLE 24: SUMMARY TABLE SENSITIVITY ANALYSIS LENGTH OF STAY

Capacity	*Successful Surgeries*	*Cancelled Surgeries (OT Unavailability)*	*Cancelled Surgeries (Ward Unavailability)*	*Overtime Occurrences*	*Total number of surgeries*	*Times a ward had to exceed capacity*	*OT utilisation*	*Ward utilisation*
10%	24147	7207	80	3675	31434	0	1,19	0,18
50%	19667	4171	7588	3252	31434	569	1,10	0,50
100%	13537	2016	15865	2164	31434	870	0,93	0,66
200%	9168	1080	21167	1535	31434	482	0,85	0,77
1000%	4484	557	26362	968	31434	15	0,93	0,93

Table 24 shows that reducing the length of stay to 10% resulted in a significant increase in successful surgeries and a relatively low number of cancellations due to ward unavailability. However, combined at the same time with a substantial number of cancellations due to OT unavailability and increased occurrences of overtime. When increasing to 50%, these went down again, but with an incomparable increase in surgeries cancelled due to ward unavailability.

Doubling the length of stay to 200% resulted in an expected further decrease in successful surgeries, which was even worse at 1000%. More surgeries are cancelled due to ward availability and fewer due to OT; since more surgeries are already cancelled, there are fewer overtime occurrences. Interestingly, the need for exceeding capacity decreases as well. This is explained by the occurrence of over-occupation, which only happens when a patient needs to be moved after surgery; since more surgeries are cancelled, this happens less frequently. As the length of stay increased, the OT utilisation decreased as the ward utilisation increased. Overall, the model behaves as expected when decreasing and increasing the length of stay.

5.3.2.3 SENSITIVITY ANALYSIS SURGERY DURATIONS

During the sensitivity analysis for the variable surgery duration, the time drawn from the distribution is first lowered to 10% and 50% and later increased to 200% and 1000%. However, the averages and the values the distributions are based on are unchanged; this would entail that the expected surgery duration remains the same.

When the surgery duration is lowered, there will be an increased turnover of the number of surgeries, and the utilisation of the OTs will be reduced along with the overtime. Additionally, the OT will become available faster since surgeries take up less time and fewer surgeries will be cancelled due to OT unavailability. However, based on the previous analysis, the biggest reason for cancelling surgeries was the availability of wards, so the increase in the number of successful surgeries will most likely be limited.

Increasing the surgery duration would mean surgeries take longer than expected, more surgeries will be cancelled due to delays caused earlier in the day, and surgeries that are performed will cause increased overtime. The increased surgery durations and overtime will also have an increasing effect on OT utilisation. Ward utilisation will decrease slightly since fewer patients will be operated on, so they will not require a bed after surgery. However, during the waiting time before surgeries, patients will also occupy a bed and only be sent home when it is no longer expected that the surgeries can finish in time, which means it is still possible they take up a bed for the larger part of the day, increasing the ward utilisation.

TABLE 25: SUMMARY TABLE SENSITIVITY ANALYSIS SURGERY DURATION

Capacity	*Successful Surgeries*	*Cancelled Surgeries (OT Unavailability)*	*Cancelled Surgeries (Ward Unavailability)*	*Overtime Occurrences*	*Total number of surgeries*	*Times a ward had to exceed capacity*	*OT utilisation*	*Ward utilisation*
10%	14413	7	16998	35	31434	1781	0,11	0,68
50%	14005	1146	16267	1803	31434	1412	0,49	0,67
100%	13537	2016	15865	2164	31434	870	0,93	0,66
200%	12495	3550	15374	2832	31434	382	1,74	0,65
1000%	7213	13067	11138	3844	31434	4	6,33	0,61

Table 25 shows that reducing the surgery duration to 50% slightly increases the number of successful surgeries, with another slight increase when reducing to 10%. It is caused by the decrease in the total number of surgeries cancelled due to OT unavailability. However, the lack of ward availability seems to be the biggest bottleneck. Table 25 shows a decreasing OT utilisation for the decreasing surgery duration.

Doubling the surgery duration to 200% resulted in a decrease in successful surgeries and an increase in cancellations due to OT unavailability. Cancellations from ward unavailability slightly decreased. When the surgery duration was increased to 1000%, the number of successful surgeries decreased fast, along with fewer surgeries cancelled due to ward unavailability. Most likely because more surgeries are being cancelled due to OT unavailability, the patients are not staying after the surgery. However, the average ward utilisation remains the same. Table 25 shows extreme OT utilisation when the surgery durations increase along with spikes in overtime.

So overall, the system is more vulnerable to an increase in surgery duration than a decrease. Increased surgery durations can cause additional bottlenecks, causing extra KPIs to worsen. So, the model's tendency to overestimate surgery duration, according to section 0, does not cause significant problems since a decrease would not significantly change the system. Overall the model does behave as expected with the changes in surgery duration.

5.3.2.4 SENSITIVITY ANALYSIS ICK ASSIGNMENT

The percentage of patients required to go to ICK was determined in collaboration with the hospital as an estimation per surgery group for how many of the surgeries it would be likely that a request would be made for the patient to be moved to ICK afterwards. In total, this averaged about 7% of all surgeries. An example in literature estimated this number to be a lot smaller (Patel et al., 2018), so another variable to be checked in the sensitivity analysis to see the system impact and to consider is the percentage of patients sent to the ICK. However, the probability is defined per surgery group, so it cannot be higher than 100%, and when multiplying this factor, surgeries with zero probability will remain zero. This means the factor of multiplying is not the same as the output.

Since the ICKs are not causing any surgeries to be cancelled in the base run, it is assumed that the system will not be very vulnerable to a decrease in the percentage of patients sent to the ICK. A slight increase in the number of surgeries cancelled due to ward unavailability is expected due to more patients staying on the already full MCUs. The impact on the other KPIs is expected to be relatively minor.

When the percentage of patients sent to the ICK increases, the number of ward occupations in the ICKs is also expected to increase. Some surgeries might be cancelled due to, in advance, already known unavailability of the ICK. However, this will also cause a decrease in the number of surgeries cancelled due to ward unavailability since the capacity for the ICK will be used more. It is not likely that there will be a significant impact on the OT utilisation or overtime since patients are only moved to the ICK after surgery, and patients cancelled due to ICK unavailability will still be filled up by patients that would have otherwise been sent home due to lack in MCU availably.

TABLE 26: SUMMARY TABLE SENSITIVITY ANALYSIS ICK

Capacity	*Successful Surgeries*	*Cancelled Surgeries (OT Unavailability)*	*Cancelled Surgeries (Ward Unavailability)*	*Overtime Occurrences*	*Total number of surgeries*	*Times a ward had to exceed capacity*	*OT utilisation*	*Ward utilisation*
0,1	0,66%	13502	2006	15910	2155	31434	870	0,93
0,5	3,29%	13492	2002	15923	2152	31434	871	0,93
1	6,58%	13537	2016	15865	2164	31434	870	0,93
2	11,32%	13495	2003	15920	2155	31434	871	0,93
10	21,02%	13489	2002	15927	2153	31434	874	0,93

Table 26 presents the results of the sensitivity analysis for the ICK probability. As expected, no changes are found in the average utilisation. Additionally, no fundamental changes are seen in any of the other runs as the percentage of patients being sent to the ICK increases. This indicates that the capacity of the ICK might be overestimated since, in reality, it is known to cause surgery cancellation.

5.4 CONCLUSION MODEL SETUP

Based on the validation and verification of this chapter, the model performs as intended and behaves as expected, deeming it valid for its purpose. Despite some vulnerabilities identified in this chapter, the simulation model is capable of evaluating and comparing various input schedules. However, when considering the results in the experimental phase, it is essential to acknowledge several findings from this chapter. These include an overestimation in surgery duration when using the distributions compared to the empirical data. This means that surgeries often take longer in the model than in real life, which could cause an increase in overtime or surgeries being cancelled due to OT availability. However, the latter is not seen as a significant factor since the biggest bottleneck in the system, the number of surgeries cancelled due to ward unavailability, seems to cause the number of surgeries cancelled due to OT unavailable to remain low.

The estimation for the length of stay when using the distributions seemed similar to the real data, which is interesting since fewer groupings appeared to find a fitting distribution, as discussed in section 4.3.

The model behaviour of sensitivity analysis would suggest that ward capacity is a more significant bottleneck than the capacity of the OT. However, in this conclusion, it should be considered that the schedule used in this chapter prioritises OT utilisation and does not consider the levelling of the wards. Additionally, the increased vulnerability to ward capacity implies that the incorrect estimation of the length of stay is more problematic than the overestimation of surgery duration, according to the validation results. Lastly, the model seems not to be influenced by changes in probability for the ICK, suggesting there might be a slight overestimation in the capacity.

An exploration of the model concerning the allowed overtime was also conducted. Various analyses revealed that overtime did not surpass the acceptable limit when the other restrictions were enforced. Although instances of excessively long overtime occurred the frequency of overtime is low. Even with the cutoff adjustment to 16:15, the 25% threshold for overtime occurrences was not exceeded. Consequently, the general guideline for determining whether to proceed with surgery was adjusted to a closing time of 16:15 instead of 15:30. However, any surgery extending beyond 15:30 is still considered overtime.

6 EXPERIMENTATION AND SCENARIOS

The goal of this chapter is to explore the different schedules as explained in 0. This outlined four different schedules that already consider the model's ward capacity and processing capabilities, the models are named A, B, C and D. The first two schedules, A and B, give equal priority to improving OT utilisation and ward levelling. In contrast, schedules C and D give higher priority to the levelling of the wards. The second characteristic is the processing ability of the model. In A and C, the availability of the wards is checked every hour, and in B and D, every 15 minutes. The experiment will aim to explore these different schedules under different scenarios. Running the simulation for each schedule and for each of the scenarios. As defined in 5.1 the model runs for six years, each time running seven times. So, when considering the summary table, these are the number of surgeries over six years. The overtime is considered to be acceptable for two days a week for a maximum of 45 minutes, which would mean overtime is acceptable for 624 days across the 11 OTs.

The first step in this chapter is to show the model results under regular circumstances in the base run. The base run means the run without changing anything else in the system. All variables are set the way they are explained in Chapter 4. After this, the schedules will be tested under two different types of uncertainty: the capacity of the wards and the Length of Stay. Which will be further elaborated on in the following section.

Section 4.5 explained how all the model output was set up; this similar way of output setup is used in this chapter. However, since for each type of scenario, the model is run for each schedule, a summarised overview is presented here; the other results can be viewed in Appendix F.

The values are put into percentages for the scenario output to enable a quicker comparison. The number of surgeries cancelled and successful are set to percentages of the total number of attempted surgeries. The number of overtime occurrences is a percentage of the total number of surgery days in the system.

6.1 BASE RUN

This section discusses the base run for the entire system. Meaning all models are run with the settings discussed in the previous chapters across seven repeats for six years. This section discusses the results, the full detailed output including the full summary table, the OT utilisation across the 28-day cycle, the ward utilisation across the 28-day cycle and the overtime visualised per OT can be found in Appendix F.

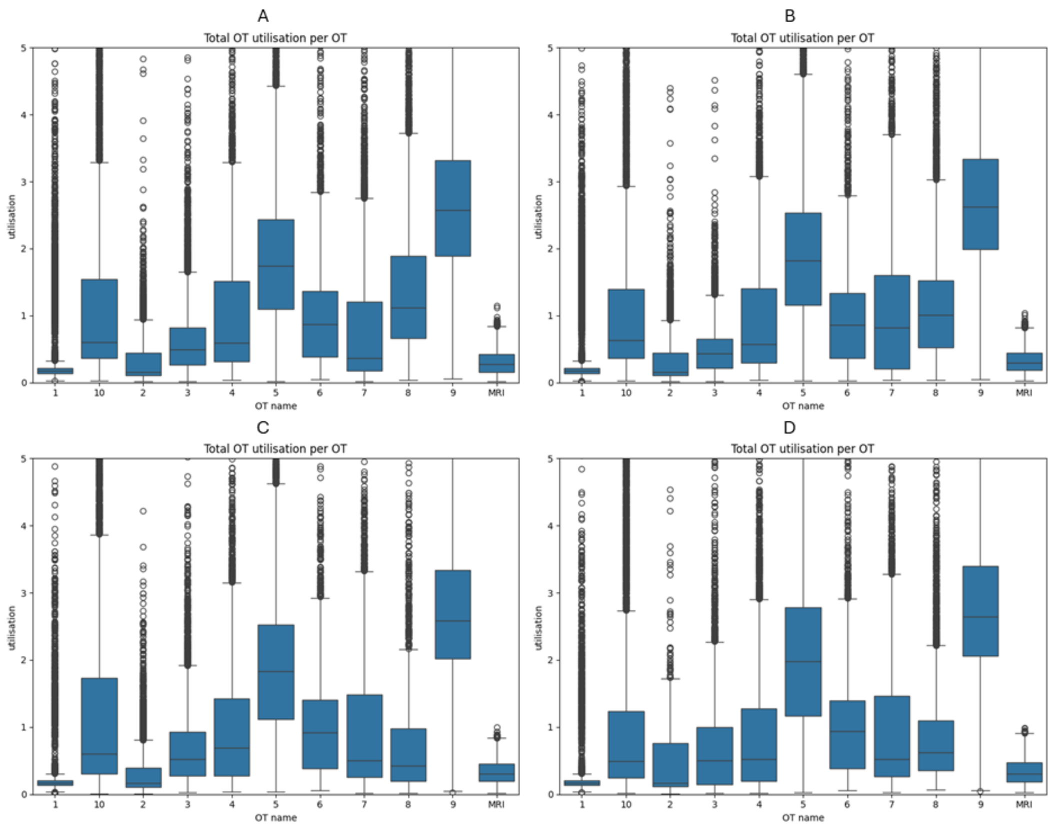


FIGURE 29: OT UTILISATION BASE RUN

First Figure 29 show the OT utilisation for the base run, comparing the four different types of schedules. Here it can be seen that some OTs experience much higher utilisation rates than others. For OT 9, all schedules increase to over 200%, while OT 1 and MRI come closer to 0. However, there seems to be little to no difference between schedules A and B, who equally prioritise the levelling of the wards and increase the OT utilisation, and C and D, who prioritise the levelling of the wards.

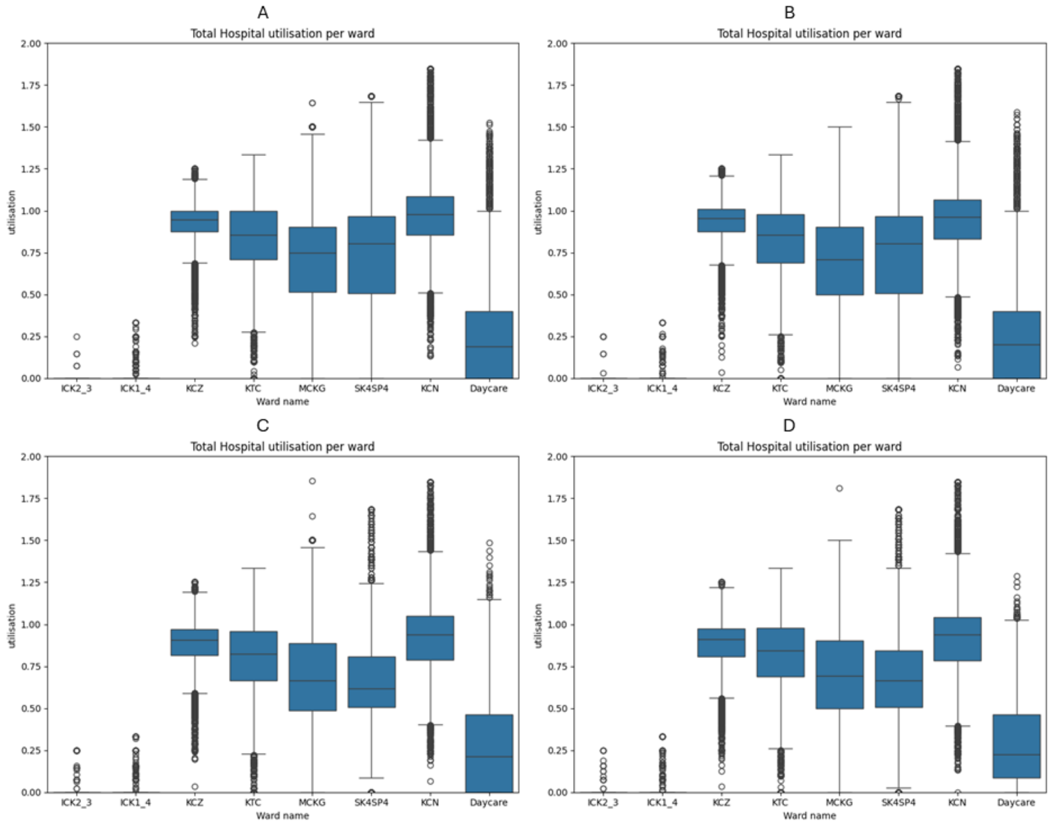


FIGURE 30: WARD UTILISATION BASE RUN

However according to Figure 30 the ward utilisation is stable throughout all the models and does not exceed 1. Slight differences can be found for the schedules that prioritise ward levelling, models C and D, as they experience slightly lower utilisation, except for the daycare unit, which experiences an increased utilisation throughout some of the runs.

In Table 27 the number cancelled due to ward unavailability is significantly lower in the schedules that level ward occupancy, C and D. As this number lowers, the number of surgeries cancelled due to OT availability and overtime occurrences increases. However, the number of scheduled surgeries has also dropped. Because there is a difference between the number of scheduled surgeries across the different models, the results will be compared using percentages. For Successful surgeries and cancelled surgeries, this will be a share of the total number of planned surgeries. For overtime occurrences, this will be a percentage of the total number of surgery days. In the case of this model defined simulation time, this is 20 surgery days per schedule repeated across six years for 11 OTs, resulting in a share out of 17 160. Good to note is that none of the schedules even come close to the acceptable limits for overtime.

Another interesting fact when comparing the schedules is that the models prioritising bed levelling, C and D, have a higher share of successful surgeries. However, they do not have a higher OT utilisation. If more surgeries are being performed, but that does not cause an increase in average OT utilisation, it could mean that shorter surgeries can continue while longer surgeries are cancelled.

Also, even though over 45% of all surgeries are cancelled across all models, OTs are all fully utilised. For this result, it has to be considered that the model had a slight overestimation of surgery duration, which could lead to this extreme utilisation. However, it might also be the case that all schedules are already planning too many surgeries to begin with because the OTs and wards are already quite fully utilised.

TABLE 27: SUMMARIZATION BASE RUN

Model version	Successful Surgeries		Cancelled Surgeries; OT Unavailability		Cancelled Surgeries; ward Unavailability		Overtime Occurrences		Surgery total	Times a ward had to exceed capacity	Average OT utilisation	Average ward utilisation
A	13976	44%	2573	8%	14949	47%	2421	14%	31512	755	0,99	0,65
B	14387	46%	2489	8%	14467	46%	2481	14%	31356	770	1,01	0,64
C	15229	52%	3111	11%	10741	37%	2687	16%	29094	781	0,97	0,61
D	15693	54%	2718	9%	10748	37%	2611	15%	29172	973	1,01	0,62

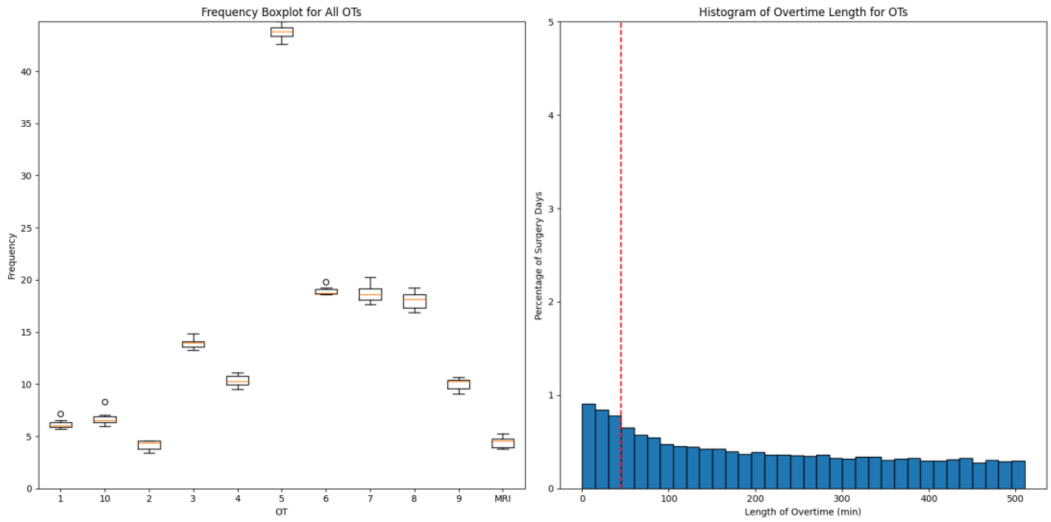


FIGURE 31: OVERTIME VISUALISATION MODEL A

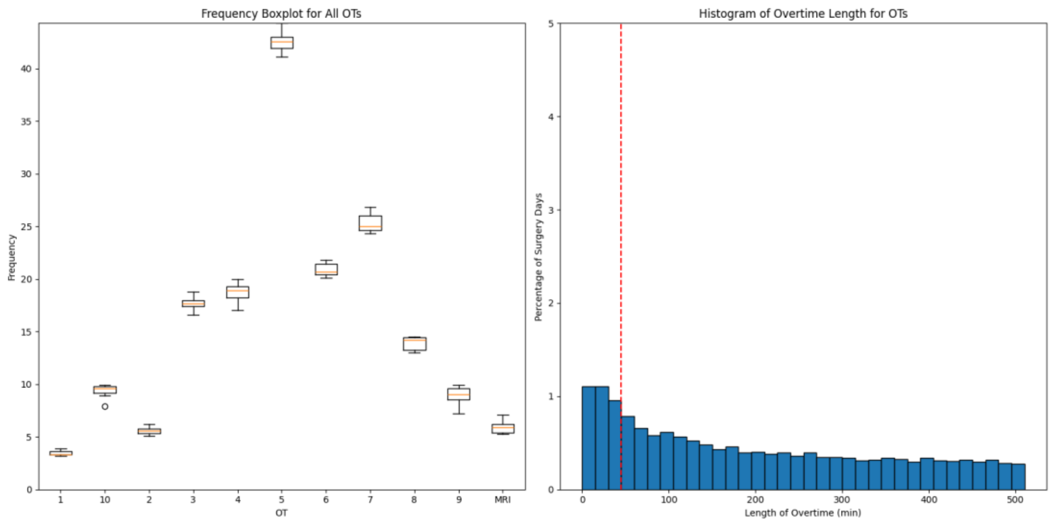


FIGURE 32: OVERTIME VISUALISATION MODEL B

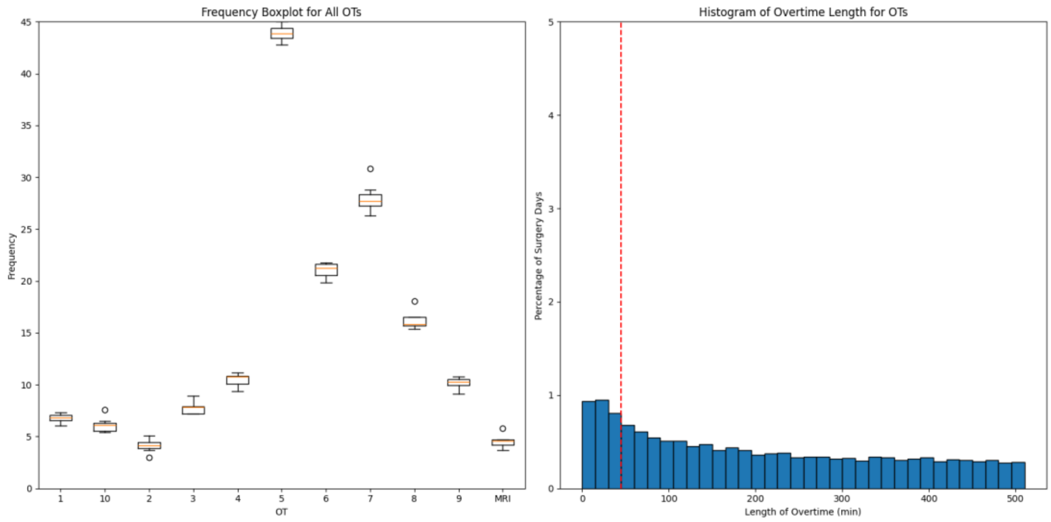


FIGURE 33: OVERTIME VISUALISATION MODEL C

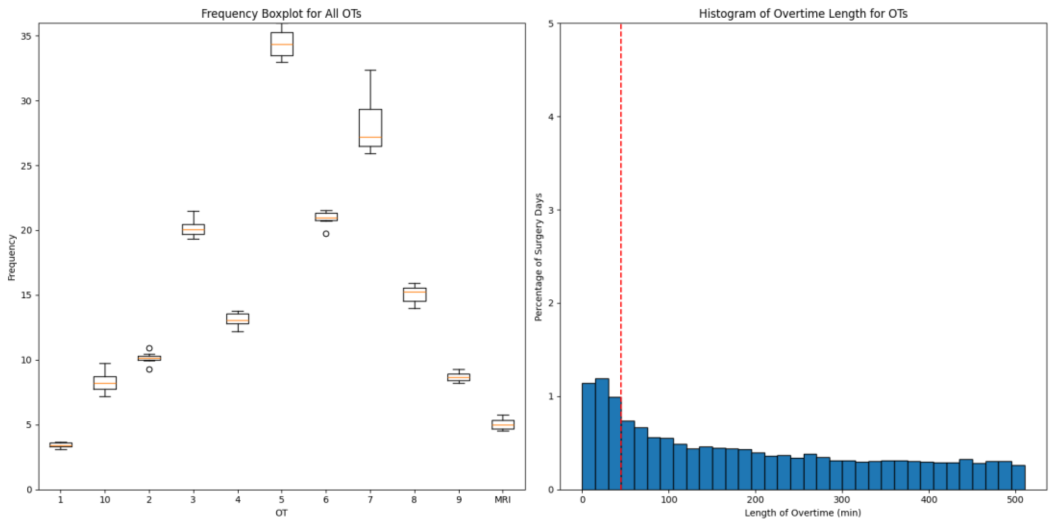


FIGURE 34: OVERTIME VISUALISATION MODEL D

Table 27 already concluded that the overtime levels were not problematic when looking at the count of occurrences for all schedules. It also showed that the overtime increased for the schedules that prioritised levelling of the wards, models C and D. Figure 31, Figure 32, Figure 33, and Figure 34 give a more detailed insight into the occurrences of overtime. The figures on the left show the percentage of days that experience overtime across a 28-day cycle (containing 20 surgery days) for each OT. It can be seen that across three of the four schedules, OT 5 and OT 7 show unacceptable levels of overtime, while in schedule A, only OT 5 shows extreme levels. In all other OTs, the overtime count is not worrying.

The figures on the right show the percentage of days that experience a certain length of overtime. Every bin represents 15 minutes of overtime. Considering this, it can be seen that even though the counts of overtime might be acceptable the length of overtime is not. The red line represents the 45-minute limit. Across all schedules, about 3% of the 20 surgery days in a cycle experience an acceptable length of overtime. However since the overtime is between 14% and 16% across the different schedules, the other 11-13% of surgery days experience unacceptable levels of overtime. However, the number of unacceptable overtime occurrences does not vary much across the different schedules. Appendix F includes an overview of the overtime across the cycle per OT.

TABLE 28: SURGERY CANCELATION DUE TO OT UNAVAILABILITY

OT	*A*	*B*	*C*	*D*
1	0,0%	0,1%	0,1%	0,1%
2	0,6%	0,9%	0,7%	6,4%
3	0,6%	2,0%	2,8%	4,2%
4	14,9%	16,3%	20,6%	16,3%
5	38,9%	38,0%	32,9%	34,5%
6	12,9%	9,7%	8,6%	9,7%
7	11,2%	12,2%	17,1%	9,3%
8	2,0%	1,5%	0,5%	1,2%
9	16,1%	18,0%	13,0%	15,1%
10	1,4%	1,2%	3,6%	3,2%
MRI	0,1%	0,1%	0,1%	0,1%

Table 28 gives an overview of which OTs are the main cause of the cancellation. For the OTs, it can be seen that especially OT 5 is causing problems. Figure 29 underlines that this is an OT with high utilisation value, so it is to be expected that this would take up a fair share of the number of cancellations. However, across all schedules, the highest utilisation can be found across OT 9, and this one is not even the main cause of the cancellations. This might suggest that this OT might especially be vulnerable to surgery duration overestimation. When also considering the schedule itself, found in Appendix B, it can be seen that OT 9 does not even have surgery scheduled every day. This OT is always used for paediatric cardiac surgery; it can be seen that especially the third surgery group of this department seems to have a high value for the scale parameter of the distribution, indicating extreme values for surgery duration in this category. This means the average is most likely an underestimation when considering whether the surgery would be cancelled, increasing the overtime occurrences. Overall, the share in cancellations does not differ a lot across the different schedules. As the OT becomes a bigger bottleneck, the share for OT 5 and 9 decreases while many others increase (not all). It is showing that the pressure for the different OTs level out.

TABLE 29: SURGERY CANCELATION DUE TO WARD UNAVAILABILITY

	A	*B*	*C*	*D*
Daycare	0%	0,0%	0,0%	0,0%
ICK 1_4	0,0%	0,0%	0,0%	0,0%
ICK 2_3	0,0%	0,0%	0,0%	0,0%
SK4 / SP4	0,4%	0,4%	0,1%	0,2%
KCN	27,3%	28,5%	26,0%	27,4%
KCZ	46,7%	46,0%	41,9%	41,2%
KTC	3,3%	3,0%	4,0%	3,0%
MCKG	22,3%	22,1%	28,0%	28,1%

Table 29 presents an overview of which wards are the leading cause of cancellation. Here, it can be seen that the Daycare unit and ICKs never cause the surgeries to be cancelled. Which is aligned with the visualisation in Figure 30 as these show low utilisation rates for these wards. SK4 / SP4 have slightly higher utilisation rates but are still not the cause of cancellation; they also, for most schedules, do not come close to 100% utilisation. The KCN and KCZ seem to cause the biggest problems. The contribution of the KCZ is also higher in the schedules not prioritizing ward levelling, models A and B. At the same time, for MCKG, it is a little higher for those that are prioritizing levelling the wards, models C and D. It would seem that when prioritising levelling the bed occupancy, the pressure is spread out a little more across the wards; however, some are still under more pressure than others.

A detailed examination of the base run highlights significant system pressures, particularly considering the high cancellation rates across various OTs and wards. This suggests that the new scheduling strategy remains insufficient, with disparities in OT utilisation. Some of the OTS are being overutilised, while others are underutilised. Additionally, while overtime frequency is acceptable, the excessive duration of these overtime occurrences across all schedules suggests room for improvement (see Appendix F for more detail on overtime).

While the schedules that prioritise the levelling of ward occupancy, C and D, at first glance, seem to execute more successful surgeries, the effectiveness is questioned due to the lack of increase in OT utilisation or changes in pressure across the different OTs, which could mean the system preferers shorter surgeries over longer ones.

When considering increased capacity, it can also be seen that some wards are more pressured by capacity constraints than others. This is improved when prioritising levelling the wards, but still, great differences can be seen across the different wards. So, overall, slight changes can be seen across the different schedules; these results would suggest it is insufficient.

In conclusion, while slight improvements are observed with different scheduling strategies, the simulation model would suggest the system is still insufficient, and the differences across the different prioritisation levels are not very prominent.

6.2 SCENARIO'S

To test the robustness of the different models and their behaviour under uncertainty, the scenario analysis will vary two variables: Length of stay and capacity of the wards. These two variables are selected because the validation showed that the system is mainly impacted by changes in these variables.

First, let's focus on the choice of the capacity of the wards. As explained in section 4.3.5, the capacity used in the model is based on historic use and availability. But the actual capacity depends on even more factors, including the availability of the resources (beds, nurses, machinery) and the inflow of patients from other specialties. For example, if a major accident happens, the number of ICK beds available for elective patients will decrease since the emergent patient inflow will increase. Or something even worse that would also not allow the patients to be able to be moved to other hospitals, a global pandemic. The lack of ICK beds was a common topic during the pandemic. However regular beds, MCU beds, were also very much limited not only by physical resources but also by the shortage of qualified workers (Federatie Medisch Specialisten & V&VN, 2021). Even though the virus did not significantly impact children, the resources dedicated to these specialities were also limited because they had to be dedicated to adult patients (NOS, 2020). The Dutch government determined that regular care had to be at least 80% of what it had been before the outbreak of the pandemic (Ministerie van VWS, 2023). Additionally, the number of non-emergent patients lowered in 2020, with respect to 2019, by about 19% (CBS, 2023). So, for the insecurity of the capacity of the wards, the model will be tested under a lowered capacity of 20%.

During the sensitivity analysis, it was found that the ward capacity was one of the more limiting factors in the number of successful surgeries. In section 4.3.5 it was explained that the ward capacity was rounded down because past data suggested that the actual number of elective patients on the wards was often lower. And in Chapter 1 it was noted that the resources, specifically healthcare employees, required up to a 10% increase in the upcoming ten years. So, for the uncertainty increase of capacity, it will be seen if schedules start performing differently when the capacity is increased by 10% and the ward capacity is rounded up instead of down. This last step is also required because otherwise, for most wards, the slight increase of 10% would not make a difference because they would be rounded back down again.

The validation found that the model was specifically vulnerable to the length of stay variable. Cross-validation revealed that while the distributions for length of stay do not differ much from the real data in the testing data, the average LOS in the testing data was consistently 10% lower than in the training data. This shows the potential for uncertainty in the model, which needs to be considered during the scenario analysis, especially since the model seems sensitive to the length of stay. Therefore, for the scenario analysis, the length of stay will be systematically increased and decreased by 10%.

6.3 RESULTS SCENARIOS

The combination of the variation in the two variables creates four different scenarios of uncertainty. Table 30 gives an overview of each of the scenarios and what their exact changes are. The following sections present the results for the schedule performance under each of these scenarios. Additional information on the model output can be found in Appendix F.

TABLE 30: SCENARIO OVERVIEW

Scenario	*Length of stay*	*Ward capacity*
1	110%	80%
2	90%	80%
3	110%	110%
4	90%	110%

6.3.1 SCENARIO 1: ENHANCED PATIENT AND STAFF SATISFACTION

The first scenario is about the lowering of the capacity and the increase in the length of stay. So simultaneously, as patients stay longer, the wards also have lower availability. This 'Enhanced patient and staff satisfaction' scenario is about balancing the extreme challenges in the healthcare system. Patients require more care, but the staff needs breathing room to stay afloat.

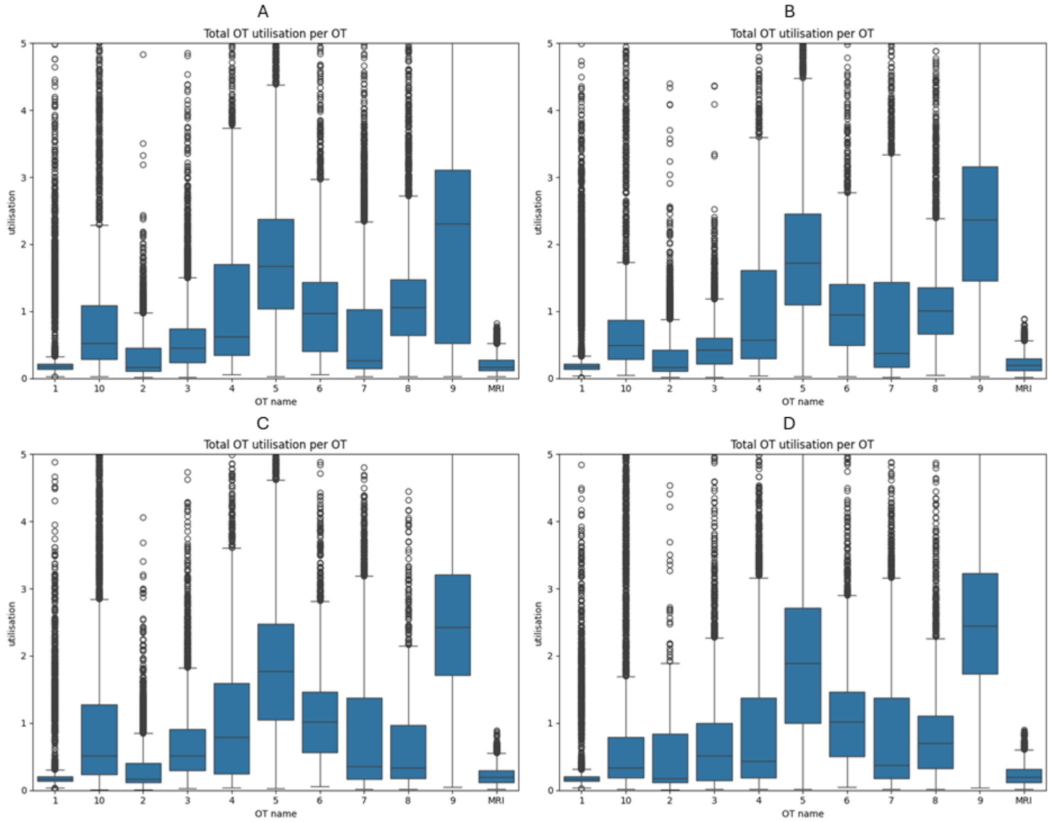


FIGURE 35: OT UTILISATION SCENARIO 1

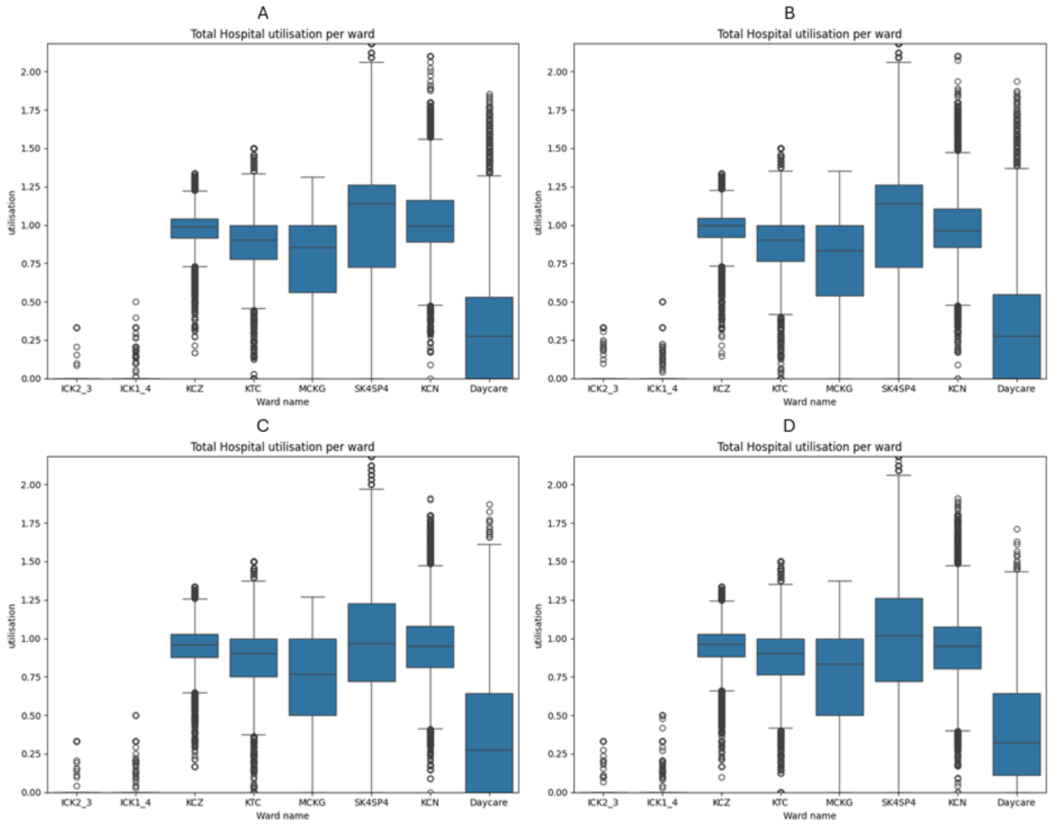


FIGURE 36: WARD UTILISATION SCENARIO 1

Figure 35 show minor changes in the OT utilisation. As in schedules A and B, a higher number of OTs experience over-utilisation compared to C and D. Overall, it can be seen that all schedules still experience big differences in utilisation across the OTs. Table 31 suggest a slightly higher utilisation for the schedules checking availability every hour (B and D) instead of every 15 minutes and again somewhat higher for those levelling bed occupancy (C and D). However, the differences in OT total utilisation are quite small. Overall, the overall utilisation has decreased, as more surgeries are cancelled due to ward unavailability caused by the constraints on the capacity.

Figure 36 illustrates that models that do not prioritise ward occupancy levelling experience, A and B, overutilisation in the SK4/SP4 ward. Similar to the base case, the daycare unit experiences slightly higher utilisation in model D. However, other wards maintain relatively stable utilisation rates. Interestingly Table 31 shows that the ward utilisation experiences an increase in the schedules not levelling for bed occupancy, models A and B. Meaning that these models are slightly less resilient to the extra pressure on the capacity. Overall the ward utilisation has increased compared to be base run caused by less capacity and an increased number of times a ward had to exceed its capacity.

Similar to the base run, the number of cancelled surgeries due to ward unavailability is lower in the schedules levelling the wards. However, in this case, cancellations due to OT unavailability see barely see any increase. Overall, the number of successful surgeries is higher when there is a focus on ward levelling. Although the values differ slightly due to longer patient stays and reduced capacity, the general behaviour remains the same. In conclusion, when comparing the schedules, none appear exceptionally vulnerable to the uncertainties of this scenario as the behaviour stays the same. However the values do worsen caused by the extra pressure on the system.

TABLE 31: SUMMARY TABLE SCENARIO 1

Model version	*Successful Surgeries*	*Cancelled Surgeries (OT Unavailability)*	*Cancelled Surgeries (Ward Unavailability)*	*Total number of surgeries*	*Days with overtime*	*Times a ward had to exceed capacity*	*Average OT utilisation*	*Average ward utilisation*
A	34%	5%	61%	31512	11%	817	0,92	0,71
B	35%	5%	60%	31356	12%	829	0,94	0,71
C	41%	6%	53%	29094	13%	926	0,93	0,68
D	42%	5%	53%	29172	12%	1054	0,95	0,68

6.3.2 SCENARIO 2: SOFTENING THE DAMAGE

The second scenario is about the circumstances where the capacity is lowered, and the length of stay of the patient is also lower. So even though there is a lower capacity this should be slightly compensated by patient staying shorter. This "softening the damage" scenario explores the uncertainty of having lower-than-estimated capacity coupled with overestimated lengths of stay.

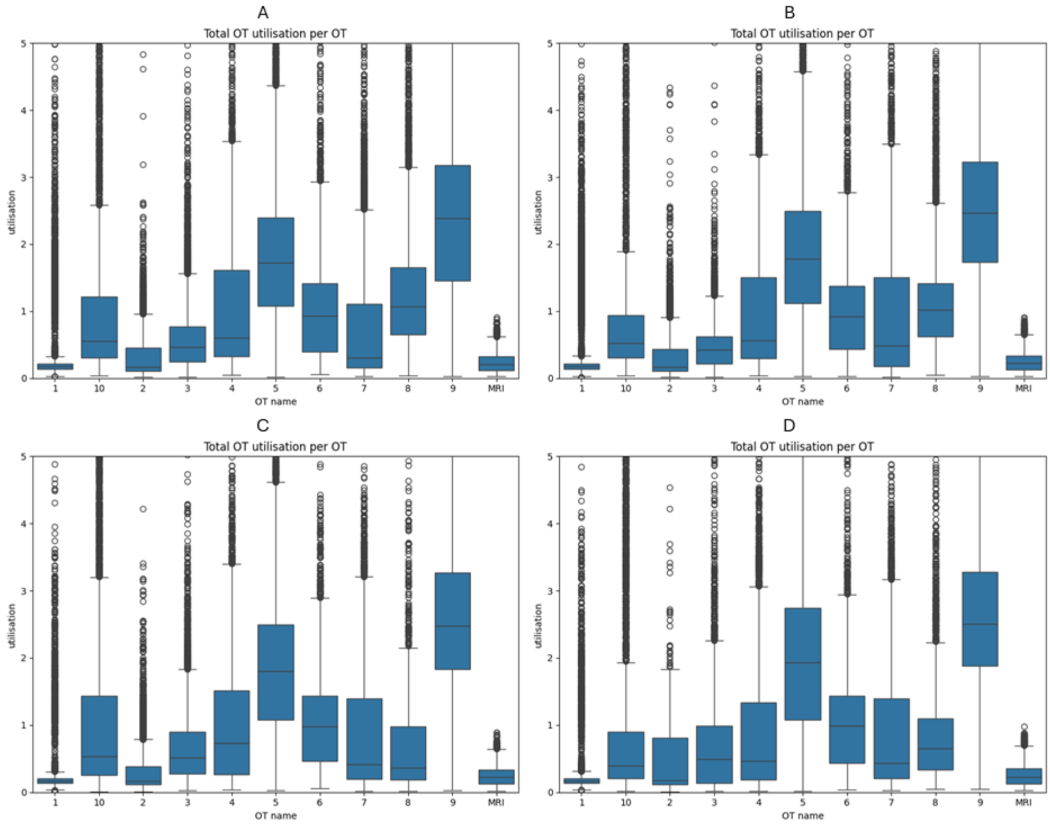


FIGURE 37: OT UTILISATION SCENARIO 2

The primary observation based on Figure 37 is that the differences across the OTs are still quite large in this scenario. In all cases, three or four OTs experience overutilisation while the other 7 or 8 experience underutilisation. According to Table 32 overall, this scenario decreased the average utilisation of the OTs, with the schedules checking for the availability every 15 minutes, B and D, experiencing higher utilisation than those checking every hour.

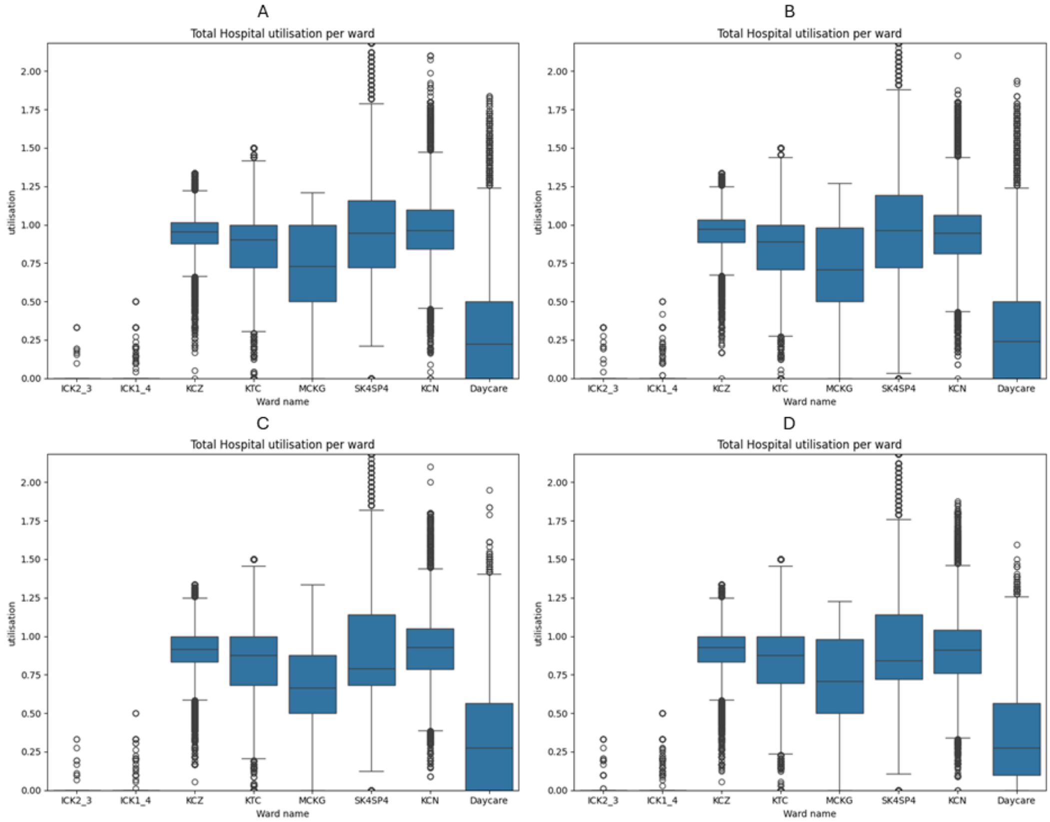


FIGURE 38: WARD UTILISATION SCENARIO 2

Figure 38 shows similar behaviour compared to the base case. With none of the wards overutilisation on average, especially the medium care units are getting close to full utilisation. So even though the patients are staying shorter the pressure still seems to be high on these units. Table 32 still, the ward utilisation is slightly lower for those levelling bed occupancy. Interestingly the ward utilisation is higher compared to the base case, even though patients are staying shorter. However, this is probably caused by the decrease in capacity.

Table 32 shows a lower number of successful surgeries. Less of these are caused by OT unavailability and more by ward unavailable, demonstrating the increased pressure on the wards caused by the lowered capacity. Showing that the decrease in length of stay is insufficient to compensate for the decrease in capacity. Overtime experiences a slight decline, which can be explained by fewer successful surgeries. Model A now performs slightly better when it comes to overtime, while model B and D are equal.

The experiment demonstrates that while the scenario constraints affect performance metrics, the overall behaviours and trends from the base run remain stable. None of the schedules exhibit exceptional vulnerability to the uncertainties of the scenario, highlighting the robustness of the schedules.

TABLE 32: SUMMARY TABLE SCENARIO 2

Model version	*Successful Surgeries*	*Cancelled Surgeries (OT Unavailability)*	*Cancelled Surgeries (Ward Unavailability)*	*Total number of surgeries*	*Days with overtime*	*Times a ward had to exceed capacity*	*Average OT utilisation*	*Average ward utilisation*
A	38%	6%	56%	31512	12%	815	0,94	0,67
B	39%	6%	55%	31356	13%	843	0,96	0,67
C	45%	8%	47%	29094	14%	932	0,94	0,64
D	46%	7%	47%	29172	13%	1106	0,96	0,64

6.3.3 Scenario 3: Futile Attempt to Improve

In this scenario, the healthcare facility experiences higher capacity and longer lengths of stay. So even though they were able to increase the capacity, the improvements are dumped by the increased length of stay. This "Futile attempt to improve" highlights the challenges of expanding capacity while the length of stays turns out higher than expected.

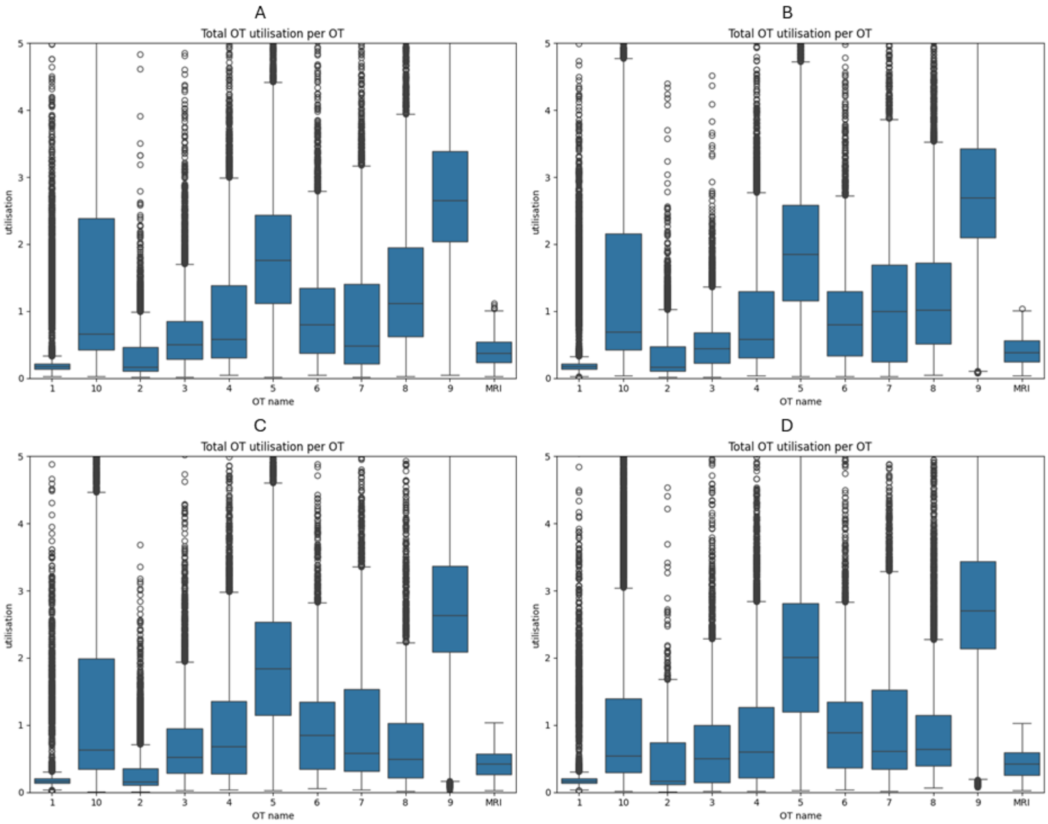


Figure 39: OT utilisation scenario 3

The first thing that can be noticed in Figure 39 is the extremely long range for OT 10 for the schedules A, B and C. The utilisation rates for this OT can be quite high in some circumstances. A first glance would also say that utilisation for some of the OTs, such as 5,6 and 9, are quite higher in the models levelling for bed occupancy, C and D. Overall Table 33 shows that this scenario experiences increased OT utilisation rates across all schedules. With model C getting the closest 100% and all the others experiencing overutilisation.

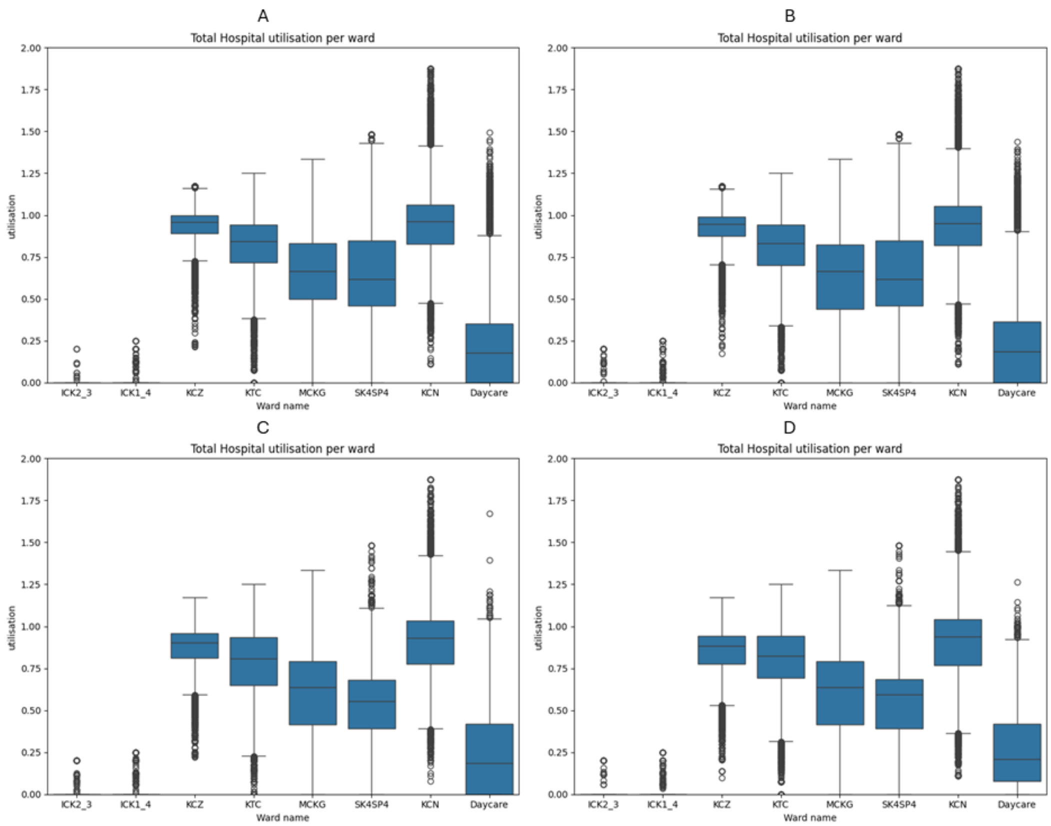


FIGURE 40: WARD UTILISATION SCENARIO 3

The most interesting thing to be seen in Figure 40 is that the SK4 / SP4 experiences decreased utilisation rates for schedules A and B compared to the based case. Overall Table 33 proves that the average utilisation rates for the wards are slightly lower compared to the base case. Especially for schedules C and D, a decrease in the number of times a ward had to exceed capacity. Additionally, a significantly lower number of surgeries is cancelled due to ward unavailability, causing an increase in surgeries cancelled due to OT unavailability. Overall the number of successful surgeries increases. This shows once again that the availability of the wards is the biggest bottleneck in the system, and the increase in capacity is more effective than the negative effects of the increase in the length of stay.

The behaviour maintains consistent trends despite the scenario changes. Models prioritising ward levelling continue to outperform others in minimising cancelled surgeries due to ward unavailability and maximising successful surgeries within acceptable over time. In conclusion, none of the schedules are vulnerable to the uncertainty of this scenario.

TABLE 33: SUMMARY TABLE SCENARIO 3

Model version	*Successful Surgeries*	*Cancelled Surgeries (OT Unavailability)*	*Cancelled Surgeries (Ward Unavailability)*	*Total number of surgeries*	*Days with overtime*	*Times a ward had to exceed capacity*	*Average OT utilisation*	*Average ward utilisation*
A	49%	10%	41%	31512	15%	751	1,03	0,62
B	52%	10%	38%	31356	16%	733	1,05	0,61
C	58%	13%	29%	29094	17%	685	1,00	0,58
D	61%	12%	27%	29172	17%	850	1,04	0,58

6.3.4 Scenario 4: The Golden Era

In this scenario, the healthcare facility operates under optimal conditions, with both high capacity and low lengths of stay. This "The Golden Era" scenario highlights the best-case scenario where the system efficiently can increase the capacity and all the lengths of stays are shorter than originally estimated.

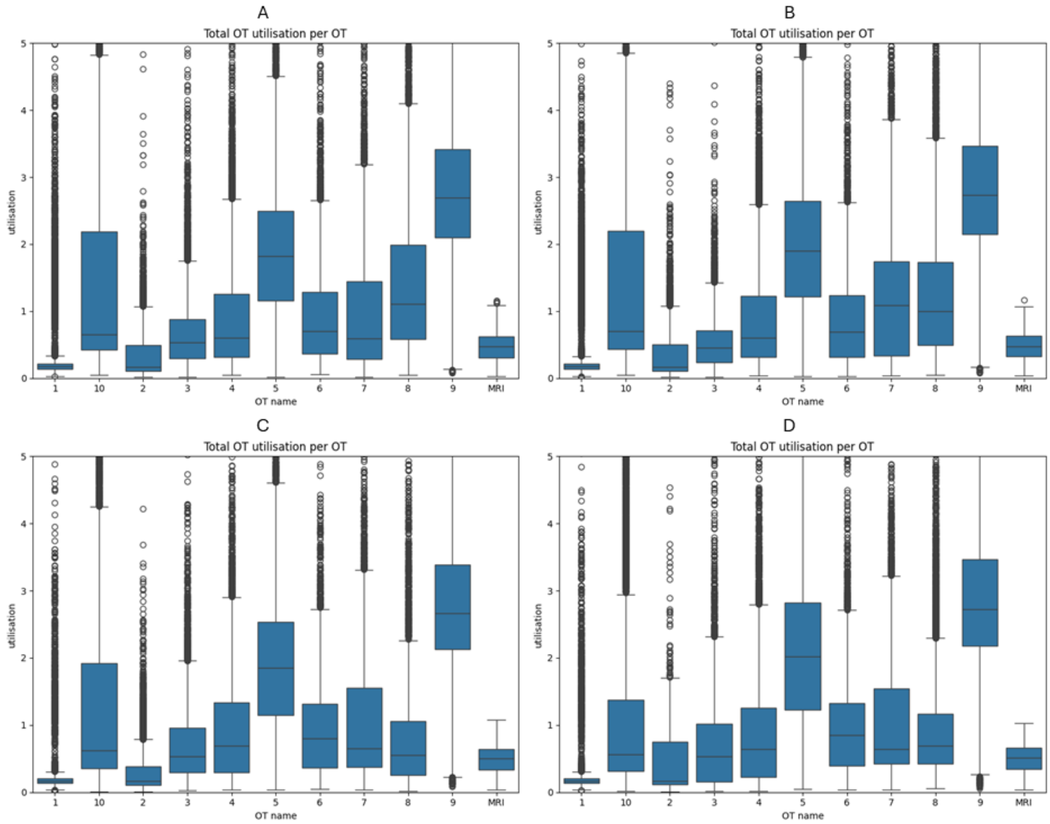


Figure 41: OT utilisation scenario 4

According to Figure 41 the gap between the different utilisation rates across the OTs seems to have decreased slightly in the schedules levelling ward occupancy, models C and D, with increased utilisation for the typically lower utilised OTs, especially in schedule D. According to Table 34 in all schedules the OTs, on average, are overutilised. Schedule C has the utilisation closest to 1, while schedule B is the furthest from 1. This behaviour is in accordance with the base case; however, the fact that schedule A has the same level of utilisation as schedule D is not.

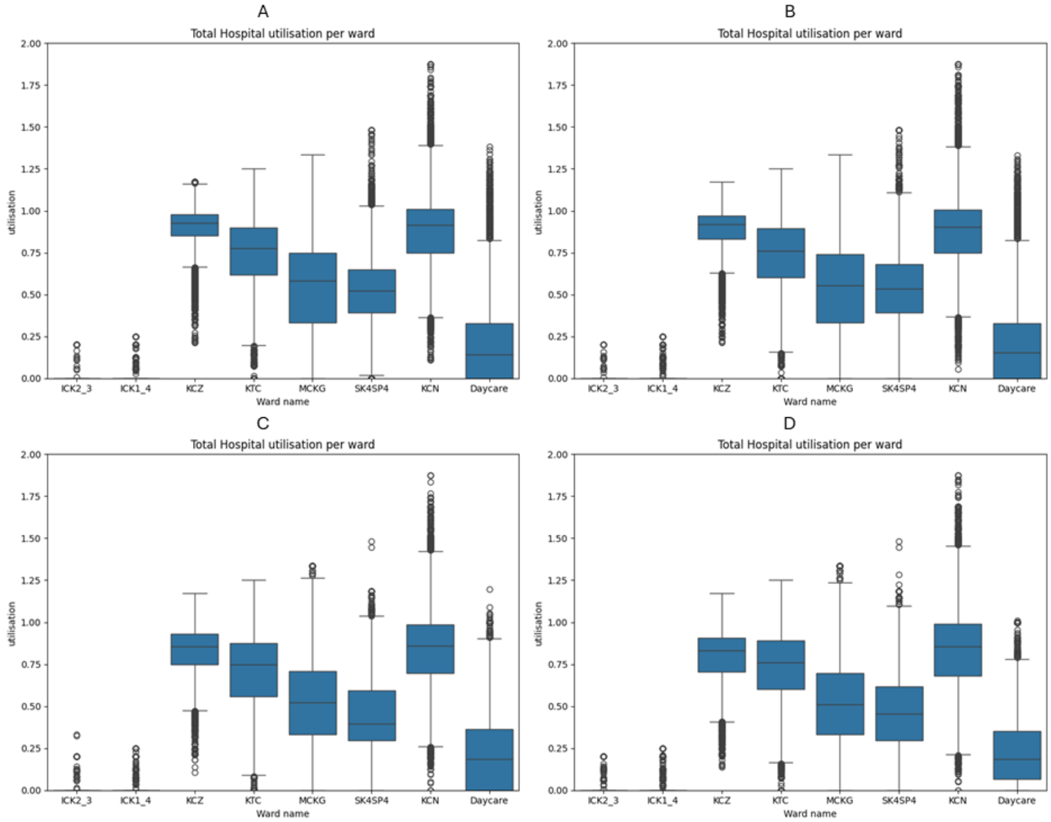


FIGURE 42: WARD UTILISATION SCENARIO 4

The ward utilisation, in Figure 42, is slightly lowered for the schedules levelling the ward occupancy, models C and D, especially for the normally quite overutilised medium care units. For schedules A and B, it can be seen that even though they are still quite close to one, they do not experience over-utilisation either. The results in Table 34 confirm this, the average utilisation is significantly lower than the base case and is the lowest in the schedule C and D.

However, the gaps between the different models are bigger and based on successful surgeries, the outperformance of schedule D over the others increases. Except for the variable cancelled surgeries due to OT availability, most likely due to the extreme decrease in the number of surgeries cancelled due to ward unavailability. Having more surgeries requires the resources of the OT.

TABLE 34: SUMMARY TABLE SCENARIO 4

Model version	*Successful Surgeries*	*Cancelled Surgeries (OT Unavailability)*	*Cancelled Surgeries (Ward Unavailability)*	*Total number of surgeries*	*Days with overtime*	*Times a ward had to exceed capacity*	*Average OT utilisation*	*Average ward utilisation*
A	56%	12%	32%	31512	17%	719	1,07	0,57
B	58%	12%	30%	31356	18%	718	1,08	0,56
C	64%	15%	20%	29094	18%	618	1,02	0,53
D	67%	15%	18%	29172	18%	783	1,07	0,53

6.4 CONCLUSION SCHEDULE PERFORMANCE

Based on the model's conclusions, it can be said that the general behaviour is quite robust under uncertainty. The system is not vulnerable to changes in the length of stay and when the capacity decreases. However, the size of the differences between the different models does change a little throughout the various scenarios. This analysis begins with an examination of the successful surgeries, Table 35. In each scenario, the models considering levelling of the wards, C and D, outperform A and B. And then again, D outperforms C. The differences are small in the scenarios that decrease ward capacity but increase in those that increase ward capacity. So, the effectiveness of the optimisation model checking the availability more often increases when there is an increase in ward capacity.

TABLE 35: SUCCESSFUL SURGERIES, SCENARIO ANALYSIS

	A	B	C	D
Base run	*44%*	46%	52%	54%
Scenario 1	*34%*	*35%*	*41%*	*42%*
Scenario 2	*38%*	*39%*	*45%*	*46%*
Scenario 3	*49%*	*52%*	*58%*	*61%*
Scenario 4	*56%*	*58%*	*64%*	*67%*

TABLE 36: CANCELLED SURGERIES DUE TO WARD, SCENARIO ANALYSIS

	A	B	C	D
Base run	*47%*	46%	37%	37%
Scenario 1	*61%*	60%	53%	53%
Scenario 2	*56%*	55%	47%	47%
Scenario 3	*41%*	38%	29%	27%
Scenario 4	*32%*	30%	20%	18%

Similar results can be seen for the number of cancelled surgeries due to ward unavailability, which is the lowest across all scenarios for schedule C and D. With a difference between the two in scenarios 3 and 4. So, when the pressure on the ward capacity decreases, the optimisation model's effectiveness also increases.

For the overtime occurrences given in Table 37, , slight increases can be seen in models C and D. However, they consistently remain below the allowed 25% limit with minimal differences across the models. In Appendix F the length of these overtime occurrences can be found. While the frequency of unacceptably long overtime varies across different scenarios, it remains consistent across the models. Thus, the optimisation model impacts the occurrence of overtime but does not affect the occurrence of unacceptably long overtime.

Table 38 shows that the number of times a ward had to exceed its capacity is always the highest in model D. However, since the average utilisation of the wards remains below zero, see Table 39, and the plots across the experiments show that the overutilisation occurrence where lower in the models levelling ward occupancy, C and D, which would indicate that exceedance of capacity is an incident of a small number of patients on a spread out number of occurrences.

TABLE 37: DAYS WITH OT OVERTIME, SCENARIO ANALYSIS

	A	B	C	D
Base run	*14%*	14%	16%	15%
Scenario 1	*11%*	12%	13%	12%
Scenario 2	*12%*	13%	14%	13%
Scenario 3	*15%*	16%	17%	17%
Scenario 4	*17%*	18%	18%	18%

TABLE 38: EXCEEDING OF WARD CAPACITY, SCENARIO ANALYSIS

	A	B	C	D
Base run	*755*	770	781	973
Scenario 1	*817*	829	926	1054
Scenario 2	*815*	843	932	1106
Scenario 3	*751*	733	685	850
Scenario 4	*719*	718	618	783

TABLE 39: OVERVIEW, UTLISATION, SCENARIO ANALYSIS

	A - OT	*B - OT*	*C - OT*	*D - OT*	*A - Ward*	*B - ward*	*C - Ward*	*D -ward*
Base run	*0,99*	1,01	0,97	1,01	*0,65*	0,64	0,61	0,62
Scenario 1	*0,92*	0,94	0,93	0,95	*0,71*	0,71	0,68	0,68
Scenario 2	*0,94*	0,96	0,94	0,96	*0,67*	0,67	0,64	0,64
Scenario 3	*1,03*	1,05	1,00	1,04	*0,62*	0,61	0,58	0,58
Scenario 4	*1,07*	1,08	1,02	1,07	*0,57*	0,56	0,53	0,53

Based on the results across the different scenarios, it can be concluded that model D outperforms the other models. This is primarily because cancellations due to ward unavailability are the biggest bottleneck in the system, and model D is the most effective in levelling the wards. However, model D requires greater computational resources compared to the other models.

According to the simulation model results, an increased capacity, scenarios 3 and 4, does improve the general number of successful surgeries. However, it is accompanied by more surgeries being cancelled due to OT unavailability and overtime, highlighting a trade-off within the system. Even though ward unavailability is the biggest bottleneck in the system, an increase does not automatically solve your problem since more surgeries will be cancelled due to OT unavailability.

Additionally, it is good to note that the ward occupancies show that the number of elective surgery patients on the ICK is limited, so if the overflow of the ICK happens, it is most likely not caused by the elective patients. According to the literature, the model overestimates the number of patients sent to the ICK post-surgery, and even when this number increases, the utilisation of the available beds remains low. However, they are considered in the average utilisation, so this might cause the average utilisation to be lowered, which might be higher if the ICK was not considered.

If further research would look into improving the model it would be recommended to have a more detailed look into ward capacity. As noted in the section on the ward capacity, 4.5, the capacity is determined by more factors than just the physical bed. Having a more detailed look could further explore the bottlenecks within the system and give better advice on what needs to be done to decrease this number. The simulation model built for this research does not fit this purpose, as the focus was to compare the effectiveness of each of the schedules.

7 CONCLUSION

This research began by addressing the complexities of the healthcare sector and the need for solutions to improve the efficiency of OT scheduling. The study explored two primary methods: optimisation and simulation modelling. The application of these methods revealed both strengths and limitations. Optimisation modelling has the ability to optimise across various parameters. Simulation modelling excelled at accounting for system complexities and environmental variability. However, a problem statement was identified: Optimisation enhances OT scheduling but fails to account for its complexities and uncertainties, highlighting the necessity for a deeper exploration of these theoretically sound solutions. Using this information, the study identified a knowledge gap, leading to the formulation of the following research question:

"How can Discrete Event Simulation be used to evaluate an optimisation-generated Master Surgery Schedule for operating theatres?"

To effectively answer this question, it is decomposed into three sub-questions. The literature aided in answering the first research question by further exploring the knowledge gap. It mainly highlighted that the sequencing of simulation and optimisation enables the ability to improve on each other's weaknesses. Together, they can address various parameters tested under uncertainty and different scenarios. It also showed that this application had been successfully used before but in a less complex setting, as it was used only for singular specialities. Simulation is considered a common method to aid as a decision support tool.

Using a MSS increases the complexity of shared resources, but it also enables a more efficient use of these resources, including higher OT utilisation. Additionally, this part of the literature review brought to light a trade-off between utilising the OTs and the pressure on the reset of the system, including the wards. Often when the system was further explored, the biggest bottleneck was not necessarily the utilisation of the OTs, and aiming to increase OT utilisation was futile if not properly considering all resources in the system. These conclusions aided in answering the first sub-question:

1) What are the key considerations and performance indicators for setting up a Discrete Event Simulation model to evaluate an optimisation-generated Master Surgery Schedule?

The next step for answering this sub-question was taking these lessons learned and using them in the model's setup. This information was used to set up the KPIs that explored beyond the OT utilisation and looked into the resources across different specialties, considering the total hospital resources and the use of resources per ward and OT used by the different specialties. Many of the case studies in the research advised against striving for full utilisation, as aiming for full utilisation often caused other factors in the system to be overutilized and left less room for the uncertain nature of the healthcare system. By including different KPI's the focus was on improving more than just OT utilisation. The research also considered the utilisation of the wards, the surgeries cancelled the occurrence of overtime and the length of overtime. Enabling a more complete picture of the system performance.

The second part of the literature review focused on exploring standard practices in healthcare simulation modeling. First, it highlighted the use of distributions to set up input variables, with their fit tested using a KS test. Secondly, to address system behaviour, it demonstrated that applying sensitivity analysis is useful for managing model uncertainties, which often occur in variables such as length of stay and surgery duration. Thirdly, it identified how these uncertainties could be utilized in a scenario analysis during the experimentation phase. These conclusions then aided in answering the second research question:

2) What type of uncertainties does the discrete simulation model need to take into account when evaluating Master Surgery Schedules?

During the model's setup and development, several variables were identified as potential sources of uncertainty, including length of stay, surgery duration, ward capacity, and the assignment of ICKs. A sensitivity analysis was conducted to explore the impact of these uncertainties, revealing that the most significant uncertainties were in ward capacity and length of stay, as variations in these variables had the largest impact on the system. Cross-validation indicated that the length of stay was overestimated in the model, as the output showed higher values compared to real data. However, this overestimation did not significantly affect overall system behaviour. This information could then be used to set up the different scenarios for the experimentation phase.

The final sub-question focuses on what can be learned from the model and how simulation modelling can be utilised to evaluate optimisation-generated MSS:

3) How do the identified uncertainties impact the performance of the Master Surgery schedule?

Chapter 6 begins to address this question by comparing different scheduling methods. Initially, the chapter examines the behaviour of each schedule under normal conditions, revealing that ward utilisation remained stable and, on average, below full capacity across the various scheduling methods. There were some changes in OT utilisation as, in some schedules, the OTs were overutilised. Nevertheless, the behaviour across the different schedules remained quite similar. Across all scheduling models, many surgeries were cancelled due to ward unavailability, resulting in a relatively low number of successful surgeries. However this number did decrease for the schedules prioritising on levelling the wards.

In the base case, schedules that prioritised ward levelling outperformed those with equal prioritisation on OT utilisation and ward levelling. Schedule D performed better than Schedule C on all but two variables. As the number of successful surgeries increased and cancellations due to ward unavailability decreased, the occurrences of overtime and instances of wards operating above capacity also increased. While the increase in overtime occurrences remained below the 25% threshold, the overtime duration frequently exceeded the 45-minute limit. For instances of wards operating above capacity, no threshold had been defined.

Considering the uncertainties identified during the validation phase, particularly the potential impact of the uncertainty in the length of stay variable, the outcome of almost half of the surgeries being cancelled due to ward unavailability may be somewhat high. Additionally, ward capacity was another significant uncertainty. These two factors were chosen for further exploration in the scenario analysis across the schedules, resulting in four scenarios. In each of these scenarios, different combinations of an increase or decrease in the capacity of the wards and the length of stay were combined. The main conclusion from these scenarios was that the behaviour of the generated schedules remained consistent. The ranking of schedules for each KPI remained unchanged. While some performance gaps widened slightly, Schedule D consistently outperformed the others when decision-makers were willing to accept a certain level of ward exceeding its capacity. These schedules not only prioritise on levelling the wards, but the system also has a more frequent check of the bed availability. The latter requires a high er computational ability for the model.

So, to answer the third research question, the uncertainties change the outcome of the system across all scenarios but do not change the behaviour across the different models. Across all scenarios model D outperforms the others when the decision maker is willing to accept an increase in the overtime occurrences and the occurrences of exceedance of the ward capacity.

The system is primarily constrained by ward capacity. However, increasing this capacity does not result in an equally sized increase in the successful number of surgeries as the limitation presented by the availability of the OT becomes a limiting factor, and other KPIs, including overtime, also worsen. The optimisation model only considered the goal of levelling the bed occupancy and did not look directly at the capacity of the wards. The goal was to avoid high peaks in the wards so fewer surgeries would have to be cancelled due to the unavailability of the wards. The simulation model showed that this is true; the schedules considering the levelling of the wards have a lower level of the number of surgeries being cancelled due to ward unavailability.

The optimisation model focused on levelling bed occupancy without directly addressing the limitation of the ward capacity. The goal was to avoid high peaks in ward occupancy to reduce the number of surgeries cancelled due to ward unavailability. The simulation showed that schedules prioritising ward levelling resulted in fewer cancellations, confirming that the set goal was achieved. However, it also indicates that a schedule levelling the wards does not solve the problems that the hospital is facing. Even though fewer surgeries are cancelled, it seems that the system is still not performing as intended, and many surgeries continue to be cancelled.

In addressing the main research question, this study has demonstrated that using simulation for further exploration of the system enables a more detailed analysis of the different schedules. The scenario analysis indicates that the optimisation model fulfils the intended purpose and remains robust under system uncertainty. However, it would call into question not the model itself but the goal. The simulation model revealed that while high peaks in ward occupancy were initially defined as the primary problem, they might be a symptom of deeper issues within the system. So, simulation modelling did not only effectively evaluate the schedules to see if they serve their purpose but also identified new directions for improvement.

Furthermore, the simulation highlighted trade-offs that decision-makers need to consider. Defining thresholds for certain KPIs can be beneficial when determining policy, such as the trade-off between overtime occurrences and the number of cancelled surgeries. This research contributes to the domain by providing insights into the complexities of hospital scheduling and the potential of simulation modelling to evaluate healthcare scheduling and identify domains of improvement for the optimisation models.

8 DISCUSSION

Now that the research question has been answered, this chapter focuses on how that answer contributes to the broader domain of study, how this study has been limited and how further research can continue on the outcomes of this research.

8.1 ACADEMIC CONTRIBUTION

The literature review of Chapter 2 discussed that simulation to asses an optimisation-generated solution in a healthcare setting has proven to be a valuable tool. It enables the ability to expose a solution to different what-if scenarios and test the system under uncertainty. DES was identified as a standard simulation method and chosen for this research due to its ability to queue entities and use decision rules to move them through the system. The DES model has provided several conclusions that contributed that have contributed to the domain of OT scheduling. This section discusses the contributions specific to the model conclusion and the contributions made based on the method.

8.1.1 MODEL CONTRIBUTIONS

The research table, Table 3, identified that applying DES to testing a MSS generated by an optimisation model was still an unresearched topic. The MSS brings about additional complexity in the system as different departments share different resources. Some of these departments have different requirements for the type of OT or the pre- or post-surgery care. The main advantage of open scheduling, or MSS, is the increased OT utilisation (Xiao and Yoogalingam, 2022). This is crucial as OT unavailability is an important factor in the cancellation of surgeries (Fayed et al., 2016). However, the literature review of Chapter 2 highlighted clear trade-offs for healthcare scheduling decision-making. While it is possible to increase OT utilisation, this often places additional strain on other resources within the system. This finding is supported by experiments and tests conducted using the simulation model. Even though the OTs were already experiencing high utilisation levels, most surgeries were cancelled due to the constraints of the wards. The models with a higher priority on OT utilisation performed worse on almost all KPIs across the different scenarios. Nevertheless, not all OTs experienced similar strains. Some OTs did not even come close to full utilisation, while others experienced extreme overutilisation, indicating that the optimisation model did not adequately account for fluctuations across different OTs. Therefore, when using the MSS efficiently, the primary challenge is not merely to increase OT utilisation. Instead, it is crucial to balance this with the efficient use of other essential resources and consider OT-specific characteristics to improve individual utilisation.

According to the research table the largest uncertainties were found in the length of stay and the surgery duration. Chapter 5 discussed that the surgery duration was slightly overestimated in the simulation model. This overestimation was visual in the model's outcome during both the sensitivity analysis and scenario experimentation. However, it did not significantly impact the outcome as surgery duration was not a real limitation of the system. The more critical factor was the uncertainty in the length of stay. Thought the cross-validation highlights this factor as very different from the real data, many distributions were considered an improper fit. As the length of stay is one of the more limiting factors of the system, this uncertainty in its fit is also considered an important factor to consider in the model outcomes.

Lastly, the most impactful factor was the capacity of the wards. The schedule for the capacity of the wards was an estimation of how many beds are, on average, available for elective surgery patients. Changes in this capacity had the biggest impact on the system, with most surgeries being successful during an increase and the least number of surgeries being successful during a decrease. So the system is mostly impacted by the limitations posed by this variable.

So, all in all, the model highlights the trade-off where an increase in OT utilisation and the other KPIs in the system, which is considered even more important when using an MSS. Additionally, the model provided insight into the differences in utilisation across the different OTs and wards that were not properly addressed in the optimisation model. The length of stay and the capacity of the ward as the most important factors, and the uncertainty in these variables have the largest impact on system behaviour.

8.1.2 METHOD CONTRIBUTIONS

Erdogan et al. (2011) highlighted that few studies have focused on the effects on post-surgery resources when optimising OT utilisation. This study has started to address this gap by investigating the use of simulation to evaluate optimisation-generated scheduling and looking at a broader range of KPIs that also consider additional resources. By employing an optimisation model that balances OT utilisation and ward levelling, the simulation model revealed significant differences in the number of successful surgeries based on the prioritisation of these variables. This highlights the importance of this more global approach and correctly considering the trade-off.

Section 2.4 of the literature review discussed how simulation modelling enables the system to be tested under different uncertainties, which is considered an advantage compared to only using the optimisation approach. The simulation model demonstrated that the schedules generated by the optimisation approach are robust across different scenarios, indicating low sensitivity to future uncertainty. However, the validation phase showed that the model's effectiveness is sensitive to uncertainty in the input parameters. This means carefully considering the input data and the uncertainty of the input variables is important. Changes in the input data seem to have different effects on the strain on the other resources, which are more complex considering the MSS approach.

The literature review discussed that the advantage of optimisation was the ability to consider a wide range of parameters. Simulation can also consider different parameters, but the computational capacity required increases when the parameters do. However, this research has shown that the simulation model proves helpful in identifying new parameters to be considered in the optimisation phase. This allows for an adaptive approach, where the considerations in the optimisation process can be adjusted accordingly. In the context of this study, the simulation model showed that simply levelling the wards is not enough, and more factors must be considered to improve the system effectively. For example, here, it could be the capacity of the wards and the exact reasons for cancellation.

Overall, the model demonstrated the added value of using simulation to evaluate optimisation-generated scheduling, aligning with findings from similar research by Saadouli et al. (2015) and Hamid et al. (2018). While previous studies focused on individual specialities, this research extends the analysis to the entire surgery speciality of the Sophia Children's Hospital. This increases the number of factors to be considered, for which optimisation lends itself well. At the same time, simulation contributes by accounting for the complexity of shared resources across multiple specialities. Different trade-offs and areas of improvement can be found, enabling an iterative approach. This method of testing optimisation-generated scheduling using simulation proves to be a valuable tool in the decision-making process.

8.2 LIMITATIONS

The healthcare sector is highly interconnected, making establishing clear boundaries within the system difficult. For this model, the decision was made to focus solely on elective patients. This scope brought about some uncertainty regarding ward capacity assumptions. The hospital does not allocate beds exclusively for elective patients, and the number of beds available for these patients often varies based on the demand of other patient flows. Consequently, setting a fixed capacity in the simulation model limits the validity compared to the real system.

Across all scenarios, the model indicates a high number of surgeries being called due to ward unavailability. One of the model's assumptions, see Table 16, was that surgeries are only cancelled due to either the unavailability of the wards or the unavailability of the OTs. However, in reality, other factors can also lead to surgery cancellations. Less than one-third of all elective surgeries are called on the surgery day itself (Garg et al., 2009), which would be the case for the unavailability of resources. This implies that the actual number of surgeries cancelled due to ward unavailability may be lower. One of the reasons for same-day cancellations is patients not showing up for surgery or medical reasons (Kumar & Gandhi, 2012). Additionally the system assumed that patients always arrive on time so all pre-surgery procedures can be concluded before the start time of the surgery. Delays caused by late arrivals can also impact the system's efficiency.

In determining the surgery duration and the length of stay, the surgeries are split up into pre-defined groupings and their occurrences of the surgery duration and length of stay are used to set up a distribution for each grouping, as explained in a section 4.3.2 and 4.3.3. However, there are a few limitations to this approach. Firstly, the type of surgery is not the only factor influencing a patient's surgery duration and length of stay (Fairley et al., 2018). Other variables, such as weight, age, and sex, can also significantly impact the required care, which this model does not consider.

Secondly, when assigning the distributions, many groupings could not find a suitable fit among the chosen distributions based on the KS test. While only a few groupings of surgery durations faced this issue, a significant number of groupings for the length of stay variable did. The QQ plots were then used to find the best fit, but it is important to note that the best fit does not necessarily imply a good fit, and some groupings are most likely not well represented by these distributions.

Lastly, the model relies on the average duration of a surgery to determine if the surgery can be completed in time. However, even though surgeries are grouped based on duration, there can still be significant variability within each grouping. As a result, the average duration for the entire group may sometimes be too strict or too lenient as a constraint. They are causing underutilisation or extreme lengths of overtime.

One more noteworthy thing is that the literature review does not delve into simulation applications for schedule testing in sectors beyond healthcare. This decision was made due to the broad scope of the topic, which necessitated a more focused approach. By narrowing the focus to healthcare, the review could provide better analysis and more insights into the specific challenges, methodologies, and findings within the relevance to that sector.

The DES model developed for this research was designed to compare various schedules produced by the optimisation model for the OTs of the Sophia Children’s Hospital. So, the simulation model's input variables and decision rules are also specific to this setting. While input variables such as capacity and schedule can be modified without altering the model, other elements, including model assumptions and ward assignments, require code changes. So, using the exact model in a different setting might be less effective. However, the model's structure and approach can be reused and adapted for different environments.

Additionally, if further research would continue in a similar setting, the model could be reused, provided the model's original purpose is considered. It can be directly employed to compare different schedules. However, additional modifications and a new validation will be necessary if the model is intended for a different purpose.

8.3 RECOMMENDATIONS FOR FURTHER RESEARCH

The previous section identified some limitations that influenced the model and the ability to represent the real world. Future research should consider these limitations and how they can be improved. The first part of this section will elaborate on how these limitations result in recommendations for further research.

Despite the impact of these limitations, the model has provided valuable insight for the evaluation of MSS, and the findings of this research have contributed to the academic domain of healthcare simulation modelling and optimisation-generated MSS. The second part of this section elaborates on how future research can build upon these findings.

8.3.1 FURTHER RESEARCH BASED ON LIMITATIONS

While capacity is identified as a significant limitation, the complexity necessitates further investigation. The Sophia Children's Hospital wards and other resources are shared with emergent patients which are left out of the scope in both the simulation and optimisation model. So, even though estimations can be made about the available capacity, the exact capacity can vary based on these inflows. This made it hard for the hospital to give precise values of this capacity. Future research should focus on a more detailed definition of capacity to pinpoint specific areas for improvement.

The different surgery groups used posed some limitations during the research for both the optimisation and the simulation model. The 50 groupings were based on the length of stay, surgery duration, and different surgical specialities. However, the number of surgeries for each group varied significantly for both the test and the training data. They were posing challenges when fitting distributions. Further research should explore alternative grouping methods and assess their impact on performance in both optimisation and simulation models. The definition of the grouping could have a significant impact on the estimated surgery duration and length of stay within the simulation. Refining these groupings might improve simulation modelling. There also might be other factors that influence these variables rather than only the type of surgery they are in for. Methods such as regression analysis on a more detailed patient dataset might provide further insight.

8.3.2 Research Expanding on Findings

The limitations highlighted several scopes on which the input data could be improved for the model to provide a more realistic view. Additionally, further research not only should have better insight into these variables but might also look into what other factors influence and define these input variables. The capacity is not only defined by the number of beds in a particular ward. It is also about the number of resources available to aid this patient, such as nurses or machinery. A more detailed approach could look into what is used to define this capacity and more clearly identify its bottleneck and how it could be improved.

The model concluded that the different schedules can improve different KPIs. So, when improving the number of successful surgeries, there was an increase in overtime and over-occupation of the wards. As already defined for overtime, some negative KPIs might be acceptable. Further research could explore what trade-offs are acceptable and unacceptable, exploring which improvements are highly important to a hospital and which would simply be good to have.

Additionally, the model highlighted the effect of full utilisation of the OTs on the cancellations and the pressure on the other resources. Further research could expand on this and research the impact of aiming for lower utilisation rates on the number of surgeries that have to be cancelled. To consider changing the goal of the optimisation model to improve the overall performance.

Lastly, considering a more ward and OT specific approach when defining the optimisation model. The model highlighted large differences between the utilisation across the OTs and the wards. Further research should examine the cause of these differences and whether the schedule can better utilise this or whether these underutilised resources can be used more effectively.

9 REFERENCES

Abedini, A., Li, W., & Ye, H. (2017). An optimisation model for operating room scheduling to reduce blocking across the perioperative process. *Procedia Manufacturing*, *10*, 60–70. https://doi.org/10.1016/j.promfg.2017.07.022

Almagooshi, S. (2015). Simulation modelling in healthcare: Challenges and Trends. *Procedia Manufacturing*, *3*, 301–307. https://doi.org/10.1016/j.promfg.2015.07.155

Antonelli, D., Bruno, G., & Taurino, T. (2018). Analysis of patient flows in elective surgery: modelling and optimisation of the hospitalisation process. *International Journal of Services and Operations Management*, *31*(4), 513. https://doi.org/10.1504/ijsom.2018.096171

Asghari, M., Fathollahi-Fard, A. M., Al-E-Hashem, S. M., & Dulebenets, M. A. (2022). Transformation and Linearization Techniques in Optimisation: A State-of-the-Art Survey. *Mathematics*, *10*(2), 283. https://doi.org/10.3390/math10020283

Azari-Rad, S., Yontef, A. L., Aleman, D. M., & Urbach, D. R. (2014). A simulation model for perioperative process improvement. *Operations Research for Health Care*, *3*(1), 22–30. https://doi.org/10.1016/j.orhc.2013.12.003

Bai, Y., & Jin, W.-L. (2015). Random variables and uncertainty analysis. In *Marine Structural Design* (2nd ed.). Butterworth-Heinemann. https://doi.org/10.1016/c2013-0-13664-1

Bam, M., Denton, B. T., Van Oyen, M. P., & Cowen, M. E. (2017). Surgery scheduling with recovery resources. *IISE Transactions*, *49*(10), 942–955. https://doi.org/10.1080/24725854.2017.1325027

Banditori, C., Cappanera, P., & Visintin, F. (2013). Investigating the relationship between resources balancing and robustness in master surgical scheduling. In *Springer proceedings in mathematics & statistics* (pp. 149–162). https://doi.org/10.1007/978-3-319-01848-5_12

Boon, H., MacPherson, H., Fleishman, S., Grimsgaard, S., Koithan, M., Norheim, A. J., & Walach, H. (2007). Evaluating Complex Healthcare Systems: A critique of four approaches. *Evidence-based Complementary and Alternative Medicine*, *4*(3), 279–285. https://doi.org/10.1093/ecam/nel079

Brailsford, S. C. (2007). Tutorial: Advances and challenges in healthcare simulation modeling. *2007 Winter Simulation Conference*. https://doi.org/10.1109/wsc.2007.4419754

Brailsford S.C. and Hilton N.A. 2001. “A Comparison of Discrete Event Simulation And System Dynamics For Modeling Healthcare Systems”. Proceedings from ORAHS 2000, Glasgow, Scotland, ed. J. Riley, 2001, pp 18-39.

Cappanera, P., Visintin, F., & Banditori, C. (2014). Comparing resource balancing criteria in master surgical scheduling: A combined optimisation-simulation approach. *International Journal of Production Economics*, *158*, 179–196. https://doi.org/10.1016/j.ijpe.2014.08.002

CBS. (2020, November 23). Dutch health expenditure 10th highest in Europe. *CBS*. https://www.cbs.nl/en-gb/news/2020/47/dutch-health-expenditure-10th-highest-in-europe

CBS. (2023, June 13). In 2021 meer ziekenhuisopnamen dan in 2020. *Centraal Bureau Voor De Statistiek*. https://www.cbs.nl/nl-nl/nieuws/2023/24/in-2021-meer-ziekenhuisopnamen-dan-in-2020

Chabouh, S., Hammami, S., Marcon, E., & Bouchriha, H. (2021). A pull-strategy for the appointment scheduling of surgical patients in a hospital-integrated facility. *Health Systems*, *11*(3), 172–188. https://doi.org/10.1080/20476965.2021.1908851

Cox, J. F. (2019). Using the theory of constraints' processes of ongoing improvement to address the provider appointment scheduling system execution problem. *Health Systems*, *10*(1), 41–72. https://doi.org/10.1080/20476965.2019.1646105

Crown, W. H., Büyükkaramikli, N., Sir, M. Y., Thokala, P., Morton, A., Marshall, D. A., Tosh, J., IJzerman, M. J., Padula, W. V., & Pasupathy, K. S. (2018). Application of Constrained Optimisation Methods in Health Services Research: Report 2 of the ISPOR Optimisation Methods Emerging Good Practices Task Force. *Value in Health*, *21*(9), 1019–1028. https://doi.org/10.1016/j.jval.2018.05.003

Dashboard Arbeidsmarkt Zorg en Welzijn (AZW). (n.d.). https://dashboards.cbs.nl/v4/AZWDashboard/

Davoudkhani, M., Hamid, M., Tavakkoli-Moghaddam, R., & G, H. S. (2019). A Two-Step Stochastic Optimisation and Simulation Approach for Scheduling Operating Rooms in an. . . *IEOM Society International*. https://www.researchgate.net/publication/334785886_A_Two-Step_Stochastic_Optimisation_and_Simulation_Approach_for_Scheduling_Operating_Rooms_in_an_Ophthalmology_Surgery_Department

Debats, C. E., Dellaert, N., Pouwels, S., & Stepaniak, P. S. (2021). Balancing workload in the PACU by using an integrated OR planning methodology. *Journal of periAnesthesia Nursing/Journal of Perianesthesia Nursing*, *36*(3), 279–290. https://doi.org/10.1016/j.jopan.2020.09.004

Erdogan, S. A., Denton, B. T., & Fitts, E. (2011). Surgery planning and scheduling. *Wiley Encyclopedia of Operations Research and Management Science*. https://doi.org/10.1002/9780470400531.eorms0861

Fairley, M., Scheinker, D., & Brandeau, M. L. (2018). Improving the efficiency of the operating room environment with an optimisation and machine learning model. *Health Care Management Science*, *22*(4), 756–767. https://doi.org/10.1007/s10729-018-9457-3

Federatie Medisch Specialisten & V&VN. (2021). *Raamwerk voor optimaliseren en maximaliseren van klinische capaciteit voorafgaand aan en ten tijde van fase 3 in de COVID-19 pandemie*. Retrieved June 19, 2024, from https://demedischspecialist.nl/sites/default/files/Raamwerk%20klinische%20capaciteit%20ten%20tijde%20van%20COVID-19.pdf

Forsberg, H. H., Aronsson, H., Keller, C., & Lindblad, S. (2011). Managing health care decisions and improvement through simulation modeling. *Quality Management in Health Care*, *20*(1), 15–29. https://doi.org/10.1097/qmh.0b013e3182033bdc

Garg, R., Bhalotra, A. R., Bhadoria, P., Gupta, N., & Anand, R. (2009). Reasons for cancellation of cases on the day of surgery-a prospective study. *DOAJ (DOAJ: Directory of Open Access Journals)*. https://doaj.org/article/404cbba61555404fa957d7dce23a03d2

Garrido, J. M., Martínez-Rodríguez, D., Rodríguez-Serrano, F., Pérez-Villares, J., Ferreiro-Marzal, A., Jiménez-Quintana, M. M., & Micó, R. J. V. (2022). Mathematical model optimised for prediction and health care planning for COVID-19. *Medicina Intensiva (English Edition)*, *46*(5), 248–258. https://doi.org/10.1016/j.medine.2022.02.020

Griffiths, J. D., Jones, M. D., Read, M. D., & Williams, J. E. (2010). A simulation model of bed-occupancy in a critical care unit. *Journal of Simulation*, *4*(1), 52–59. https://doi.org/10.1057/jos.2009.22

Guerriero, F., & Guido, R. (2010). Operational research in the management of the operating theatre: a survey. *Health Care Management Science*, *14*(1), 89–114. https://doi.org/10.1007/s10729-010-9143-6

Gül, S., Denton, B. T., Fowler, J. W., & Huschka, T. R. (2011). Bi-Criteria scheduling of surgical services for an outpatient procedure center. *Production and Operations Management*, *20*(3), 406–417. https://doi.org/10.1111/j.1937-5956.2011.01232.x

Hamid, M., Hamid, M., Musavi, M., & Azadeh, A. (2018). Scheduling elective patients based on sequence-dependent setup times in an open-heart surgical department using an optimisation and simulation approach. *Simulation (San Diego, Calif.)*, *95*(12), 1141–1164. https://doi.org/10.1177/0037549718811591

Harper, A., Mustafee, N., & Yearworth, M. (2022). The issue of trust and implementation of results in healthcare modeling and simulation studies. *2022 Winter Simulation Conference (WSC)*. https://doi.org/10.1109/wsc57314.2022.10015276

Hassanzadeh, H., Boyle, J., Khanna, S., Biki, B., Syed, F., Sweeney, L., & Borkwood, E. (2023). A discrete event simulation for improving operating theatre efficiency. *The International Journal of Health Planning and Management*, *38*(2), 360–379. https://doi.org/10.1002/hpm.3589

Huschka, T. R., Denton, B. T., Gül, S., & Fowler, J. W. (2007). Bi-criteria evaluation of an outpatient procedure center via simulation. *2007 Winter Simulation Conference*. https://doi.org/10.1109/wsc.2007.4419764

Jacobson, S. H., Hall, S. N., & Swisher, J. R. (2013). Discrete-Event Simulation of Health care Systems. In *International series in management science/operations research* (pp. 273–309). https://doi.org/10.1007/978-1-4614-9512-3_12

Johnston, M., Samaranayake, P., & Dadich, A. (2009). *Modelling Radiology Department operation using discrete event simulation* [18th World IMACS / MODSIM Congress]. http://mssanz.org.au/modsim09

Jun, J., Jacobson, S. H., & Swisher, J. R. (1999). Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society*, *50*(2), 109–123. https://doi.org/10.1057/palgrave.jors.2600669

Kafadar, K., & Spiegelman, C. H. (1986). An alternative to ordinary q-q plots: Conditional q-q plots. *Computational Statistics & Data Analysis*, *4*(3), 167–184. https://doi.org/10.1016/0167-9473(86)90032-0

Kalkhoven, F., & Van Der Aalst, M. (2018). Tekorten in de zorg leiden tot problemen, maar bieden ook kansen. *Sociaal Bestek*, *80*(2), 48–49. https://doi.org/10.1007/s41196-018-0032-8

Kleijnen, J. P. (1995). Statistical validation of simulation models. *European Journal of Operational Research*, *87*(1), 21–34. https://doi.org/10.1016/0377-2217(95)00132-a

Krueger, T., Page, T., Hubacek, K., Smith, L., & Hiscock, K. (2012). The role of expert opinion in environmental modelling. *Environmental Modelling & Software*, *36*, 4–18. https://doi.org/10.1016/j.envsoft.2012.01.011

Kumar, R., & Gandhi, R. (2012). Reasons for cancellation of operation on the day of intended surgery in a multidisciplinary 500 bedded hospital. *Journal of Anaesthesiology-Clinical Pharmacology/Journal of Anaesthesiology Clinical Pharmacology*, *28*(1), 66. https://doi.org/10.4103/0970-9185.92442

Kuziemsky, C. (2016). Decision-making in healthcare as a complex adaptive system. *Healthcare Management Forum*, *29*(1), 4–7. https://doi.org/10.1177/0840470415614842

Kuzmin, E. A. (2014). “Individual” scaling and overall evaluation of system uncertainty. *Modern Applied Science*, *9*(3). https://doi.org/10.5539/mas.v9n3p34

Law, A. M. (2014). *Simulation modeling and analysis*. McGraw-Hill Education.

Liu, S., Li, Y., Triantis, K., Xue, H., & Wang, Y. (2020). The diffusion of discrete event simulation approaches in health care management in the past four decades: A Comprehensive review. *MDM Policy & Practice*, *5*(1), 238146832091524. https://doi.org/10.1177/2381468320915242

Lorscheid, I., Heine, B., & Meyer, M. (2011). Opening the 'black box' of simulations: increased transparency and effective communication through the systematic design of experiments. *Computational and Mathematical Organization Theory/Computational & Mathematical Organization Theory*, *18*(1), 22–62. https://doi.org/10.1007/s10588-011-9097-3

Lowery, J. C. (1998). Getting started in simulation in healthcare. *Winter Simulation Conference, 1*, 31–36. https://doi.org/10.5555/293172.293177

Marcon, E., & Dexter, F. (2006). Impact of surgical sequencing on post anesthesia care unit staffing. *Health Care Management Science*, *9*(1), 87–98. https://doi.org/10.1007/s10729-006-6282-x

Marmor, Y. N., Rohleder, T. R., Cook, D. J., Huschka, T. R., & Thompson, J. E. (2013). Recovery bed planning in cardiovascular surgery: a simulation case study. *Health Care Management Science*, *16*(4), 314–327. https://doi.org/10.1007/s10729-013-9231-5

Ministerie van Algemene Zaken. (2023, May 16). *Rijksjaarverslag: inkomsten en uitgaven*. Verantwoordingsdag | Rijksoverheid.nl. https://www.rijksoverheid.nl/onderwerpen/verantwoordingsdag/rijksjaarverslag-inkomsten-en-uitgaven#:~:text=Meer%20dan%20de%20helft%20van,de%20helft%20van%20de%20uitgaven.

Ministerie van Volksgezondheid, Welzijn en Sport. (2022, June 6). *Ziekenhuiszorg | Zorguitgaven*. Volksgezondheid En Zorg. Retrieved March 22, 2024, from https://www.vzinfo.nl/ziekenhuiszorg/zorguitgaven#:~:text=Uitgaven%20ziekenhuiszorg%20geraamd%20op%2029,uitgegeven%20aan%20de%20Nederlandse%20gezondheidszorg

Ministerie van Volksgezondheid, Welzijn en Sport. (2023, September 19). *Kabinet zet in op toegankelijkheid en betaalbaarheid zorg in 2024*. Nieuwsbericht | Rijksoverheid.nl. https://www.rijksoverheid.nl/actueel/nieuws/2023/09/19/kabinet-zet-in-op-toegankelijkheid-en-betaalbaarheid-zorg-in-2024

Ministerie van Volksgezondheid, Welzijn en Sport. (2024, January 31). *Personeelstekorten in de zorg*. Inspectie Gezondheidszorg En Jeugd. https://www.igj.nl/onderwerpen/personeelstekort

Ministerie van VWS. (2023). Feitenreconstructie Tijdlijn: IC-capaciteit en beademingsapparatuur. In *Ministerie Van Volksgezondheid, Welzijn En Sport*. Retrieved June 19, 2024, from https://www.eerstekamer.nl/overig/20230914/interactieve_tijdlijn_ic_3/document#:~:text=In%20totaal%20gaat%20het%20om,bezetting%20door%20COVID%2D19%20pati%C3%ABnten

Monnickendam, G., & De Asmundis, C. (2018). Why the distribution matters: Using discrete event simulation to demonstrate the impact of the distribution of procedure times on hospital operating room utilisation and average procedure cost. *Operations Research for Health Care*, *16*, 20–28. https://doi.org/10.1016/j.orhc.2017.12.001

Montgomery, D. C., & Runger, G. C. (2010). *Applied Statistics and Probability for Engineers*. John Wiley & Sons.

MSc Engineering and Policy Analysis. (2024). Tu Delft. Retrieved May 28, 2024, from https://www.tudelft.nl/onderwijs/opleidingen/masters/epa/msc-engineering-and-policy-analysis

NOS. (2020, December 22). *Nog maar enkele bedden op kinder-IC's beschikbaar door coronahulp aan volwassenen*. https://nos.nl/artikel/2361629-nog-maar-enkele-bedden-op-kinder-ic-s-beschikbaar-door-coronahulp-aan-volwassenen

Oliveira, M., Visintin, F., Santos, D. T., & Marqués, I. (2022). Flexible master surgery scheduling: combining optimisation and simulation in a rolling horizon approach. *Flexible Services and Manufacturing Journal*, *34*(4), 824–858. https://doi.org/10.1007/s10696-021-09422-x

Olsen, M., & Raunak, M. (2019). Quantitative measurements of model credibility. In *Elsevier eBooks* (pp. 163–187). https://doi.org/10.1016/b978-0-12-813543-3.00008-1

Patel, S. K., Kacheriwala, S. M., & Duttaroy, D. D. (2018). Audit of postoperative surgical intensive care unit admissions. *Indian Journal of Critical Care Medicine/Indian Journal of Critical Care Medicine*, *22*(1), 10–15. https://doi.org/10.4103/ijccm.ijccm_387_17

Persson, M., Hvitfeldt-Forsberg, H., Unbeck, M., Sköldenberg, O., Stark, A. M., Kelly-Pettersson, P., & Mazzocato, P. (2017). Operational strategies to manage non-elective orthopaedic surgical flows: a simulation modelling study. *BMJ Open*, *7*(4), e013303. https://doi.org/10.1136/bmjopen-2016-013303

Qiao, D., & Wang, Y. (2021). A review of the application of discrete event simulation in manufacturing. *Journal of Physics: Conference Series*, *1802*(2), 022066. https://doi.org/10.1088/1742-6596/1802/2/022066

Rachuba, S., Imhoff, L., & Werners, B. (2022). Tactical blueprints for surgical weeks – An integrated approach for operating rooms and intensive care units. *European Journal of Operational Research*, *298*(1), 243–260. https://doi.org/10.1016/j.ejor.2021.06.005

Reddy, A., & Scheinker, D. (2020, November 13). *The Case For Mathematical Optimisation In Health Care: Building A Strong Foundation For Artificial*. Health Affairs. Retrieved March 26, 2024, from https://www.healthaffairs.org/content/forefront/case-mathematical-optimisation-health-care-building-strong-foundation-artificial

Rifi, L., Fontanili, F., Martinez, C., Di Mascolo, M., & Fortineau, V. (2022). A Simulation-Based approach for assessing the impact of uncertainty on patient waiting time in the operating room. *2022 Winter Simulation Conference (WSC)*. https://doi.org/10.1109/wsc57314.2022.10015253

RIVM. (n.d.). *Postponed healthcare during coronavirus pandemic - consequences for health*. https://www.rivm.nl/en/coronavirus-covid-19/research/postponed-healthcare#:~:text=It%20found%20that%2C%20by%20the,years%20in%202020%20and%202021

Robone, S., Rice, N., & Smith, P. (2011). Health Systems' responsiveness and its Characteristics: A Cross-Country Comparative Analysis. *Health Services Research*, *46*(6pt2), 2079–2100. https://doi.org/10.1111/j.1475-6773.2011.01291.x

Saadouli, H., Jerbi, B., Dammak, A., Masmoudi, L., & Bouaziz, A. (2015). A stochastic optimisation and simulation approach for scheduling operating rooms and recovery beds in an orthopedic surgery department. *Computers & Industrial Engineering*, *80*, 72–79. https://doi.org/10.1016/j.cie.2014.11.021

Sciomachen, A., Tanfani, E., & Testi, A. (2005). Simulation models for optimal schedules of operating theatres. *International Journal of Simulation*, *6*(12–13), 26–34.

Smith, H., Varshoei, P., Boushey, R. P., & Kuziemsky, C. (2020). Use of simulation modeling to inform decision making for health care systems and policy in colorectal cancer screening: Protocol for a systematic review. *JMIR Research Protocols*, *9*(5), e16103. https://doi.org/10.2196/16103

Stanimirović, D., & Brinovec, R. P. (2023). Management of health care workforce. *Management : Journal of Contemporary Management Issues*, *28*(1), 29–43. https://doi.org/10.30924/mjcmi.28.1.3

Tien, J. M., & Goldschmidt-Clermont, P. J. (2009). Healthcare: A complex service system. *Journal of Systems Science and Systems Engineering*, *18*(3), 257–282. https://doi.org/10.1007/s11518-009-5108-z

Traoré, M. K., Zacharewicz, G., Duboz, R., & Zeigler, B. P. (2019). Modeling and simulation framework for value-based healthcare systems. *SIMULATION*, *95*(6), 481–497. https://doi.org/10.1177/0037549718776765

Van der Ham, R. (2024, March 15). *Salabim 24.0.5 documentation*. Salabim. https://salabim.org/manual/About.html

Vázquez-Serrano, J. I., Peimbert-García, R. E., & Cárdenas–Barrón, L. E. (2021). Discrete-Event Simulation Modeling in Healthcare: A Comprehensive review. *International Journal of Environmental Research and Public Health*, *18*(22), 12262. https://doi.org/10.3390/ijerph182212262

Vos, K. (2020). *Optimising OR planning* [Master Thesis, TU Delft]. https://repository.tudelft.nl/islandora/object/uuid%3Aa808976d-31a5-40a1-bd14-e978f6e414ff?collection=education

Wang, L., & Demeulemeester, E. (2023). Simulation optimisation in healthcare resource planning: A literature review. *IISE Transactions*, *55*(10), 985–1007. https://doi.org/10.1080/24725854.2022.2147606

Wang, Z., & Dexter, F. (2022). More accurate, unbiased predictions of operating room times increase labor productivity with the same staff scheduling provided allocated hours are increased. *Perioperative Care and Operating Room Management*, *29*, 100286. https://doi.org/10.1016/j.pcorm.2022.100286

Xiang, W., Yin, J., & Lim, G. J. (2015). An ant colony optimisation approach for solving an operating room surgery scheduling problem. *Computers & Industrial Engineering*, *85*, 335–345. https://doi.org/10.1016/j.cie.2015.04.010

Xiao, Y., & Yoogalingam, R. (2022). A simulation optimisation approach for planning and scheduling in operating rooms for elective and urgent surgeries. *Operations Research for Health Care*, *35*, 100366. https://doi.org/10.1016/j.orhc.2022.100366

Xie, J., Zhang, T., Blanchet, J., Glynn, P. W., Randolph, M., & Scheinker, D. (2022). The design and implementation of a broadly applicable algorithm for optimising Intra-Day surgical scheduling. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2203.08146

Yates, L. A., Aandahl, Z., Richards, S. A., & Brook, B. W. (2023). Cross validation for model selection: A review with examples from ecology. *Ecological Monographs*, *93*(1). https://doi.org/10.1002/ecm.1557

Yuen, A., & Wu, H. E. (2017). *Hospital Patient Flow Capacity Planning Simulation Model at Vancouver Coastal Health* [67th Annual Conference and Expo of the Institute of Industrial Engineers]. 67th Annual Conference and Expo of the Institute of Industrial Engineers 2017, Pitsburg, United States of America.

Zeng, Z., Xie, X., Li, J., Menaker, H., & Sanford-Ring, S. G. (2014). *An analytical model for performance evaluation of operating room schedules in orthopedic surgery* [IEEE International Conference on Automation Science and Engineering]. https://doi.org/10.1109/coase.2014.6899383

Zhang, X. (2018). Application of discrete event simulation in health care: a systematic review. *BMC Health Services Research*, *18*(1). https://doi.org/10.1186/s12913-018-3456-4

APPENDIX A HREC APPROVAL LETTER

Date 16-Jul-2024
Correspondence hrec@tudelft.nl

Human Research Ethics
Committee TU Delft
(http://hrec.tudelft.nl)

Visiting address
Jaffalaan 5 (building 31)
2628 BX Delft

Postal address
P.O. Box 5015 2600 GA Delft
The Netherlands

Ethics Approval Application: Thesis about simulation of hospital scheduling
Applicant: Vilsteren, Luna van

Dear Luna van Vilsteren,

It is a pleasure to inform you that your application mentioned above has been approved.

Thanks very much for your submission to the HREC which has been approved.

In addition to any specific conditions or notes, the HREC provides the following standard advice to all applicants:
• In light of recent tax changes, we advise that you confirm any proposed remuneration of research subjects with your faculty contract manager before going ahead.
• Please make sure when you carry out your research that you confirm contemporary covid protocols with your faculty HSE advisor, and that ongoing covid risks and precautions are flagged in the informed consent - with particular attention to this where there are physically vulnerable (eg: elderly or with underlying conditions) participants involved.
• Our default advice is not to publish transcripts or transcript summaries, but to retain these privately for specific purposes/checking; and if they are to be made public then only if fully anonymised and the transcript/summary itself approved by participants for specific purpose.
• Where there are collaborating (including funding) partners, appropriate formal agreements including clarity on responsibilities, including data ownership, responsibilities and access, should be in place and that relevant aspects of such agreements (such as access to raw or other data) are clear in the Informed Consent.

Good luck with your research!

Sincerely,

Dr. Ir. U. Pesch
Chair HREC
Faculty of Technology, Policy and Management

APPENDIX B SCHEDULES

TABLE B.1: SCHEDULE FROM MODEL A

DAY	MRI	1	2	3	4	5	6	7	8	9	10
1		GYN: 2	LOS: 1	KIC: 3		PLCH: 1,1	PLCH: 1,1	URO: 2,1,4	ORTR: 1	CAS: 3,2,1	NEC: 3
2	RON: 1,1,1,1,1,1	GYN: 2	KNO: 1,2,1,3	GAS: 1,3		KNO: 2,5		KIC: 2,2,2,1	ORTO: 3,1		PLCO: 5
3		GYN: 2		KNO: 2,4	KNO: 1,2,5	URO: 2,1,5		KIC: 2,2,2,2,1	ORTO: 3,1	CAS: 1,1,3	PLCO: 4,1
4		GYN: 1	LOS: 1	KIC: 1	ORTO: 2,1	URO: 1,1,5	PLCO: 2,3	KIC: 3,1	ORTR: 1		NEC: 4
5	RON: 1,1,1,1,1,2	GYN: 2		KNO: 4,2	OOG: 2,2 DER: 1,1	URO: 2,1,4	KIC: 5	KIC: 3,2,1	ORTO: 4		ORTO: 4
8	RON: 1,1,1,1,1,2	GYN: 2	LOS: 1	KIC: 4		URO: 1,2,4	PLCH: 1,1		ORTR: 1	CAS: 3,2,1	NEC: 4
9	RON: 1,1,1,1,1,2	GYN: 2	KNO: 4,2	GAS: 1,3,2		KNO: 1,1,1,2,3		KIC: 3,2,3	ORTO: 3,1		PLCO: 4,1
10		GYN: 2			KNO: 4,2	URO: 2,2,5	KAA: 2,3,2	KIC: 5,1	ORTO: 3,1	CAS: 3,3	PLCO: 2,2,1
11		GYN: 2	LOS: 1	KIC: 5	ORTO: 2,1	URO: 1,2,4	PLCO: 2,2,1	KIC: 2,2,2,1	ORTR: 1		NEC: 2,2,1
12	RON: 1,1,1,1,1,2	GYN: 3		KNO: 2,1,5	TAN: 1,1	URO: 1,3,5	KIC: 4	KIC: 3,2,1	ORTO: 3,1		ORTO: 3,1
15		GYN: 2	LOS: 1	KIC: 5		PLCH: 1,1	PLCH: 1,1	URO: 2,1,4	ORTR: 1	CAS: 3,2,1	NEC: 4
16	RON: 1,1,1,1,1,2	GYN: 2	KNO: 5,2	GAS: 1,2		KNO: 1,1,1,1,3		KIC: 2,2,2,1	ORTO: 4		PLCO: 2,3
17		GYN: 2			KNO: 2,2,1,3	URO: 1,2,4	KAA: 3,3	KIC: 2,2,2,2,1	ORTO: 3,1	CAS: 3,2	PLCO: 4,1
18		GYN: 1	LOS: 1	KIC: 3	ORTO: 2,1	URO: 3,1,3	PLCO: 2,3	KIC: 2,2,2,1	ORTR: 1		NEC: 1,1,1
19	RON: 1,1,1,1,1,2	GYN: 2		KNO: 2,2,1,2	OOG: 2,2 DER: 1,1	URO: 2,1,4	KIC: 3	KIC: 3,2,1	ORTO: 3,1		ORTO: 4
22	RON: 1,1,1,1,1,2	GYN: 2	LOS: 1	KIC: 5		URO: 1,2,4	PLCH: 1,1		ORTR: 1	CAS: 3,3	NEC: 2,2
23	RON: 1,1,1	GYN: 2	KNO: 1,2,5	GAS: 1,1,1	NEU: 1,1,1	KNO: 1,1,1,1,1,3		KIC: 5,3	ORTO: 2,1		PLCO: 5
24		GYN: 2			KNO: 4,2	URO: 2,2,2,1	KAA: 1,1,1,1	KIC: 5,1	ORTO: 2,1	CAS: 2,1,3	PLCO: 5
25		GYN: 2	LOS: 1	KIC: 4	ORTO: 2,1	URO: 2,2,2,1	PLCO: 2,3	KIC: 2,3,1	ORTR: 1		NEC: 1,1,1
26	RON: 1,1,1,1,1,2	GYN: 3		KNO: 2,1,2,3	OOG: 2,2,1,1,1	URO: 2,2,5	KIC: 4	KIC: 3,2,1	ORTO: 4		ORTO: 4

TABLE B.2: SCHEDULE FROM MODEL B

Day	MRI	1	2	3	4	5	6	7	8	9	10
1		GYN: 2	LOS: 1	KIC: 4		PLCH: 1,1	PLCH: 1,1	URO: 1,1,5	ORTR: 1	CAS: 1,2,3	NEC: 3
2	RON: 1,1,1,1,1,1	GYN: 3	KNO: 1,2,1,3	GAS: 2,1		KNO: 2,5		KIC: 3,1	ORTO: 3,1		PLCO: 2,3
3		GYN: 2		KNO: 2,4	KNO: 1,2,5	URO: 2,1,4		KIC: 2,3,1	ORTO: 3,1	CAS: 3,3	PLCO: 4,1
4		GYN: 1	LOS: 1	KIC: 1	ORTO: 2,1	URO: 3,4	PLCO: 2,3	KIC: 2,2,2,1	ORTR: 1		NEC: 4
5	RON: 1,1,1,1,1,2	GYN: 2		KNO: 4,2	OOG: 2,2 DER,1,1	URO: 2,2,5	KIC: 5	KIC: 2,3,1	ORTO: 2,1		ORTO: 2,1
8	RON: 1,1,1,1,1,2	GYN: 2	LOS: 1	KIC: 4		URO: 1,2,4	PLCH: 1,1		ORTR: 1	CAS: 3,1	NEC: 4
9	RON: 1,1,1,1,1,2	GYN: 3	KNO: 4,2	GAS: 3,1,2		KNO: 1,1,1,2,3		KIC: 3,5	ORTO: 3,1		PLCO: 4,1
10		GYN: 2			KNO: 4,2	URO: 1,3,5	KAA: 3,2,2	KIC: 2,3,3	ORTO: 3,1	CAS: 3,1,2	PLCO: 2,2,1
11		GYN: 2	LOS: 1	KIC: 5	ORTO: 2,1	URO: 1,2,4	PLCO: 2,2,1	KIC: 2,2,2,1	ORTR: 1		NEC: 4
12	RON: 1,1,1,1,1,2	GYN: 2		KNO: 2,1,5	TAN: 1,1	URO: 1,2,4	KIC: 5	KIC: 2,2,2,2,1	ORTO: 2,1		ORTO: 4
15		GYN: 2	LOS: 1	KIC: 5		PLCH: 1,1	PLCH: 1,1	URO: 2,2,5	ORTR: 1	CAS: 3,1,2	NEC: 2,1,2
16	RON: 1,1,1,1,2	GYN: 2	KNO: 5,2	GAS: 1,1		KNO: 1,1,1,1,3		KIC: 3,3	ORTO: 3,1		PLCO: 5
17		GYN: 2			KNO: 2,2,1,3	URO: 1,2,4	KAA: 3,1,1	KIC: 3,2,1	ORTO: 2,1	CAS: 3,1,2	PLCO: 4,1
18		GYN: 1	LOS: 1	KIC: 4	ORTO: 1	URO: 1,2,2	PLCO: 2,3	KIC: 2,2,2,1	ORTR: 1		NEC: 2,1,1
19	RON: 1,1,1,1,1,2	GYN: 2		KNO: 2,2,1,2	OOG: 2,2 DER,1,1	URO: 5,3	KIC: 1	KIC: 3,2,1	ORTO: 3,1		ORTO: 3,1
22	RON: 1,1,1,1,1,2	GYN: 2	LOS: 1	KIC: 4		URO: 1,2,4	PLCH: 1,1		ORTR: 1	CAS: 3,3	NEC: 2,1,1
23	RON: 1,1,1	GYN: 2	KNO: 1,2,5	GAS: 3,1,1	NEU: 1,1,1	KNO: 1,1,1,1,1,3		KIC: 2,2,2,2,1	ORTO: 4		PLCO: 5
24		GYN: 2			KNO: 4,2	URO: 2,2,2,1	KAA: 3,1,1	KIC: 3,2,1	ORTO: 4	CAS: 2,1,3	PLCO: 5
25		GYN: 2	LOS: 1	KIC: 1	ORTO: 4	URO: 2,2,2,1	PLCO: 2,3	KIC: 2,2,2,2,1	ORTR: 1		NEC: 1,1,1
26	RON: 1,1,1,1,1,2	GYN: 2		KNO: 2,1,2,3	OOG: 2,2,1,1,1	URO: 1,2,1	KIC: 5	KIC: 3,5	ORTO: 4		ORTO: 4

TABLE B.3: SCHEDULE FROM MODEL C

Day	MRI	1	2	3	4	5	6	7	8	9	10
1		GYN: 2	LOS: 1	KIC: 3		PLCH: 1,1	PLCH: 1,1	URO: 2,2,2,1	ORTR: 1		NEC: 2,1,2
2	RON: 1,1,1,1,1,1	GYN: 2	KNO: 2,2,3	GAS: 3,1		KNO: 2,1,1,2		KIC: 3,3	ORTO: 2,1		PLCO: 5
3				KNO: 1,2,1,2	KNO: 4,2	URO: 2,1,4		KIC: 2,2,2,3	ORTO: 1	CAS: 3,3	PLCO: 5
4		GYN: 2	LOS: 1	KIC: 1	ORTO: 2,1	URO: 2,1,3	PLCO: 2,3	KIC: 2,2,1	ORTR: 1		NEC: 1,1
5	RON: 1,1,1,1,1,2	GYN: 2		KNO: 2,3,2	OOG: 2,2 DER,1,1	URO: 2,2,5	KIC: 5	KIC: 5,1	ORTO: 4		ORTO: 4
8	RON: 1,1,1,1,1,2	GYN: 2	LOS: 1	KIC: 4		URO: 2,1,4	PLCH: 1,1		ORTR: 1	CAS: 3,1,2	NEC: 4
9	RON: 1,1,1,1,1,2	GYN: 2	KNO: 4,2	GAS: 1,1,2		KNO: 1,1,1,5		KIC: 3,5	ORTO: 3,1		PLCO: 4,1
10		GYN: 2			KNO: 2,4	URO: 2,1,4	KAA: 3,2,2	KIC: 2,2,2,1	ORTO: 2,1	CAS: 3,1,1	PLCO: 5
11		GYN: 1	LOS: 1	KIC: 3	ORTO: 2,1	URO: 1,2,4	PLCO: 2,3	KIC: 2,2,2,1	ORTR: 1		NEC: 2
12	RON: 1,1,1,1,1,2	GYN: 2		KNO: 2,1,5	TAN: 1,1	URO: 5,5		KIC: 3,1	ORTO: 1		ORTO: 3,1
15		GYN: 2	LOS: 1	KIC: 5		PLCH: 1,1	PLCH: 1,1	URO: 2,1,4	ORTR: 1	CAS: 3,2	NEC: 3
16	RON: 1,1,1,1,2	GYN: 3	KNO: 2,5	GAS: 1,3		KNO: 1,1,2,3		KIC: 3,1	ORTO: 2,1		PLCO: 2,1
17		GYN: 2			KNO: 1,2,1,1,2	URO: 1,2,4	KAA: 3,1,1	KIC: 3,2,1	ORTO: 1	CAS: 3,3	PLCO: 4,1
18		GYN: 2	LOS: 1	KIC: 4	ORTO: 2,1	URO: 1,1,1	PLCO: 2,3	KIC: 2,2,1	ORTR: 1		NEC: 4
19	RON: 1,1,1,1,1,2			KNO: 4,2	OOG: 2,2 DER,1,1	URO: 3,3,2	KIC: 5	KIC: 4,1	ORTO: 4		ORTO: 4
22	RON: 1,1,1,1,1,2	GYN: 2	LOS: 1	KIC: 4		URO: 1,2,4	PLCH: 1,1		ORTR: 1	CAS: 3,1,2	NEC: 4
23	RON: 1,1,1	GYN: 2	KNO: 3,1,1,3	GAS: 2,1,1	NEU: 1,1,1	KNO: 3,5		KIC: 3,5	ORTO: 3,1		PLCO: 1
24		GYN: 1			KNO: 2,1,1,1,1	URO: 2,2,5	KAA: 3,1,1	KIC: 2,2,2,1	ORTO: 1	CAS: 1,2,3	PLCO: 4,1
25		GYN: 2	LOS: 1	KIC: 2	ORTO: 1	URO: 2,2,2,1	PLCO: 2,3	KIC: 2,2,2	ORTR: 1		NEC: 1,2
26	RON: 1,1,1,1,1,2	GYN: 2		KNO: 4	OOG: 2,2,1,1,1	URO: 5,1		KIC: 2,2,1	ORTO: 4		ORTO: 4

TABLE B.4: SCHEDULE FROM MODEL D

Day	MRI	1	2	3	4	5	6	7	8	9	10
1		GYN: 2	LOS: 1	KIC: 3		PLCH: 1,1	PLCH: 1,1	URO: 1,2,4	ORTR: 1	CAS: 3,1,2	NEC: 4
2	RON: 1,1,1,1,1,1	GYN: 2	KNO: 1,1,2,3	GAS: 1,1		KNO: 1,1,5		KIC: 3,3	ORTO: 2,1		PLCO: 5
3		GYN: 2		KNO: 1,2,1,1,2	KNO: 2,1,1,3	URO: 3,1,5		KIC: 2,2,2,1	ORTO: 2,1	CAS: 3,3	PLCO: 4,1
4		GYN: 1	LOS: 1	KIC: 1	ORTO: 1	URO: 3,2,2	PLCO: 2,3	KIC: 2,2,2	ORTR: 1		NEC: 1,1,1
5	RON: 1,1,1,1,1,2	GYN: 2		KNO: 4,1	OOG: 2,2 DER,1,1	URO: 2,1,4	KIC: 5	KIC: 5,1	ORTO: 4		ORTO: 4
8	RON: 1,1,1,1,1,2	GYN: 2	LOS: 1	KIC: 4		URO: 1,2,4	PLCH: 1,1		ORTR: 1		NEC: 2,2
9	RON: 1,1,1,1,1,2	GYN: 2	KNO: 1,1,2,1,3	GAS: 1,3,1		KNO: 4,2		KIC: 3,5	ORTO: 3,1		PLCO: 5
10		GYN: 2			KNO: 2,2,1,2	URO: 3,1,5	KAA: 3,1,1	KIC: 2,2,2,1	ORTO: 2,1	CAS: 2,3	PLCO: 4,1
11		GYN: 1	LOS: 1	KIC: 1	ORTO: 2,1	URO: 2,2,2	PLCO: 2,3	KIC: 2,2,1	ORTR: 1		NEC: 1,2
12	RON: 1,1,1,1,1,2	GYN: 2		KNO: 2,5	TAN: 1,1	URO: 2,2,5		KIC: 4,1	ORTO: 4		ORTO: 1
15		GYN: 2	LOS: 1	KIC: 3		PLCH: 1,1	PLCH: 1,1	URO: 1,2,5	ORTR: 1	CAS: 1,3,2	NEC: 4
16	RON: 1,1,1,1,2	GYN: 3	KNO: 1,1,5	GAS: 3,2		KNO: 1,1,2,2		KIC: 2,5	ORTO: 2,1		PLCO: 2,1
17		GYN: 2			KNO: 2,4	URO: 1,2,4	KAA: 3,1,1	KIC: 2,2,2,1	ORTO: 3,1	CAS: 3,1,2	PLCO: 4,1
18			LOS: 1	KIC: 1	ORTO: 1	URO: 1,2,1	PLCO: 2,3	KIC: 2,2,2,1	ORTR: 1		NEC: 3
19	RON: 1,1,1,1,1,2	GYN: 2		KNO: 4,2	OOG: 2,2 DER,1,1	URO: 2,1,4		KIC: 3,5	ORTO: 4		ORTO: 4
22	RON: 1,1,1,1,1,2	GYN: 2	LOS: 1	KIC: 4		URO: 1,2,4	PLCH: 1,1		ORTR: 1	CAS: 3,3	NEC: 2
23	RON: 1,1,1	GYN: 2	KNO: 4,2	GAS: 1,1,2	NEU: 1,1,1	KNO: 2,3,3		KIC: 2,3,1	ORTO: 3,1		PLCO: 1
24		GYN: 2			KNO: 2,2,1,3	URO: 1,2,4	KAA: 2,2,3	KIC: 2,3,3	ORTO: 2,1	CAS: 1,3,1	PLCO: 5
25		GYN: 2	LOS: 1	KIC: 1	ORTO: 1	URO: 2,2,2,1	PLCO: 2,3	KIC: 2,2,2,1	ORTR: 1		NEC: 4
26	RON: 1,1,1,1,1,2			KNO: 2,5	OOG: 2,2,1,1,1	URO: 5,1		KIC: 3,5	ORTO: 4		ORTO: 4

APPENDIX C GROUPINGS

TABLE C.1: SURGERY GROUPINGS

	1		2		3		4		5	
	SURGERY DURATION	**LOS**	**SURGERY DURATION**	**LOS**	**SURGERY DURATION**	**LOS**	**SURGERY DURATION**	**LOS**	**SURGERY DURATION**	**LOS**
Dental surgery (TAN)	79 - 147									
Dermatology (DER)	20 - 159									
Gastroenterology (GAS)	≤ 48		48 - 58		> 58					
Gynecology (GYN)	≤ 68		68 - 95		> 95					
Maxillofacial surgery (KAA)	≤ 84		84 - 128		> 128					
Neurological surgery (NEC)	≤ 117	≤ 7392	117 - 154	≤ 7392	> 154	≤ 7392		> 7392		
Neurology (NEU)	26-168									
Ophthalmology (OOG)	≤ 71		> 71							
Orthopedic surgery - spinal (ORT)	98-743									
Orthopedic surgery - others (ORT)	≤ 108	≤ 2636	108 - 154	≤ 2636	> 154	≤ 2636		> 2636		
Otorhinolaryngology (KNO)	≤ 54	≤ 1516	54 - 100	≤ 1516	100 - 148	≤ 1516	> 148	≤ 1516		> 1516
Pediatric cardiac surgery (CAS)	≤ 96		96 - 134		> 134					
Pediatric pulmonary disease (LOS)	21-391									
Pediatric surgery (KIC)	≤ 59	≤ 9006	59 - 84	≤ 9006	84 - 163	≤ 9006	> 163	≤ 9006		> 9006
Plastic surgery - hand (PLC)	64-237									
Plastic surgery - others (PLC)	≤ 92	≤ 3489	92 - 135	≤ 3489	135 - 183	≤ 3489	> 183	≤ 3489		> 3489
Radiology (RON)	≤ 76		> 76							
Urology (URO)	≤ 73	≤ 3406	73 - 107	≤ 3406	107 - 127	≤ 3406	> 127	≤ 3406		> 3406

TABLE C.2: OVERVIEW OF THE DIFFERENT GOUPINGS AND SIZES OF TEST AND TRAIN DATA

Group	Category	Group number	Size of train data	Size of test data
1	CAS	1	150	38
2	CAS	2	98	45
3	CAS	3	288	63
4	DER	1	7	15
5	GAS	1	340	103
6	GAS	2	111	33
7	GAS	3	133	24
8	GYN	1	84	29
9	GYN	2	635	266
10	GYN	3	38	13
11	KAA	1	253	65
12	KAA	2	60	34
13	KAA	3	128	40
14	KIC	1	513	136
15	KIC	2	856	317
16	KIC	3	389	116
17	KIC	4	125	26
18	KIC	5	230	84
19	KNO	1	803	205
20	KNO	2	739	247
21	KNO	3	244	60
22	KNO	4	201	68
23	KNO	5	178	39
24	LOS	1	231	66
25	NEC	1	138	50
26	NEC	2	165	39
27	NEC	3	48	13
28	NEC	4	148	37
29	NEU	1	49	19
30	OOG	1	87	20
31	OOG	2	181	63
32	ORTO	1	643	208
33	ORTO	2	263	66
34	ORTO	3	126	46
35	ORTO	4	265	91
36	ORTR	1	216	73
37	PLCH	1	142	50
38	PLCO	1	313	98
39	PLCO	2	304	80
40	PLCO	3	230	69
41	PLCO	4	199	42
42	PLCO	5	199	75
43	RON	1	1643	490
44	RON	2	242	103
45	TAN	1	83	23
46	URO	1	492	156
47	URO	2	649	197
48	URO	3	115	22
49	URO	4	243	82
50	URO	5	161	58

APPENDIX D DISTRIBUTIONS SURGERY DURATION

D.1 BOXPLOTS AND HISTOGRAMS INSIGNIFICANT DISTRIBUTIONS

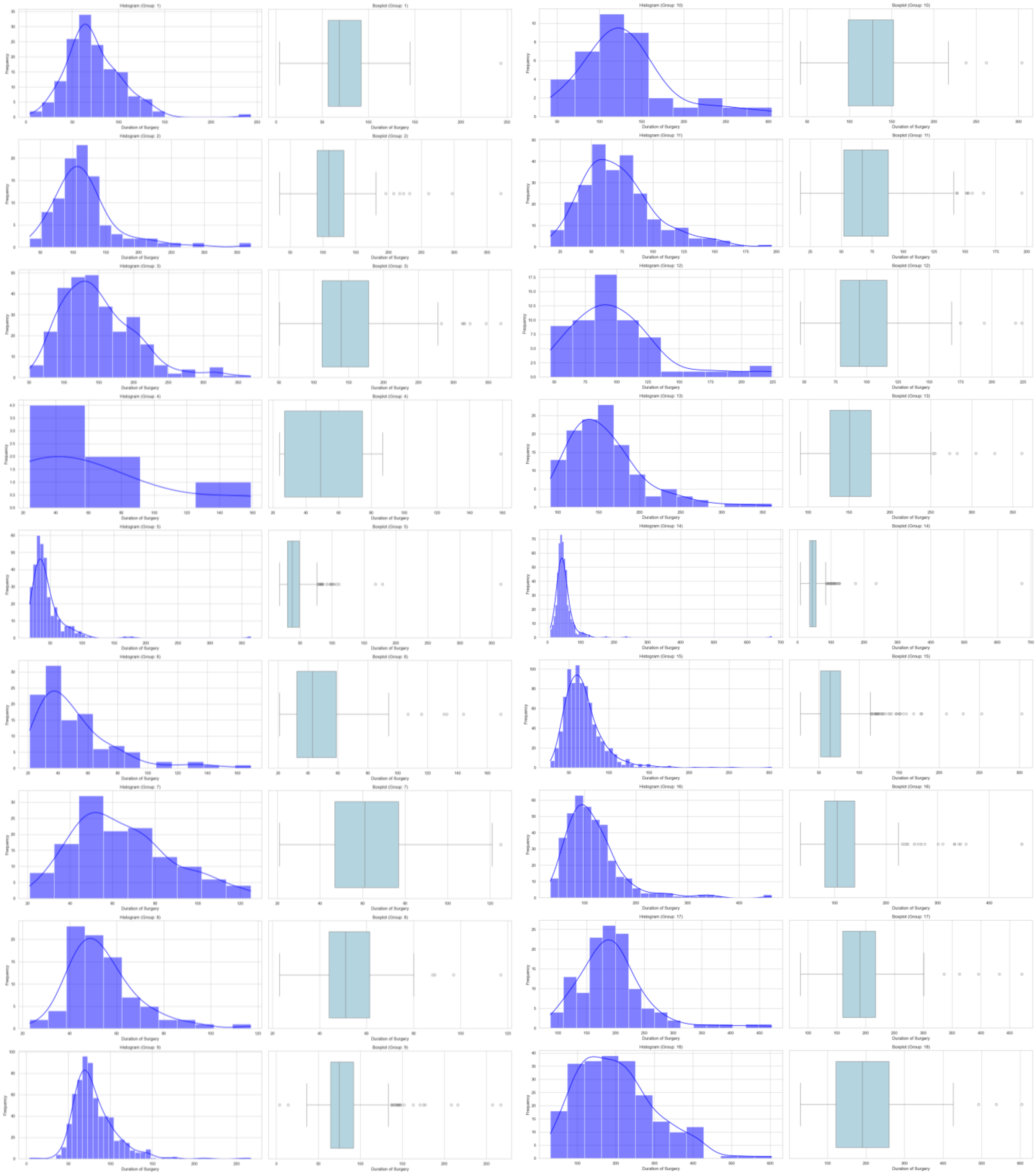


FIGURE D.1: BOXPLOTS AND HISTOGRAMS GROUP 1-18

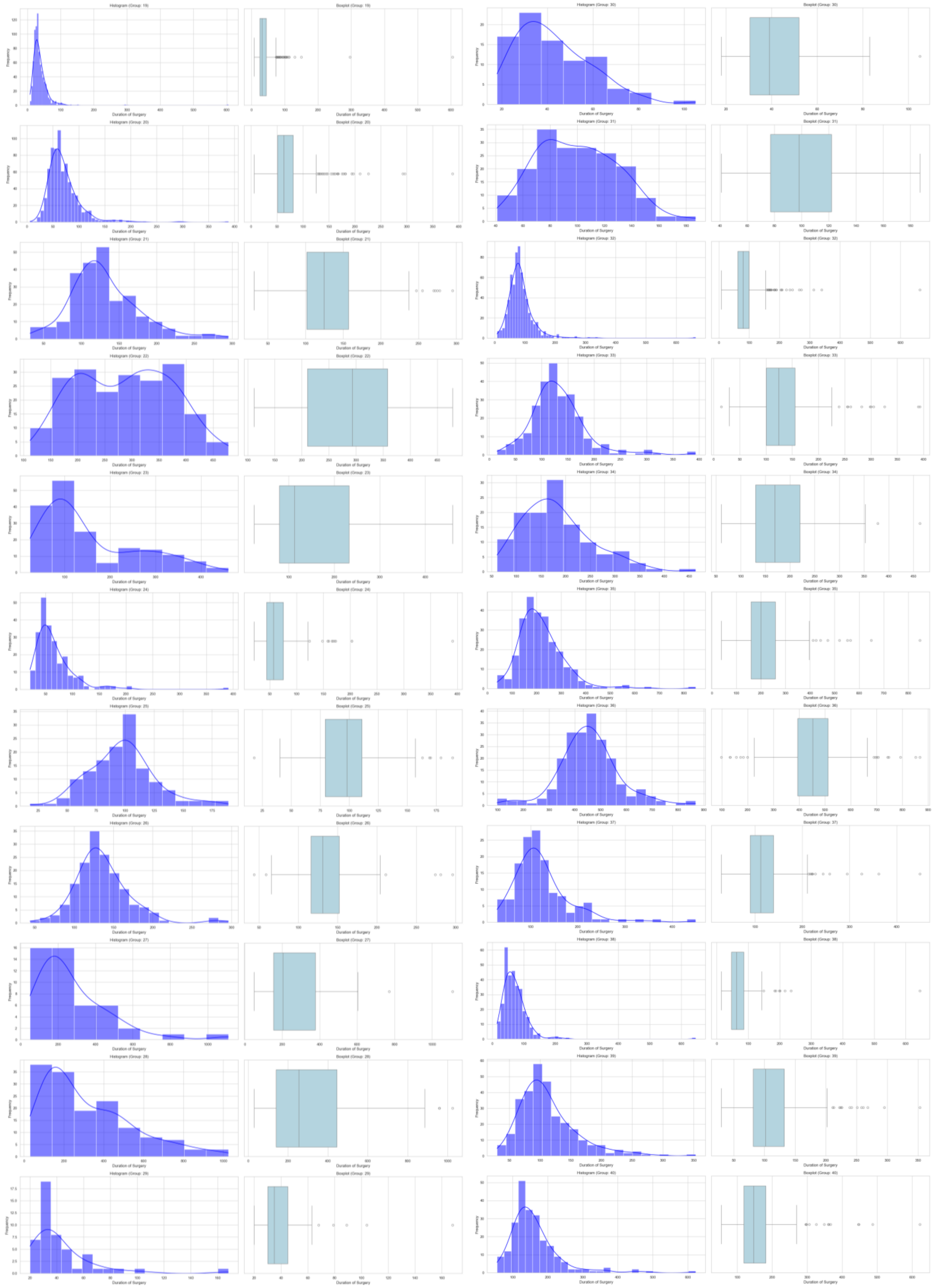


FIGURE D.2: BOXPLOTS AND HISTOGRAMS GROUPS 19-40

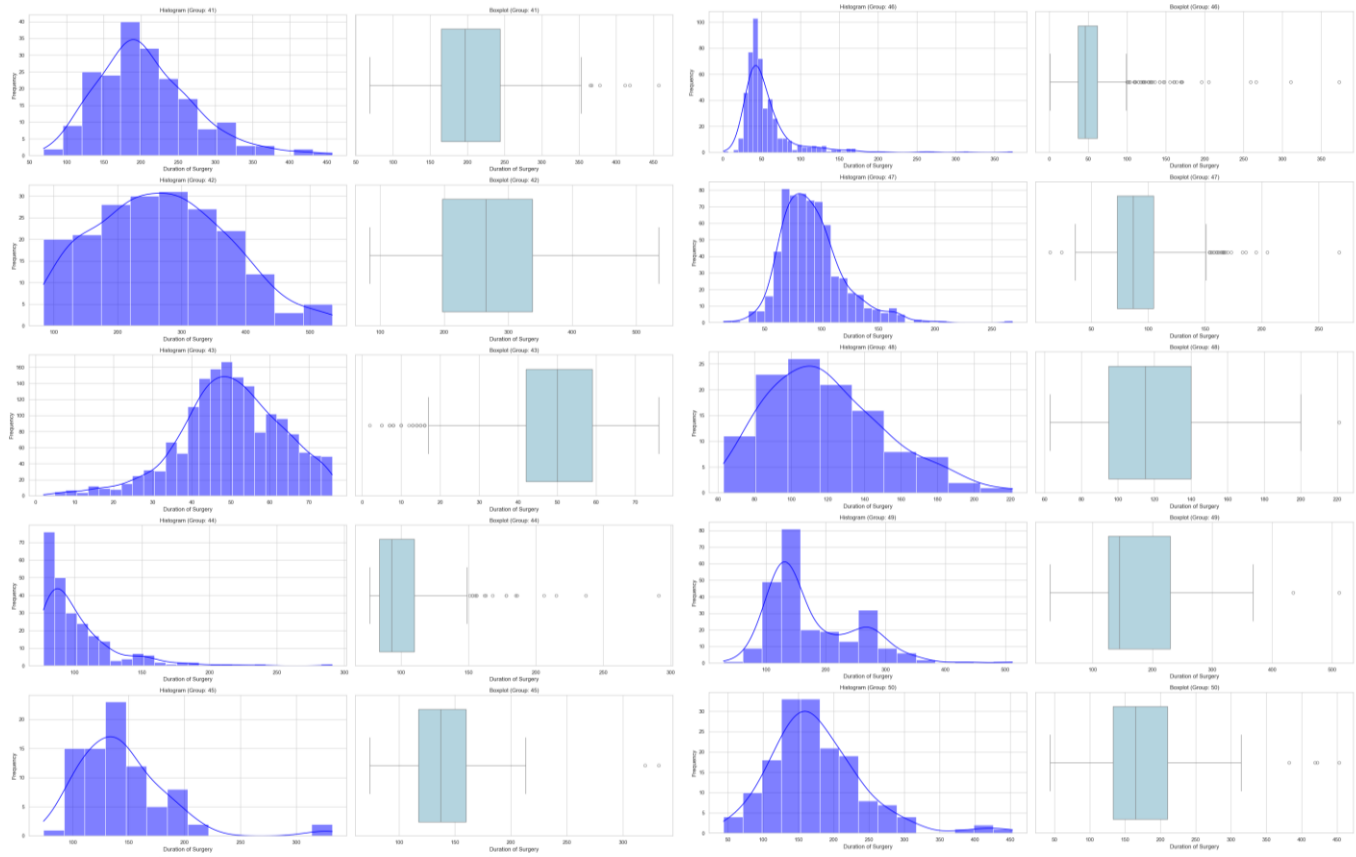


FIGURE D.3: BOXPLOTS AND HISTOGRAMS GROUPS 41-50

D.2 QQ PLOTS

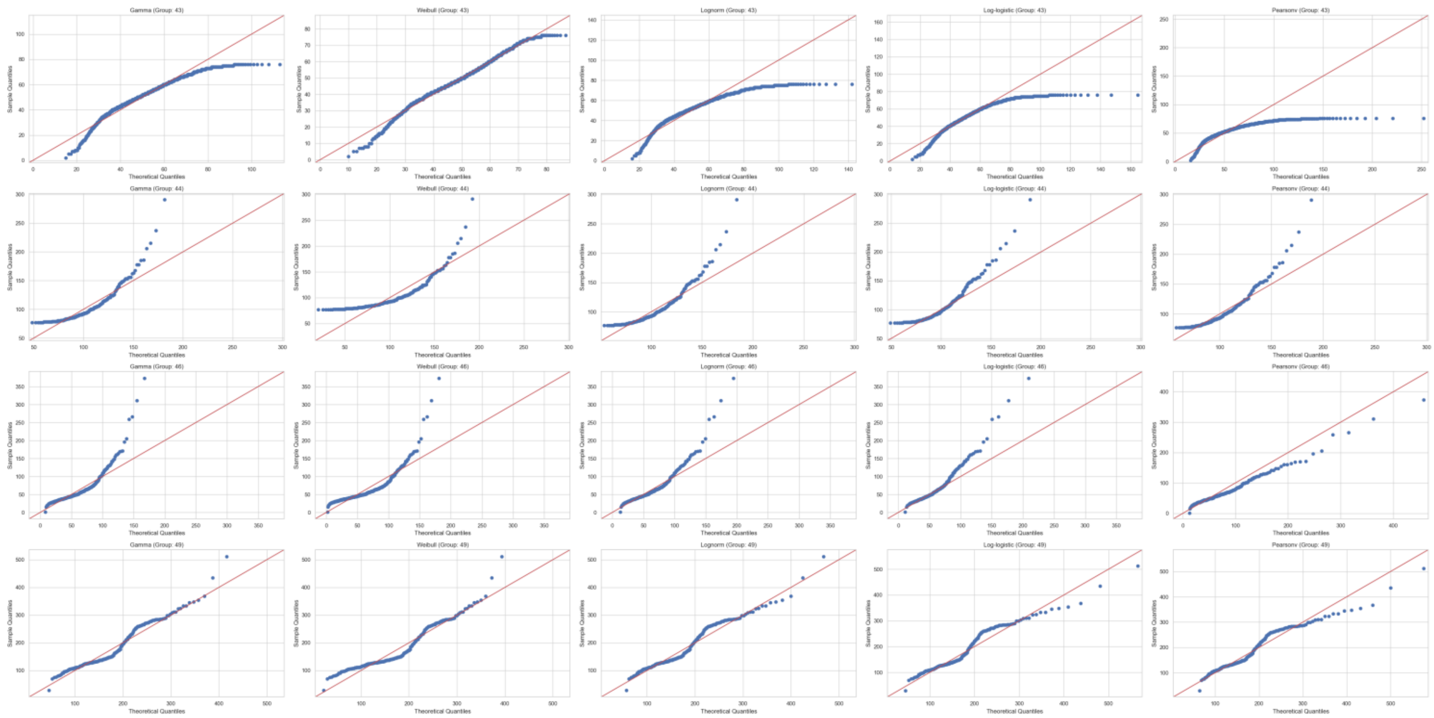


FIGURE D.4: QQ PLOTS GROUPS 43,44,46 AND 49

D.3 PARAMETERS AND CHOSEN DISTRIBUTIONS

TABLE D.1: PARAMETERS DISTRIBUTIONS SURGERY DURATION

Group	Category	Group number	Chosen distribution	Shape	Scale	KS-Test P-value
1	CAS	1	log-logistic	4,236810	69,057729	0,334489
2	CAS	2	log-logistic	4,866781	109,214794	0,765186
3	CAS	3	pearsonV	8,642639	1152,255234	0,765314
4	DER	1	lognorm	0,653978	49,558821	0,747239
5	GAS	1	log-logistic	4,270866	38,628583	0,430337
6	GAS	2	log-logistic	4,106239	44,756759	0,466767
7	GAS	3	pearsonV	7,681114	434,984572	0,744853
8	GYN	1	weibull	3,519952	59,793009	0,091554
9	GYN	2	log-logistic	6,241202	76,655155	0,144942
10	GYN	3	pearsonV	6,065362	681,728814	0,532789
11	KAA	1	pearsonV	5,613337	339,027153	0,220895
12	KAA	2	gamma	8,421799	11,877906	0,701329
13	KAA	3	log-logistic	6,523587	150,592656	0,654185
14	KIC	1	log-logistic	4,489324	44,743484	0,294456
15	KIC	2	log-logistic	5,691900	64,029860	0,633162
16	KIC	3	pearsonV	5,951093	583,085562	0,455238
17	KIC	4	gamma	11,663125	16,698783	0,309663
18	KIC	5	log-logistic	3,196743	181,785443	0,630435
19	KNO	1	pearsonV	5,547880	167,444301	0,409824
20	KNO	2	log-logistic	4,724789	64,453431	0,352014
21	KNO	3	log-logistic	5,141025	124,508361	0,630799
22	KNO	4	log-logistic	5,198326	277,107754	0,067931
23	KNO	5	pearsonV	2,226594	213,665328	0,144902
24	LOS	1	log-logistic	4,025880	57,129014	0,568990
25	NEC	1	log-logistic	5,873789	94,902278	0,257308
26	NEC	2	log-logistic	7,453696	131,807591	0,934236
27	NEC	3	log-logistic	2,741511	222,528130	0,838525
28	NEC	4	pearsonV	2,135145	417,892770	0,088504
29	NEU	1	log-logistic	4,533624	36,876278	0,689544
30	OOG	1	log-logistic	4,574814	39,974655	0,830841
31	OOG	2	pearsonV	10,431100	949,216493	0,215185
32	ORTO	1	log-logistic	4,157636	78,554852	0,172505
33	ORTO	2	log-logistic	4,644299	124,409240	0,647356
34	ORTO	3	pearsonV	6,598911	1036,051604	0,352098
35	ORTO	4	log-logistic	4,389780	202,939472	0,995646
36	ORTR	1	weibull	4,082891	498,876471	0,052917
37	PLCH	1	pearsonV	4,955444	499,357081	0,104709
38	PLCO	1	gamma	4,270718	16,752015	0,412436
39	PLCO	2	log-logistic	4,535536	103,301132	0,936728
40	PLCO	3	log-logistic	4,869976	147,000897	0,775669
41	PLCO	4	pearsonV	10,044147	1882,171991	0,275146
42	PLCO	5	gamma	6,360031	42,262996	0,441046
43	RON	1	weibull	4,340449	55,095229	0,003027
44	RON	2	lognorm	0,266985	98,997899	0,000112
45	TAN	1	log-logistic	7,160879	137,993236	0,983345
46	URO	1	lognorm	0,456665	50,410367	0,000005
47	URO	2	pearsonV	11,029817	926,795474	0,099983
48	URO	3	pearsonV	14,605072	1628,089678	0,903369
49	URO	4	gamma	6,854349	25,682964	0,000008
50	URO	5	pearsonV	6,465899	980,222100	0,080290

APPENDIX E DISTRIBUTIONS LENGTH OF STAY

E.1 HISTOGRAMS AND BOXPLOTS

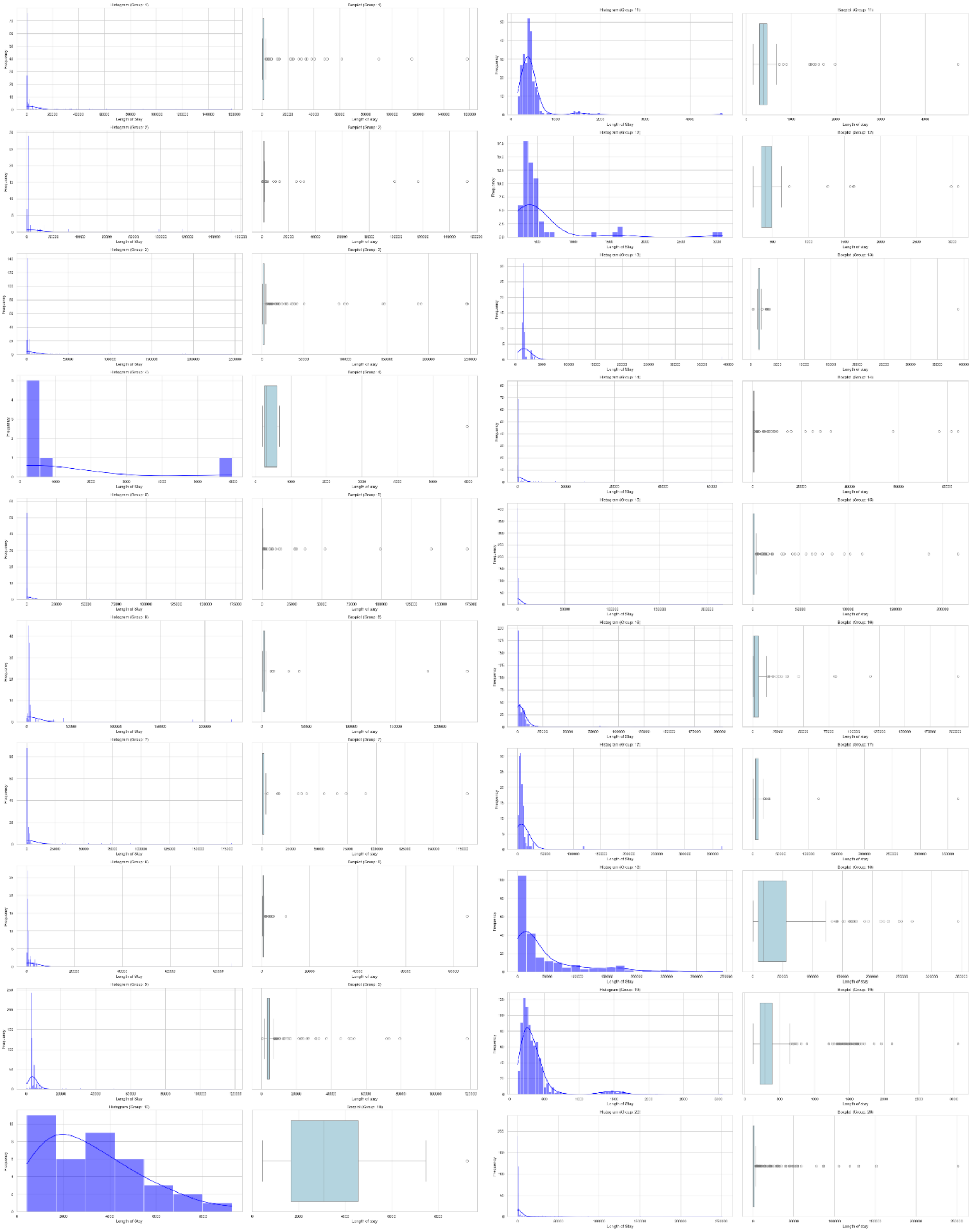


FIGURE E.1: HISTOGRAMS AND BOXPLOTS GROUP 1-20

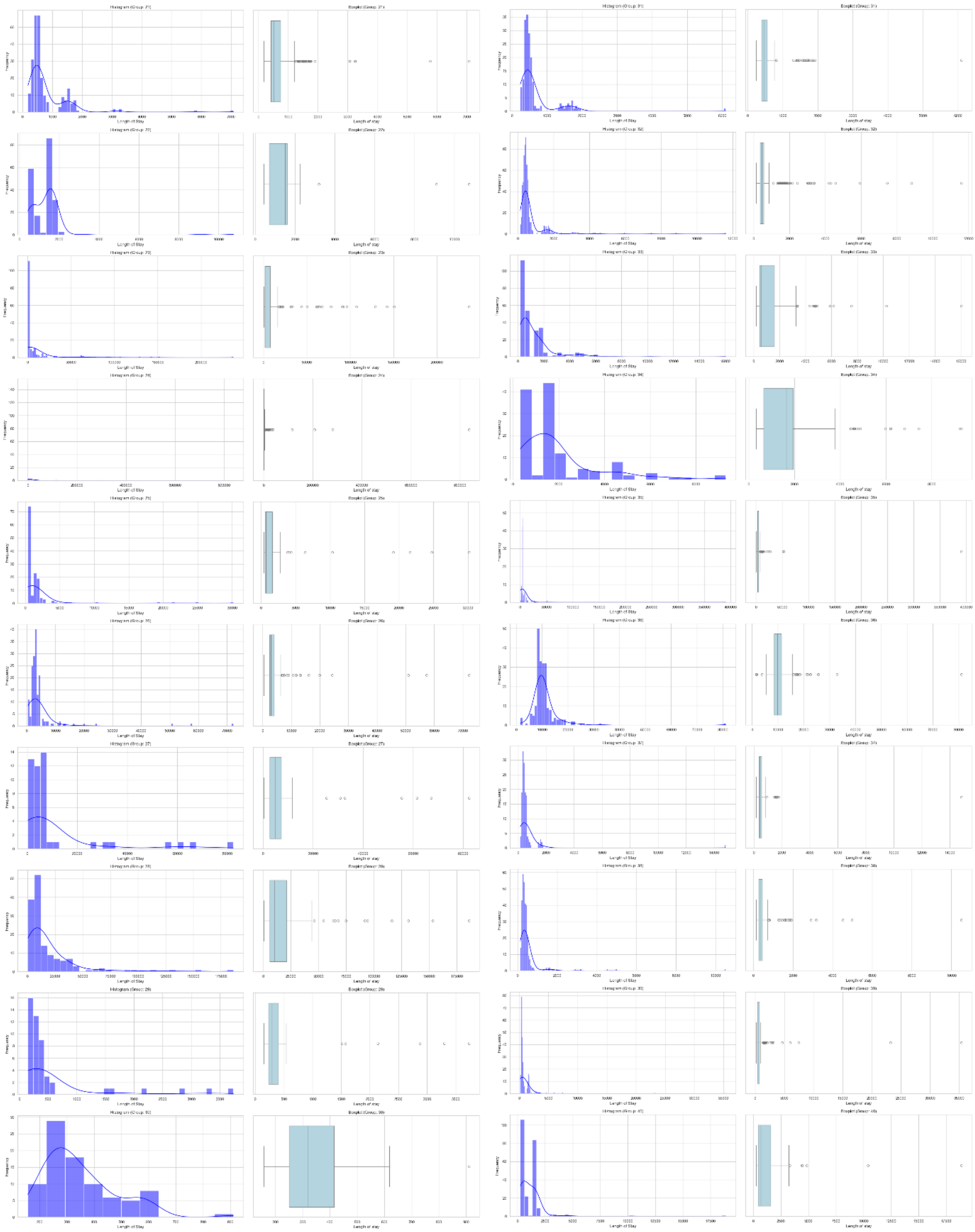


FIGURE E.2: HISTOGRAMS AND BOXPLOTS GROUP 21-40

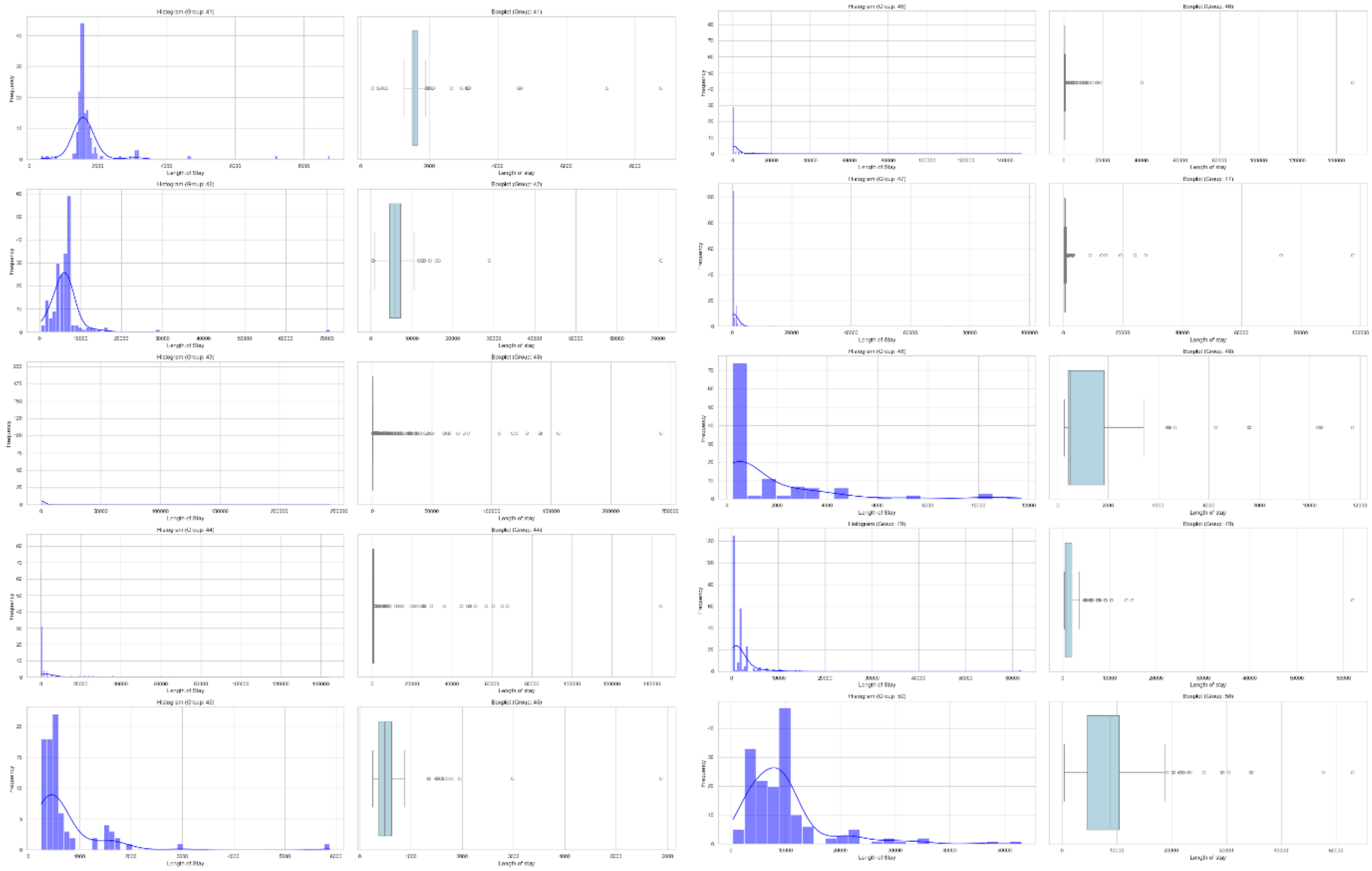


FIGURE E.3: HISTOGRAMS AND BOXPLOTS GROUPS 41-50

E.2 QQ PLOTS

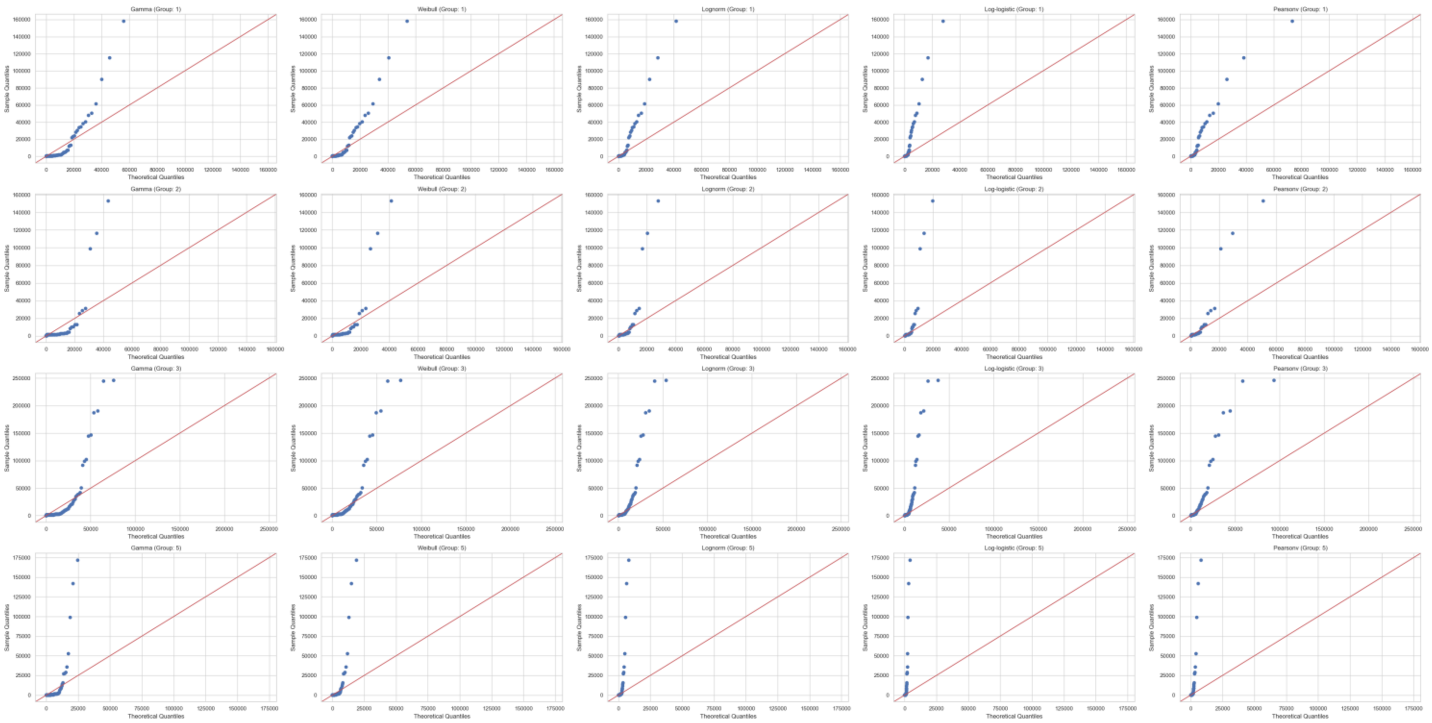


FIGURE E.4: QQ PLOTS GROUP 1,2,3 AND 5

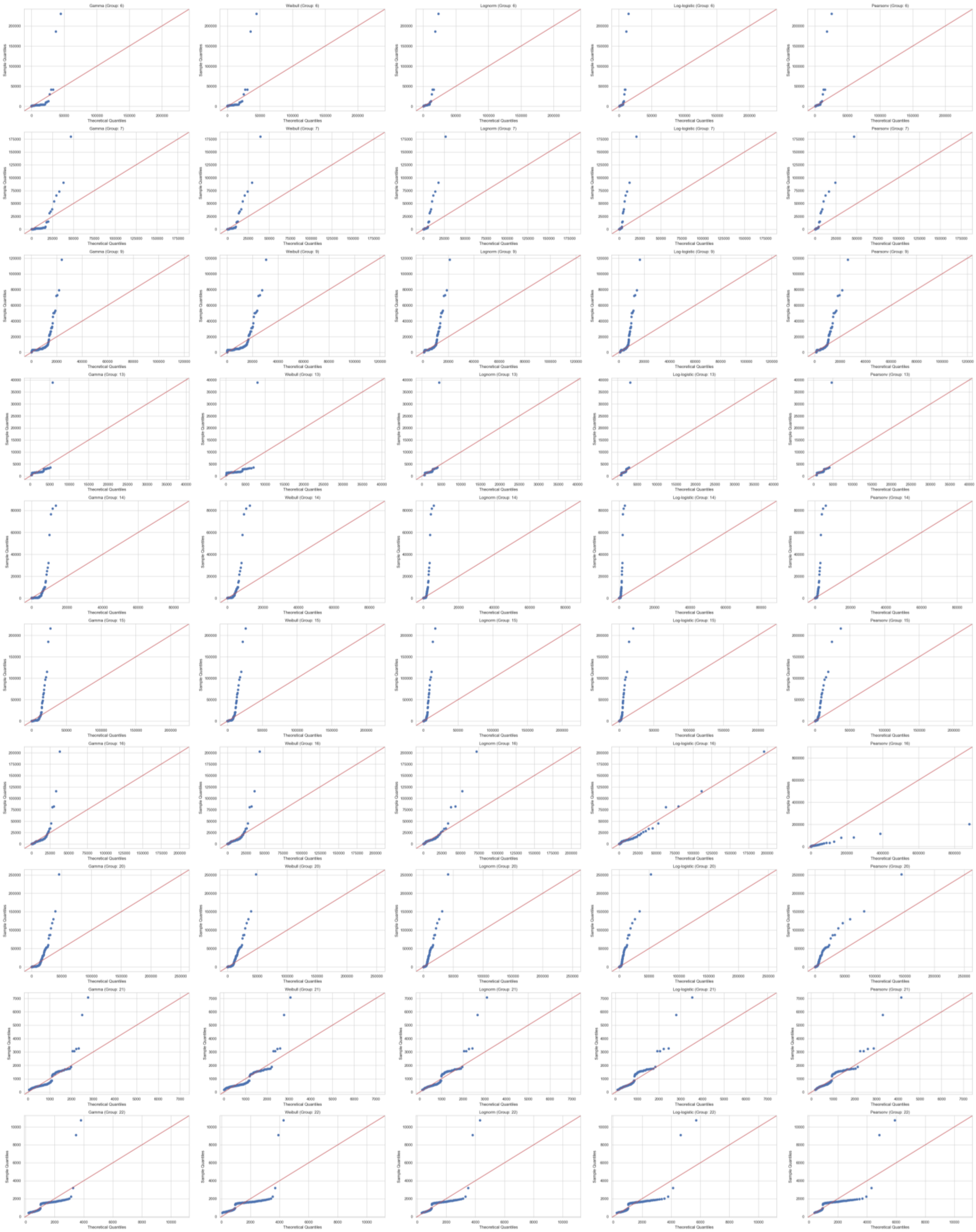


FIGURE E.5: QQ PLOTS GROUP 6,7,9,13,14,15,16,20,21 AND 22

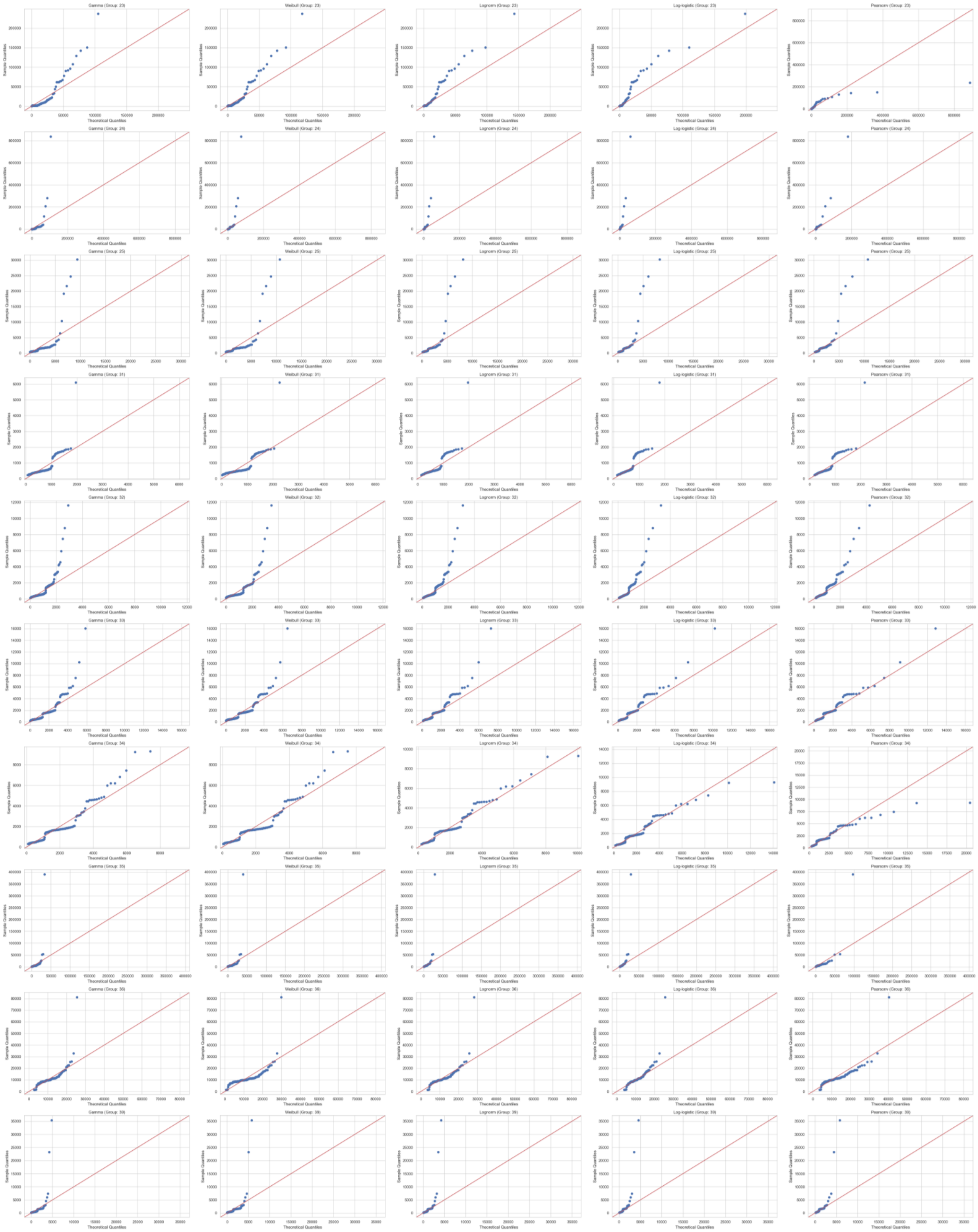


FIGURE E.6: QQ PLOTS GROUP 23,24,25,31,32,33,34,35,36 AND 39

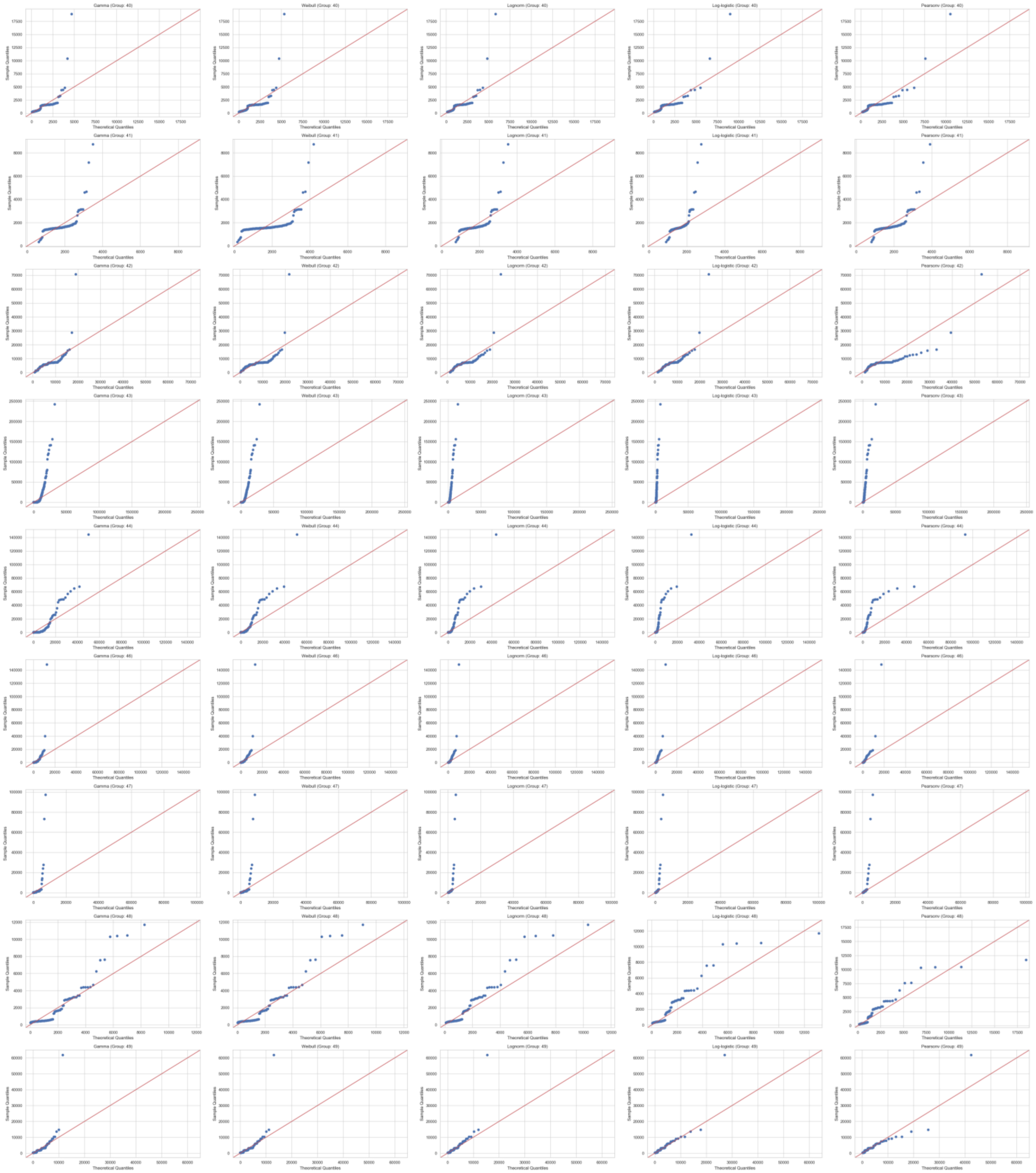


FIGURE E.7: QQ PLOTS GROUP 40,41,42,43,44,46,47,48 AND 49

E.3 PARAMETERS AND CHOSEN DISTRIBUTIONS

Table E.1 gives an overview of all the chosen distributions per grouping and their corresponding parameters.

TABLE E.1: PARAMETERS DISTRIBUTIONS LENGTH OF STAY

Group	Category	Group number	Chosen distribution	Shape	Scale	KS-test p-value
1	CAS	1	gamma	0,393095	15823,361889	0,000000
2	CAS	2	weibull	0,678949	3675,452094	0,000000
3	CAS	3	weibull	0,606203	5209,047263	0,000000
4	DER	1	log-logistic	1,788520	411,434712	0,882125
5	GAS	1	lognorm	1,098694	442,020374	0,000000
6	GAS	2	weibull	0,719582	5061,690866	0,000000
7	GAS	3	lognorm	1,435348	773,553540	0,000001
8	GYN	1	log-logistic	2,400391	701,517048	0,012519
9	GYN	2	lognorm	0,550147	4051,696612	0,000000
10	GYN	3	pearsonV	1,687151	2991,731565	0,078820
11	KAA	1	log-logistic	4,613646	381,804716	0,276278
12	KAA	2	log-logistic	4,133158	416,442033	0,236581
13	KAA	3	lognorm	0,399983	1645,602256	0,000000
14	KIC	1	weibull	0,656411	674,783191	0,000000
15	KIC	2	weibull	0,603223	1166,226575	0,000000
16	KIC	3	lognorm	1,350135	1598,036174	0,000000
17	KIC	4	log-logistic	2,496057	6523,513244	0,341982
18	KIC	5	weibull	0,798319	39218,245233	0,035977
19	KNO	1	log-logistic	3,714949	292,553771	0,028574
20	KNO	2	pearsonV	1,198625	708,885399	0,000000
21	KNO	3	gamma	2,312305	323,661780	0,000000
22	KNO	4	lognorm	0,510131	1117,928875	0,000000
23	KNO	5	weibull	0,596904	6726,209092	0,000000
24	LOS	1	gamma	0,307250	25907,269722	0,000000
25	NEC	1	lognorm	0,875421	991,691410	0,000236
26	NEC	2	log-logistic	2,689668	2963,861813	0,014662
27	NEC	3	log-logistic	1,607037	4868,470834	0,252155
28	NEC	4	pearsonV	1,055438	6710,548888	0,028603
29	NEU	1	log-logistic	2,766252	319,299982	0,320551
30	OOG	1	pearsonV	8,680143	2679,420329	0,786770
31	OOG	2	weibull	1,460764	656,195392	0,000000
32	ORTO	1	lognorm	0,643743	490,582156	0,000000
33	ORTO	2	pearsonV	2,080048	1265,795426	0,000007
34	ORTO	3	lognorm	0,772622	1362,870983	0,004891
35	ORTO	4	gamma	1,204363	4980,066410	0,000000
36	ORTR	1	lognorm	0,458150	9474,346515	0,000000
37	PLCH	1	log-logistic	3,983073	438,653431	0,538421
38	PLCO	1	log-logistic	3,746540	343,472420	0,251661
39	PLCO	2	lognorm	0,701253	557,667676	0,000000
40	PLCO	3	log-logistic	2,290153	823,376759	0,000000
41	PLCO	4	lognorm	0,329345	1625,677546	0,000000
42	PLCO	5	log-logistic	3,957160	5817,999665	0,000020
43	RON	1	weibull	0,543813	781,028724	0,000000
44	RON	2	gamma	0,360416	12327,356760	0,000000
45	TAN	1	log-logistic	3,144840	515,623951	0,149317
46	URO	1	gamma	0,608609	2402,870189	0,000000
47	URO	2	gamma	0,943945	1062,107126	0,000000
48	URO	3	lognorm	1,038105	842,108344	0,000000
49	URO	4	lognorm	0,990243	1036,151171	0,000000
50	URO	5	log-logistic	2,589625	7647,418854	0,018393

APPENDIX F MODEL EXPERIMENTATION

F.1 BASE RUN MODEL

F.1.1 SUMMARY TABLE

TABLE F.1: SUMMARY TABLE BASE RUN, MODEL A

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	14134	2634	14731	2486	31512	763	1,01	0,64
2	13700	2472	15325	2328	31512	782	0,97	0,66
3	14167	2715	14614	2482	31512	756	1,01	0,64
4	14240	2633	14624	2459	31512	757	0,99	0,64
5	13912	2536	15049	2407	31512	736	0,99	0,65
6	13757	2484	15260	2388	31512	772	0,98	0,66
7	13924	2536	15038	2395	31512	722	0,98	0,65

TABLE F.2: SUMMARY TABLE BASE RUN, MODEL B

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	14121	2378	14846	2427	31356	778	0,99	0,65
2	14059	2426	14856	2435	31356	760	1,00	0,66
3	14054	2452	14836	2416	31356	811	0,99	0,65
4	14540	2567	14237	2486	31356	756	1,02	0,64
5	14807	2621	13917	2579	31356	776	1,02	0,63
6	14701	2619	14025	2516	31356	745	1,01	0,63
7	14427	2362	14554	2508	31356	764	1,00	0,65

TABLE F.3: SUMMARY TABLE BASE RUN, MODEL C

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	15159	3108	10812	2708	29094	796	0,97	0,61
2	15484	3223	10372	2759	29094	743	0,97	0,61
3	14921	2982	11176	2598	29094	840	0,97	0,62
4	15374	3170	10538	2690	29094	726	0,98	0,61
5	15462	3204	10414	2741	29094	769	0,98	0,61
6	14959	2976	11149	2633	29094	794	0,97	0,62
7	15241	3114	10723	2681	29094	797	0,98	0,62

TABLE F.4: SUMMARY TABLE BASE RUN, MODEL D

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	16066	2766	10326	2685	29172	971	1,00	0,61
2	15715	2710	10735	2645	29172	951	1,01	0,61
3	15366	2648	11142	2534	29172	976	1,01	0,62
4	15898	2849	10411	2697	29172	959	1,02	0,62
5	15554	2676	10932	2565	29172	986	1,00	0,61
6	15679	2744	10736	2616	29172	939	1,01	0,62
7	15574	2630	10954	2537	29172	1031	1,00	0,62

F.1.2 OT UTILSIATION ACROSS SCHEDULE CYCLE

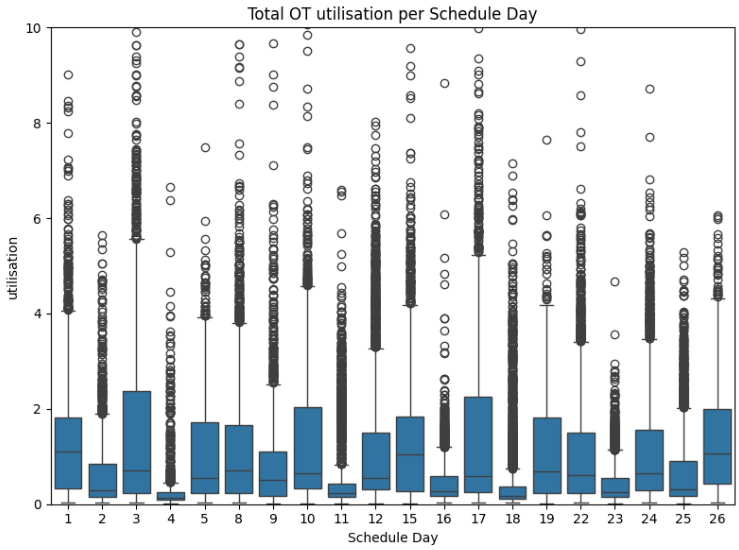


FIGURE F.1: OT UTILSATION ACROSS 28 DAY CYCLE, MODEL A

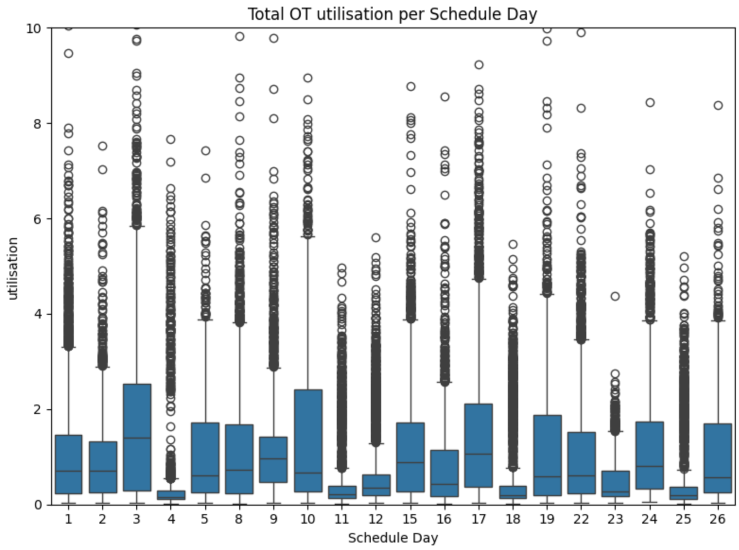


FIGURE F.2: OT UTILSATION ACROSS 28 DAY CYCLE, MODEL B

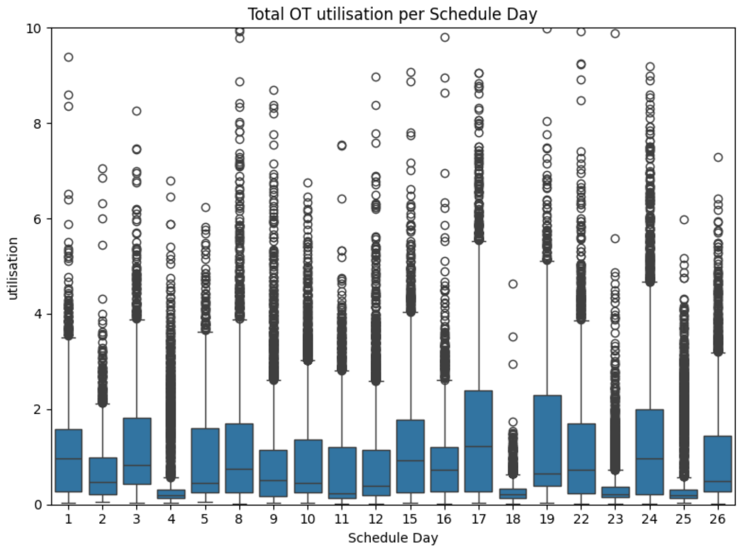


FIGURE F.3: OT UTILSATION ACROSS 28 DAY CYCLE, MODEL C

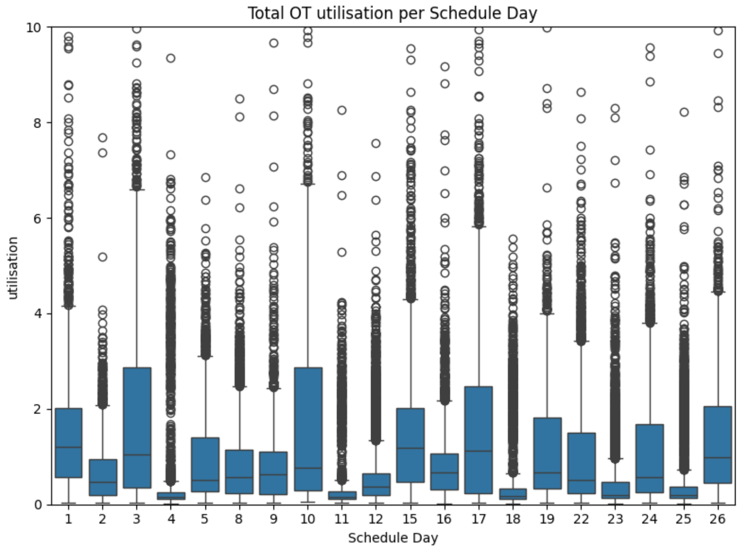


FIGURE F.4: OT UTILSATION ACROSS 28 DAY CYCLE, MODEL D

F.1.3 WARD UTILSIATION ACROSS SCHEDULE CYCLE

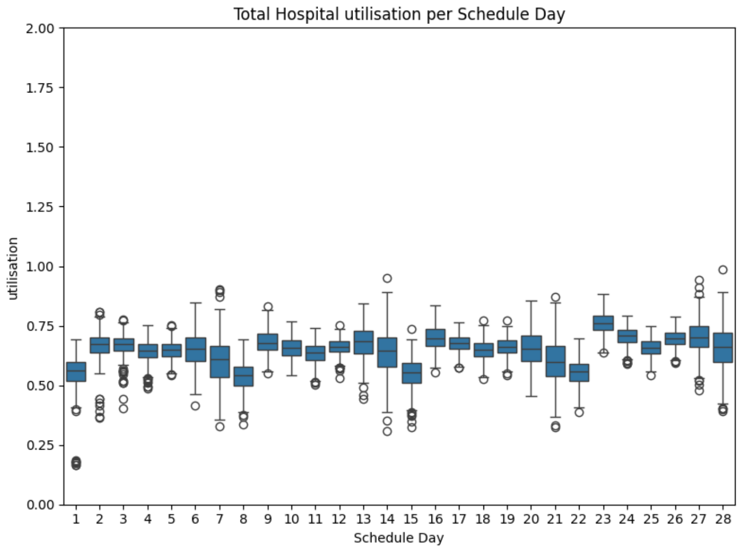


FIGURE F.5: WARD UTILISATION ACROSS 28 DAY CYCLE, MODEL A

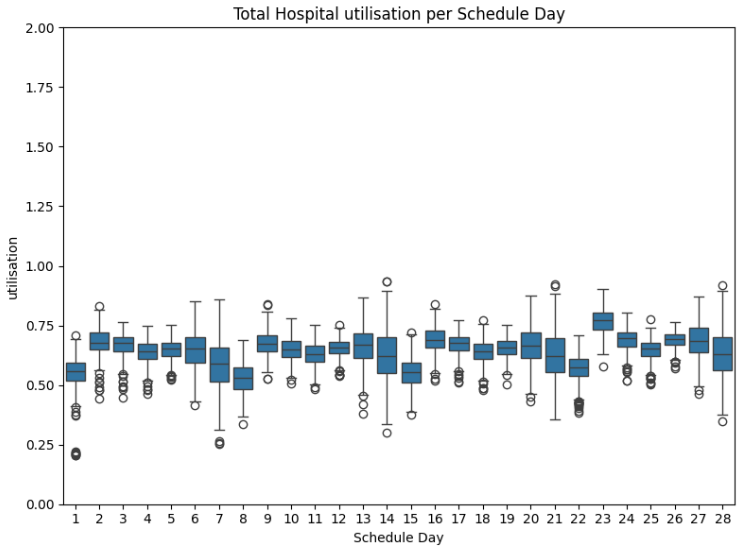


FIGURE F.6: WARD UTILISATION ACROSS 28 DAY CYCLE, MODEL B

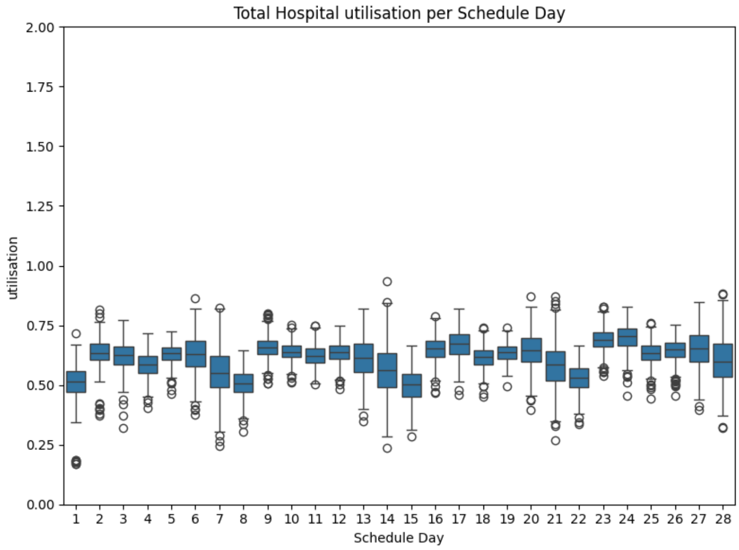


FIGURE F.7: WARD UTILISATION ACROSS 28 DAY CYCLE, MODEL C

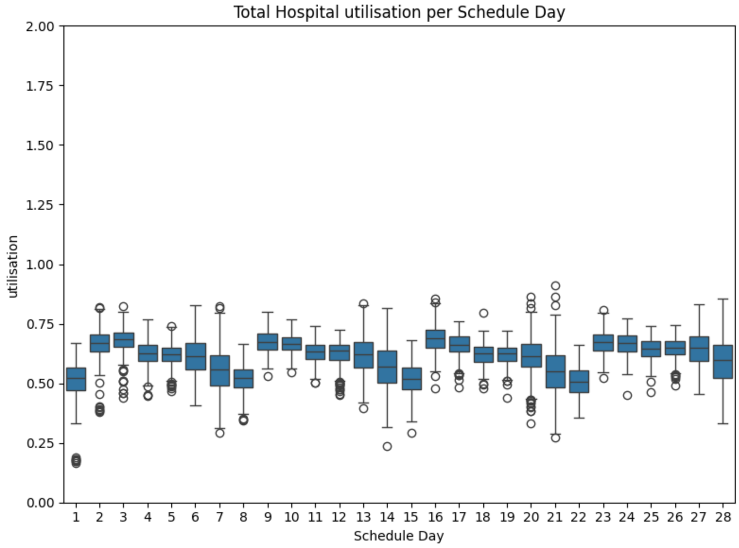


FIGURE F.8: WARD UTILISATION ACROSS 28 DAY CYCLE, MODEL D

F.1.4 OVERTIME PER OT

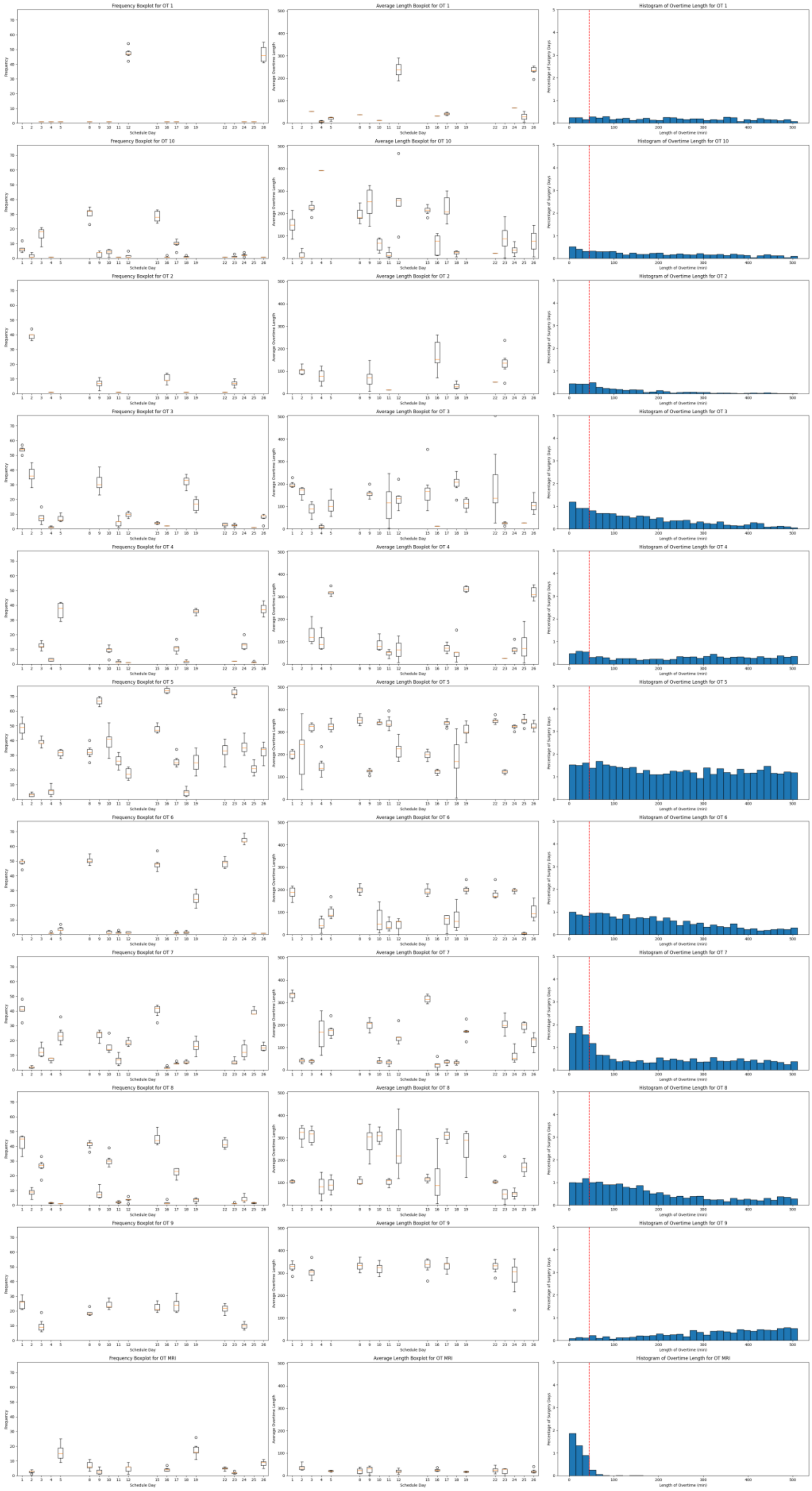


FIGURE F.9: OVERTIME PER OT, MODEL A

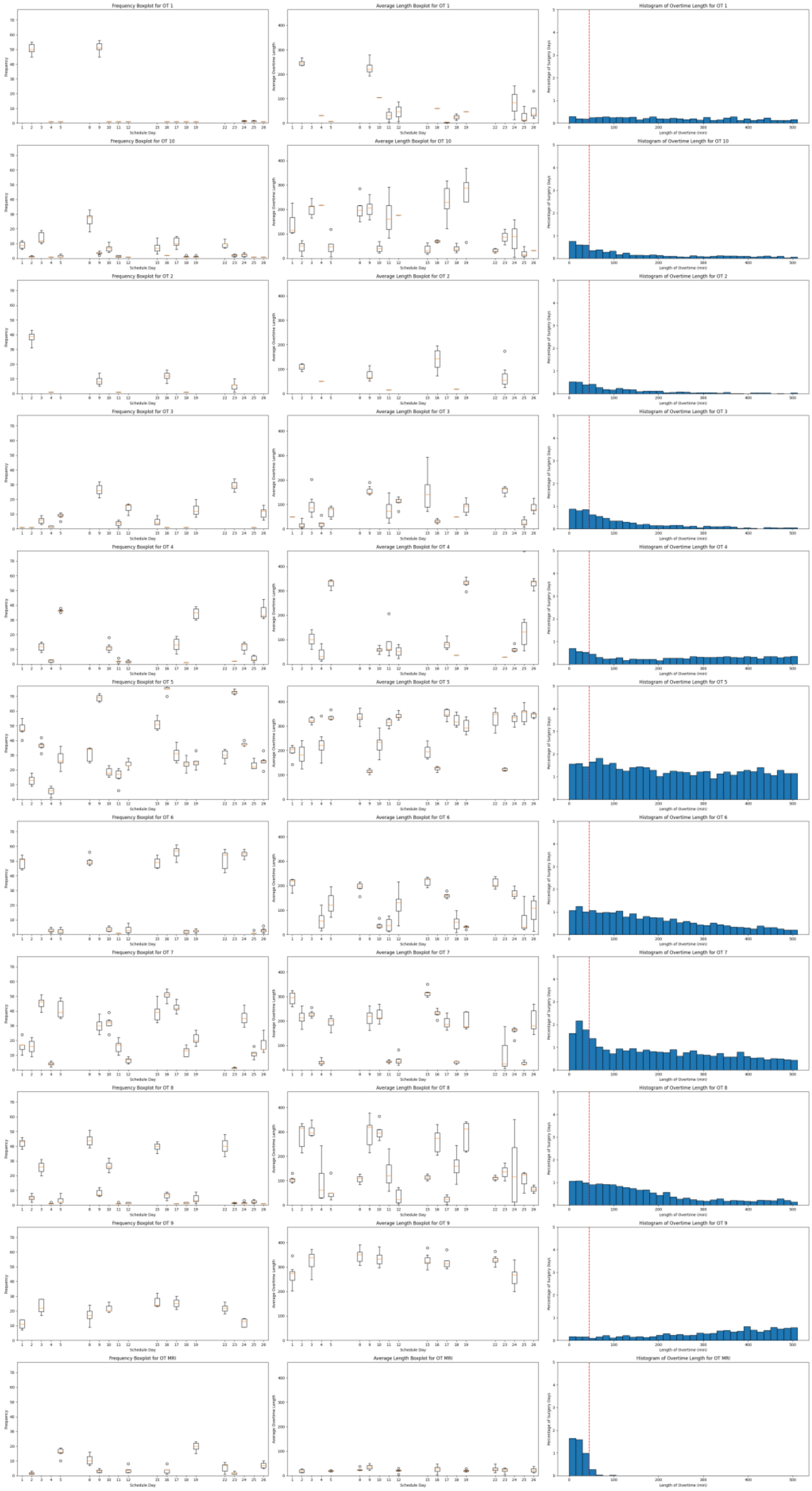


FIGURE F.10: OVERTIME PER OT, MODEL B

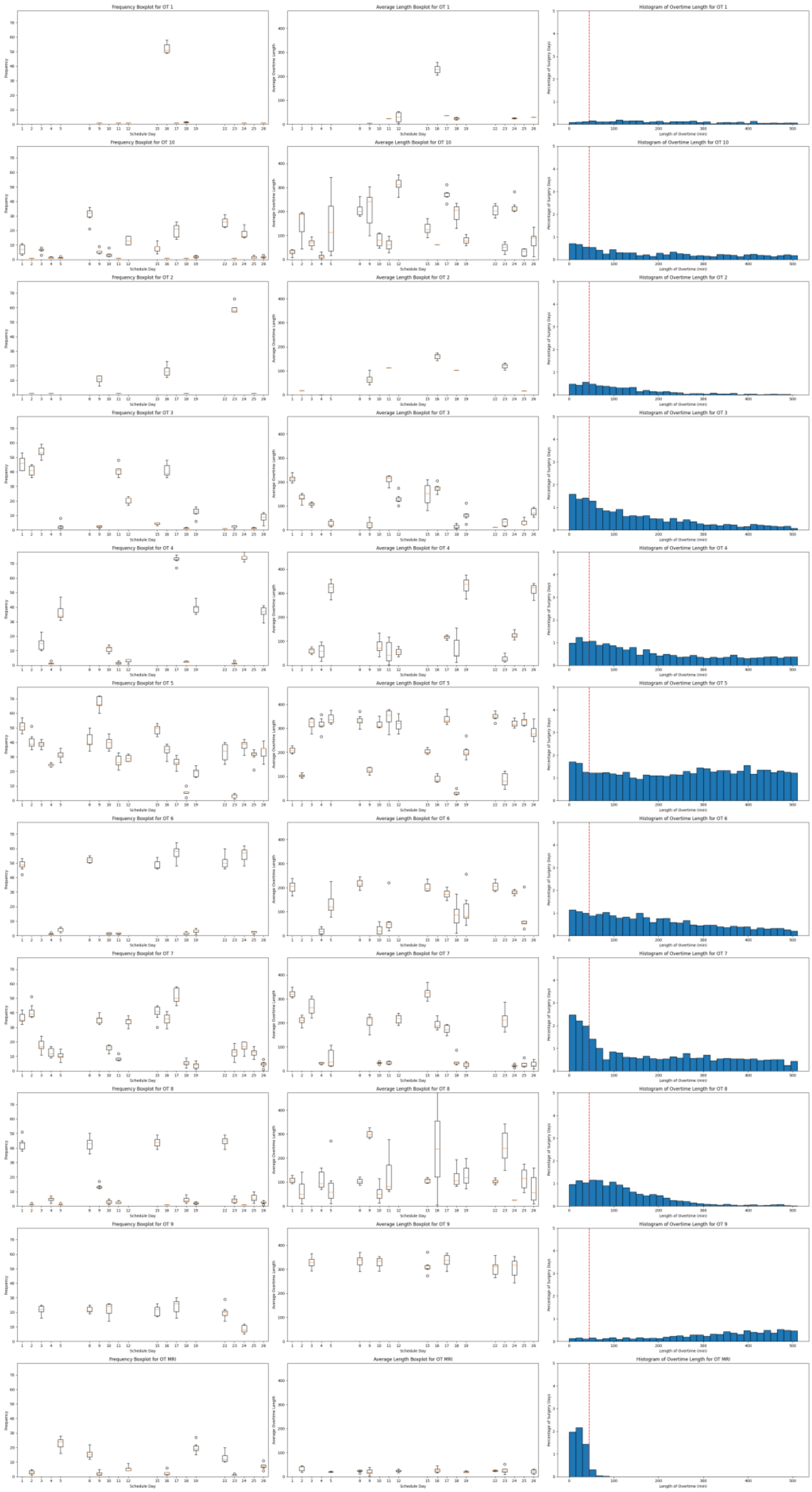


FIGURE F.11: OVERTIME PER OT, MODEL C

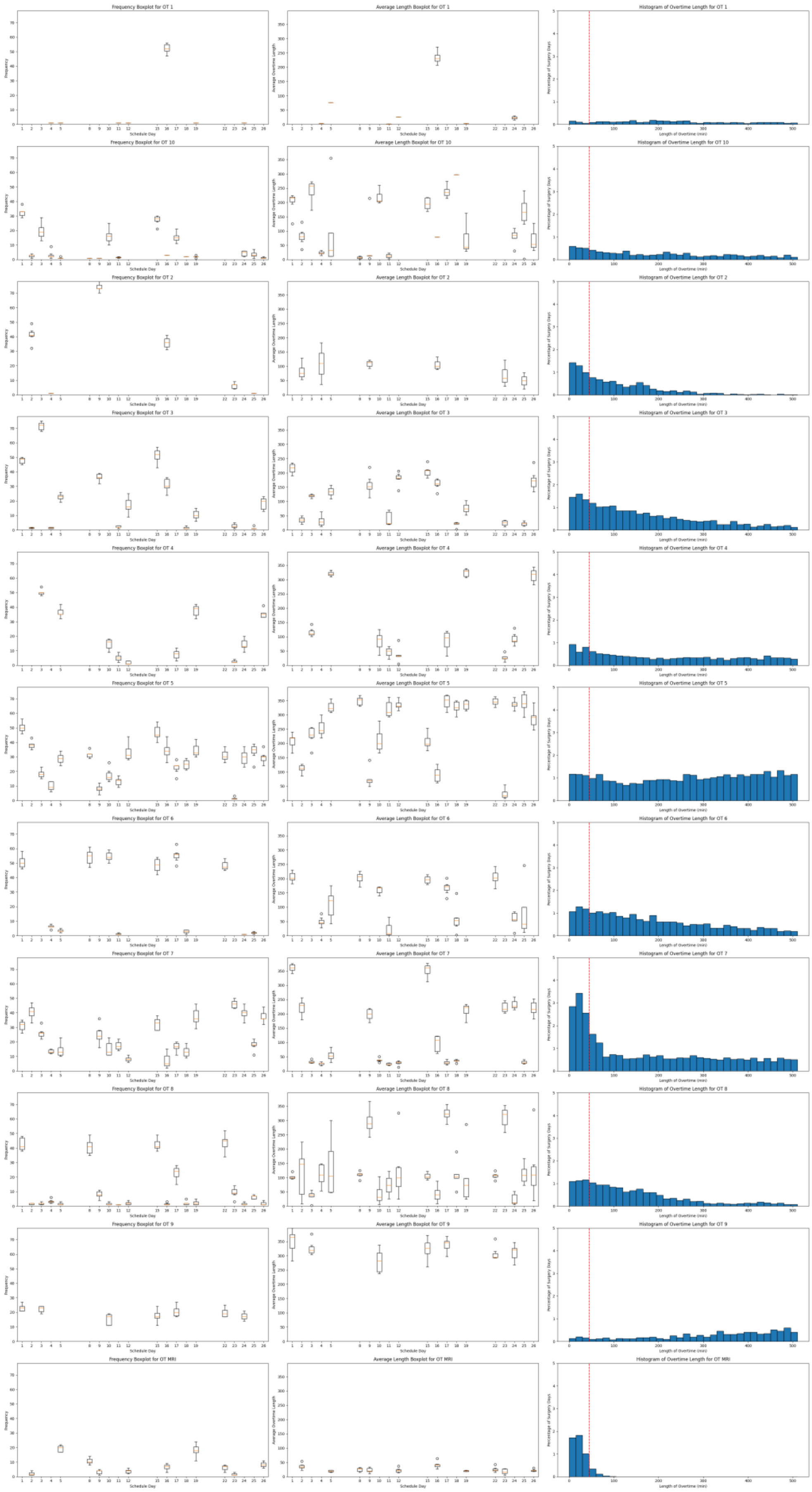


FIGURE F.12: OVERTIME PER OT, MODEL D

F.2 SCENARIO 1

F.2.1 SUMMARY TABLE

TABLE F.5: SUMMARY TABLE SCENARIO 1, MODEL A

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	10798	1631	19069	1911	31512	799	0,92	0,71
2	10338	1436	19725	1823	31512	848	0,91	0,72
3	10781	1596	19122	1920	31512	808	0,93	0,71
4	10742	1579	19182	1921	31512	813	0,93	0,71
5	10421	1490	19589	1846	31512	816	0,91	0,72
6	10652	1575	19276	1887	31512	820	0,91	0,71
7	10769	1579	19152	1880	31512	807	0,92	0,71

TABLE F.6: SUMMARY TABLE SCENARIO 1, MODEL B

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	10997	1549	18799	2018	31356	816	0,95	0,71
2	10953	1473	18917	1974	31356	862	0,92	0,71
3	10953	1416	18973	2003	31356	848	0,94	0,71
4	11210	1464	18668	2004	31356	812	0,95	0,70
5	10660	1356	19327	1947	31356	841	0,91	0,72
6	11232	1525	18589	2002	31356	805	0,94	0,70
7	11256	1485	18604	2015	31356	828	0,94	0,70

TABLE F.7: SUMMARY TABLE SCENARIO 1, MODEL C

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	11890	1832	15356	2187	29094	913	0,92	0,68
2	12223	1939	14919	2292	29094	914	0,95	0,67
3	11731	1858	15495	2152	29094	979	0,93	0,68
4	11830	1800	15452	2167	29094	882	0,93	0,68
5	11704	1716	15666	2147	29094	932	0,92	0,69
6	12018	1912	15152	2231	29094	915	0,93	0,68
7	11791	1815	15474	2206	29094	943	0,92	0,69

TABLE F.8: SUMMARY TABLE SCENARIO 1, MODEL D

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	12111	1511	15537	2084	29172	1043	0,96	0,69
2	12478	1578	15105	2133	29172	1053	0,94	0,68
3	12442	1550	15169	2171	29172	1049	0,95	0,68
4	12370	1633	15154	2186	29172	1048	0,96	0,69
5	12177	1544	15437	2098	29172	1010	0,95	0,69
6	12255	1497	15406	2071	29172	1084	0,94	0,68
7	11934	1434	15795	2017	29172	1101	0,92	0,69

F.2.2 OT UTILSIATION ACROSS SCHEDULE CYCLE

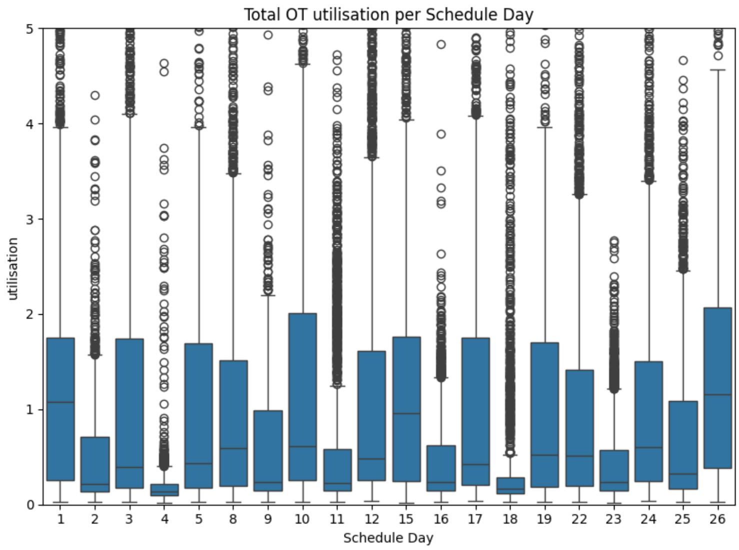


FIGURE F.13: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 1, MODEL A

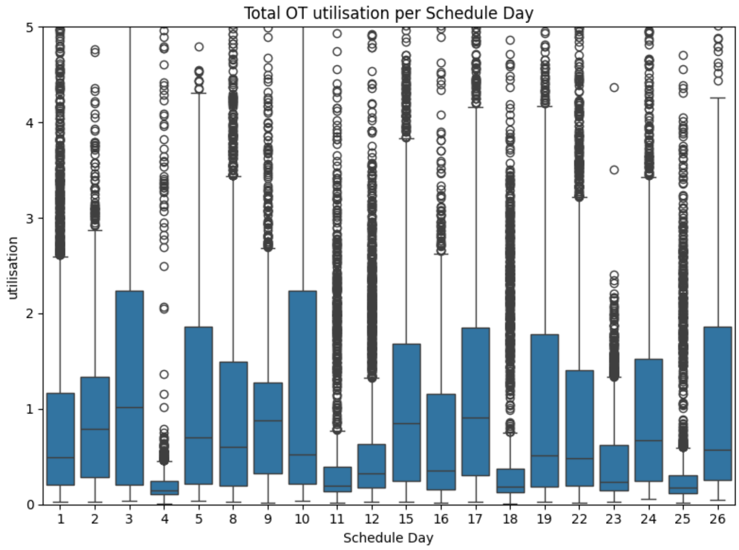


FIGURE F.14: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 1, MODEL B

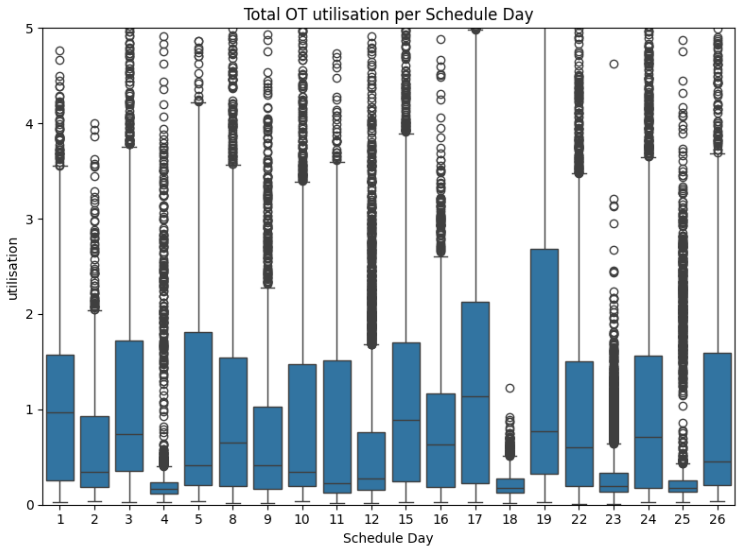


FIGURE F.15: OT UTILISATION ACROSS 28 DAY CYCL SCENARIO 1, MODEL C

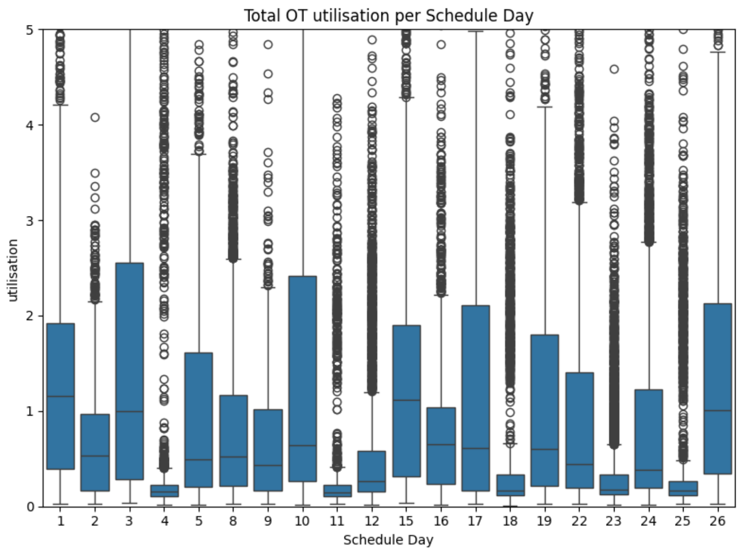


FIGURE F.16: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 1, MODEL D

F.2.3 WARD UTILSIATION ACROSS SCHEDULE CYCLE

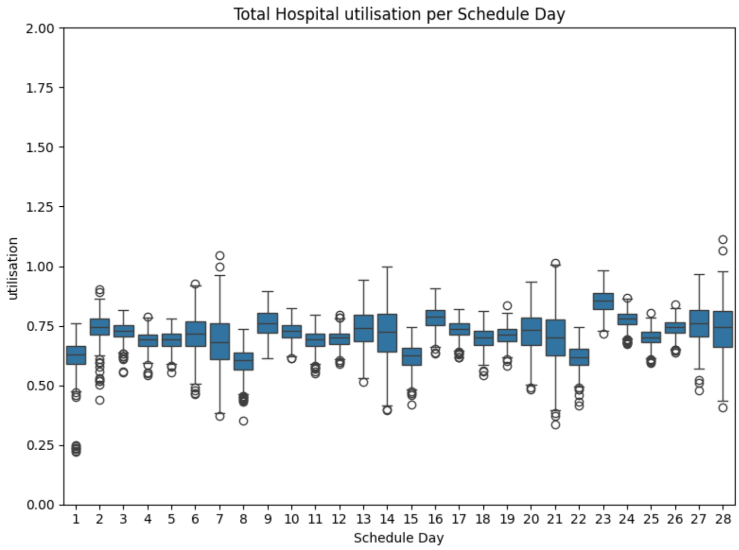


FIGURE F.17: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 1, MODEL A

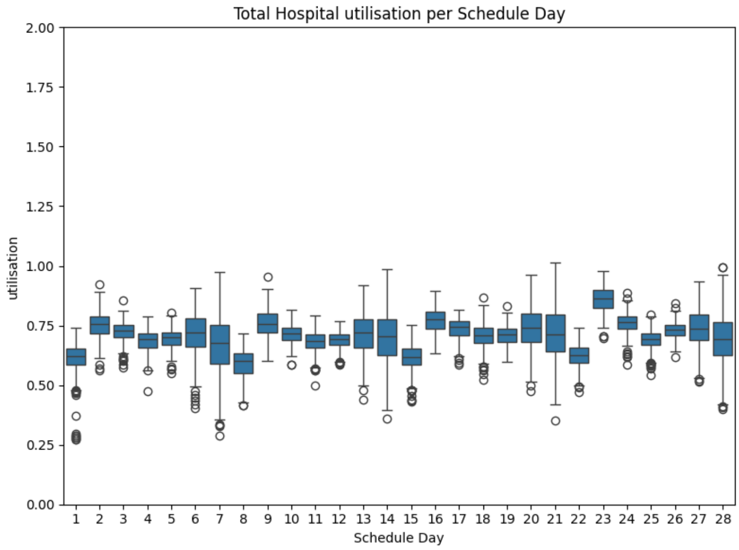


FIGURE F.18: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 1, MODEL B

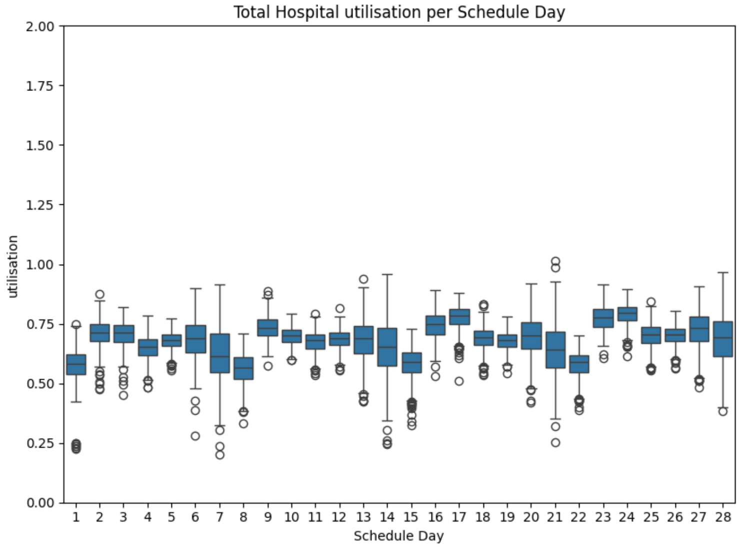


FIGURE F.19: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 1, MODEL C

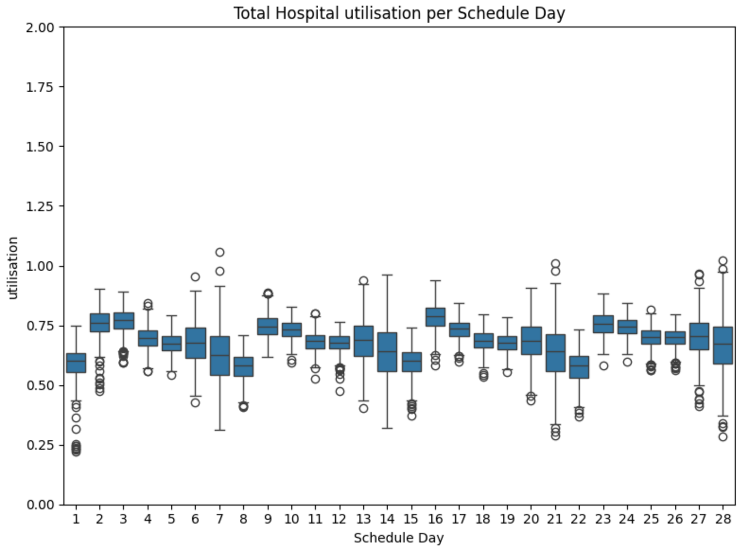


FIGURE F.20: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 1, MODEL D

F.2.4 TOTAL OVERTIME

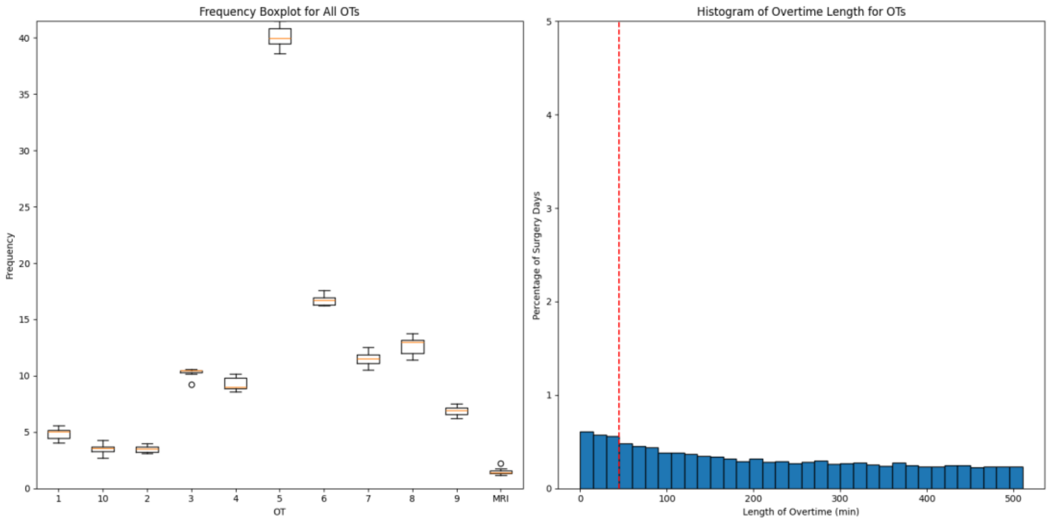


FIGURE F.21: TOTAL OVERTIME SCENARIO 1, MODEL A

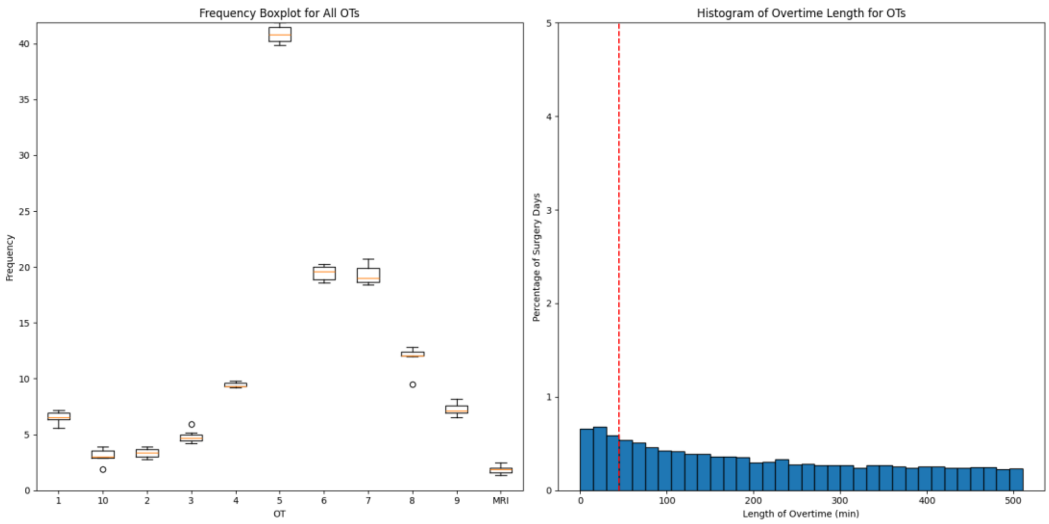


FIGURE F.22: TOTAL OVERTIME SCENARIO 1, MODEL B

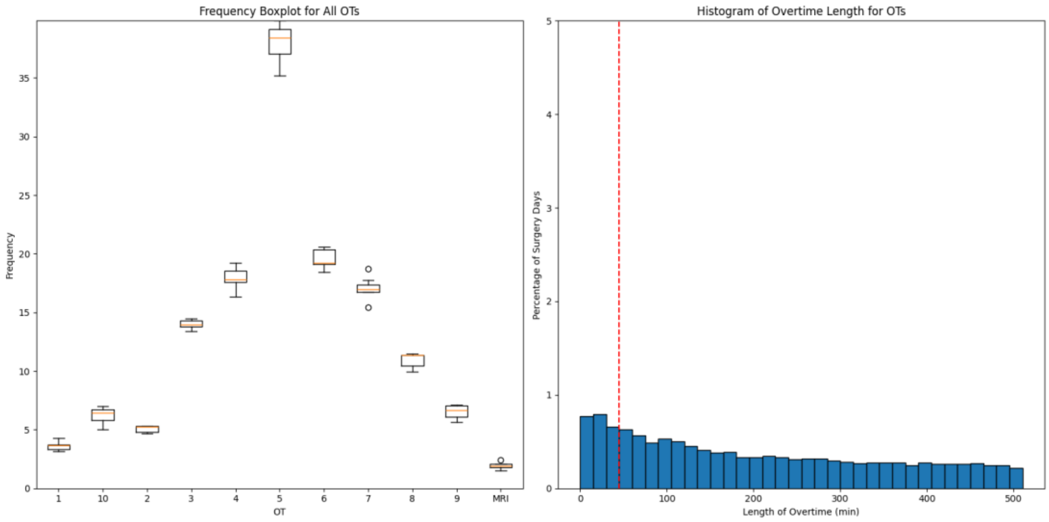


FIGURE F.23: TOTAL OVERTIME SCENARIO 1, MODEL C

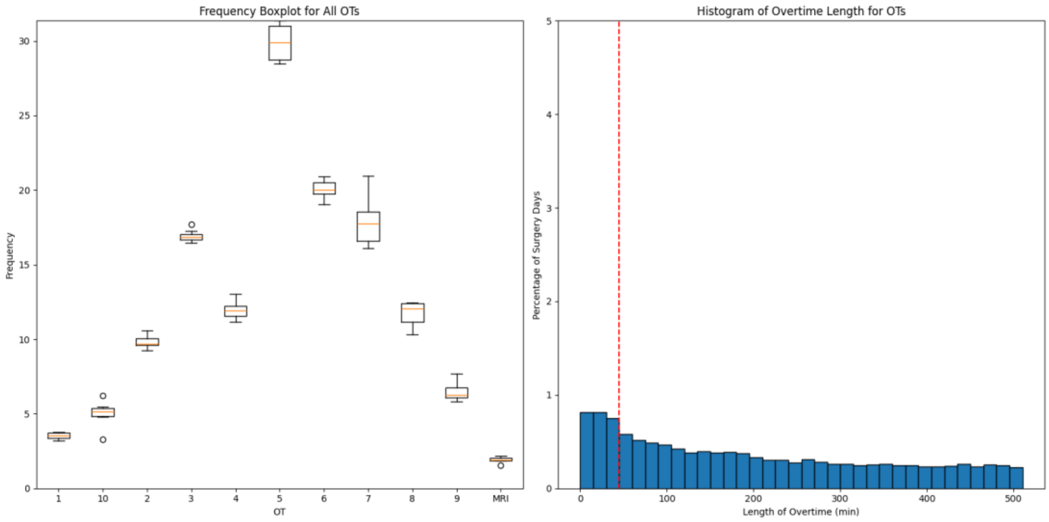


FIGURE F.24: TOTAL OVERTIME SCENARIO 1, MODEL D

F.2.5 OVERTIME PER OT

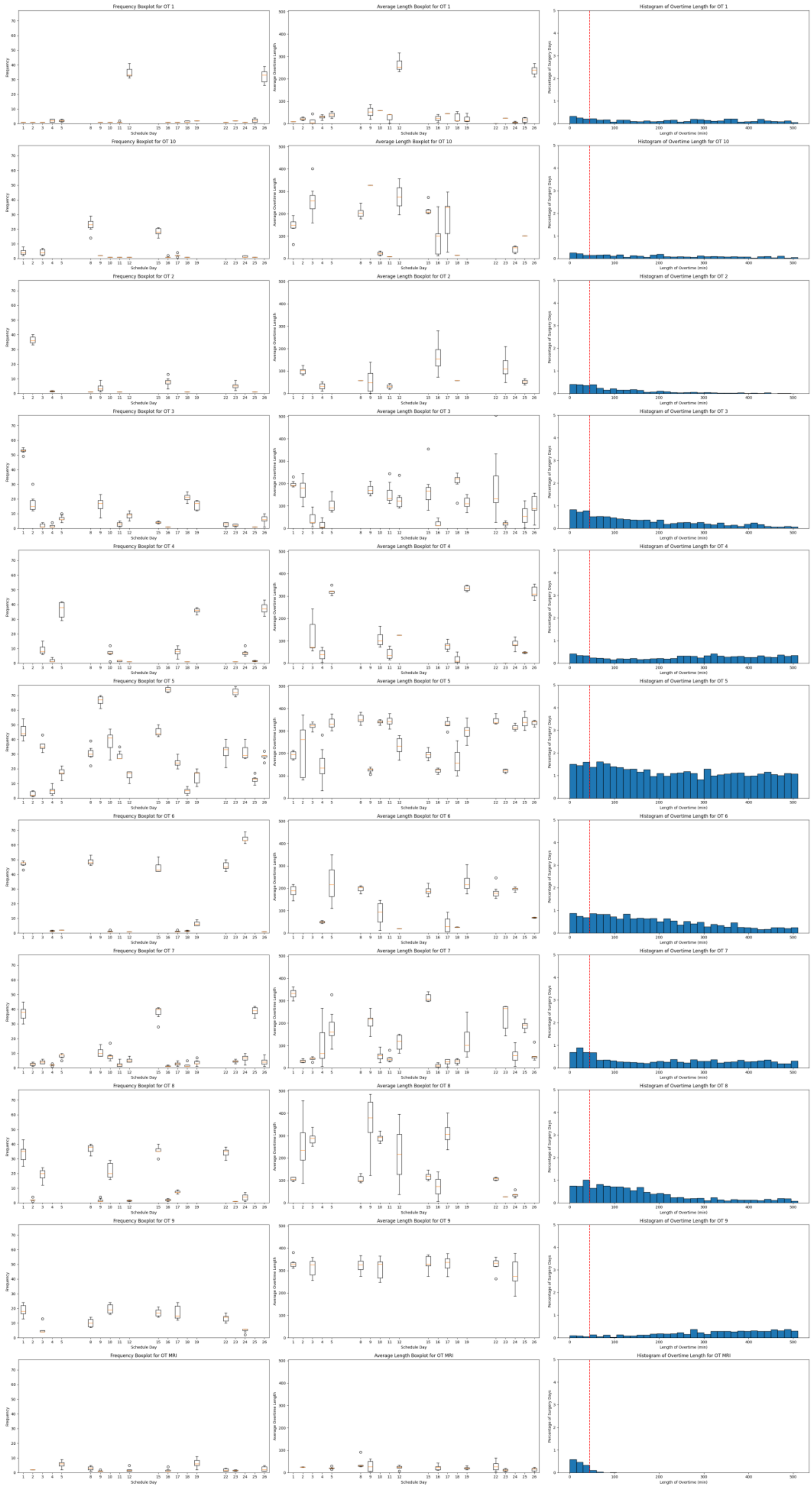


FIGURE F.25: OVERTIME PER OT SCENARIO 1, MODEL A

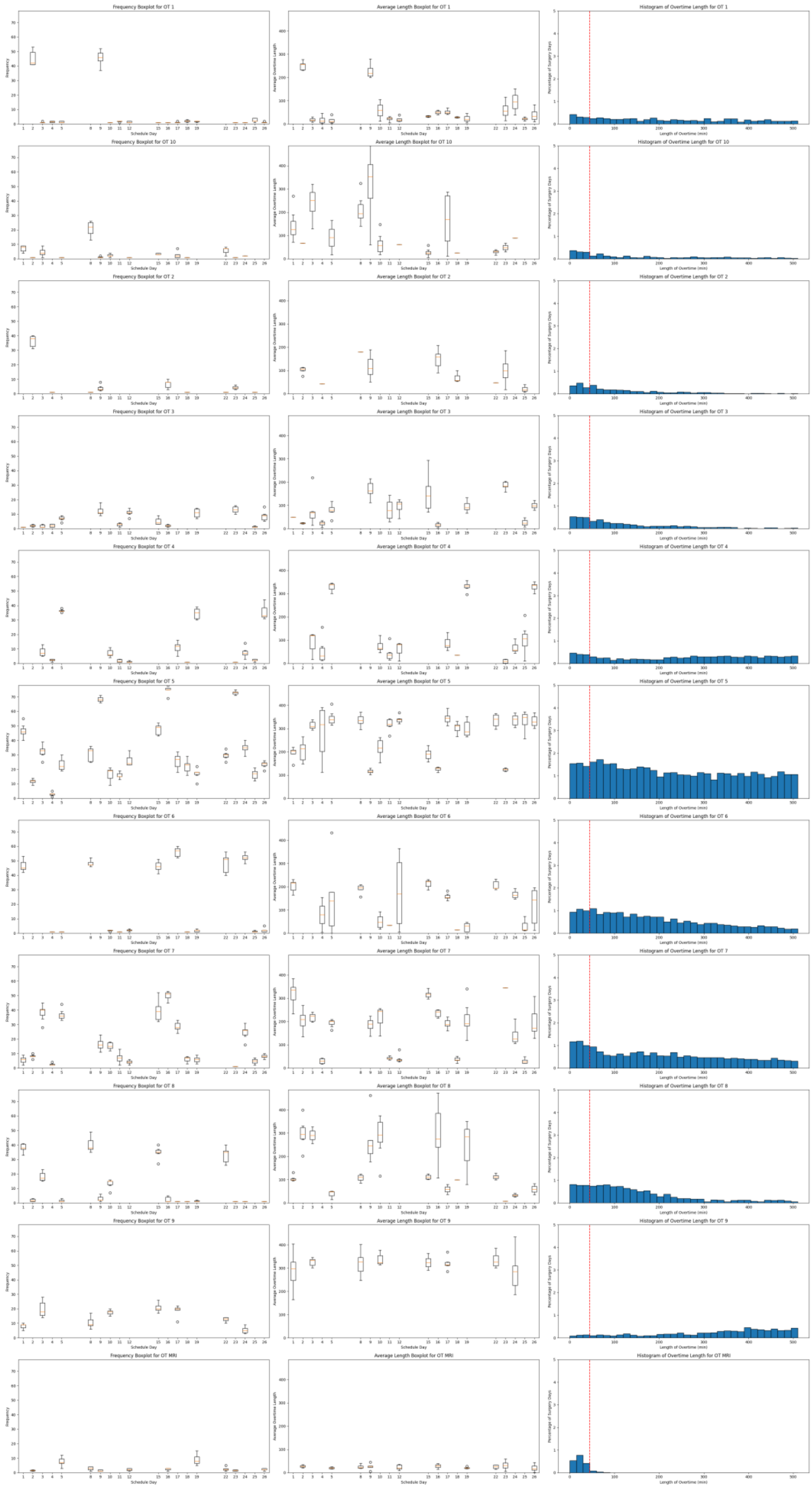


FIGURE F.26: OVERTIME PER OT SCENARIO 1, MODEL B

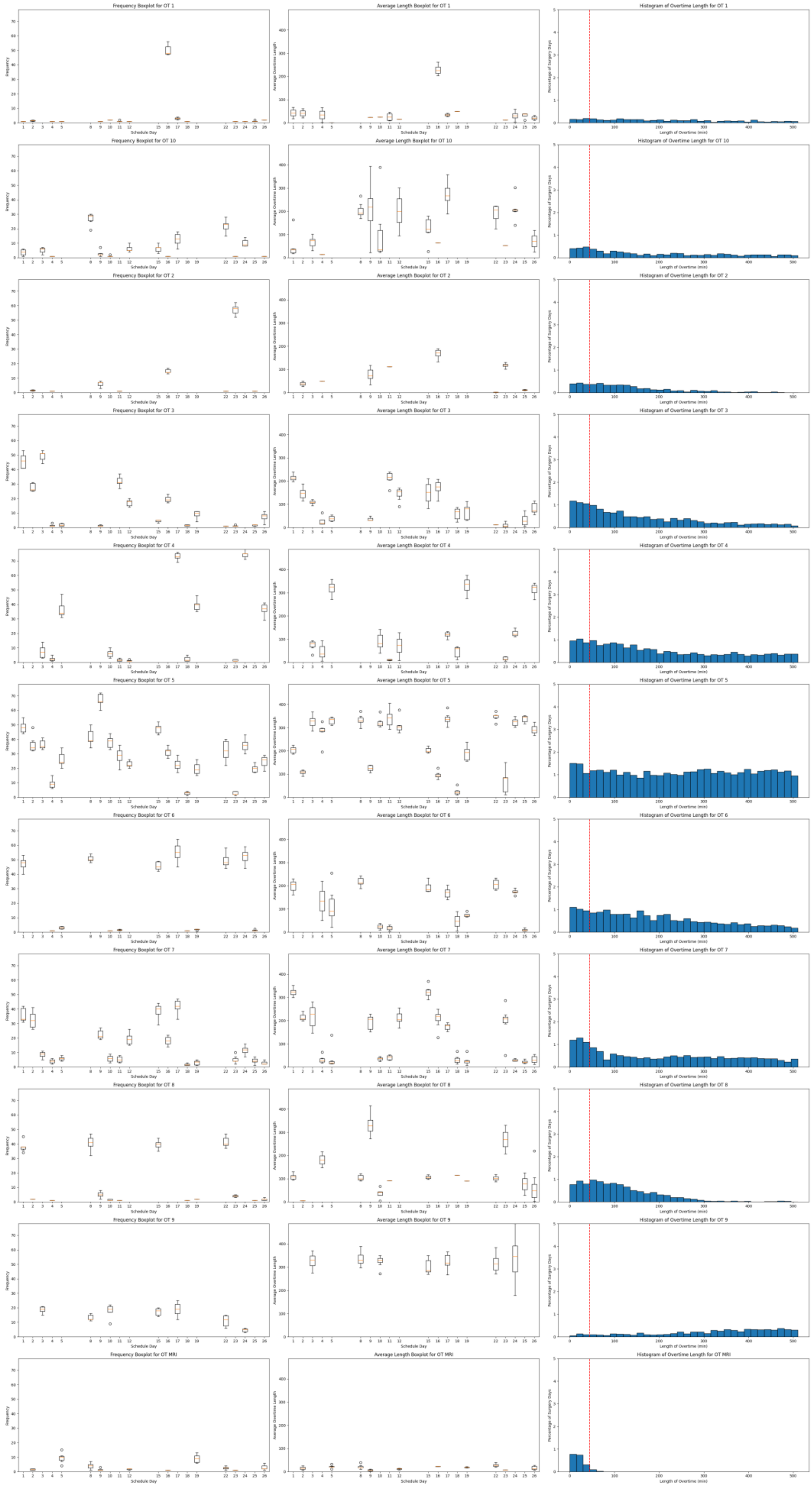


FIGURE F.27: OVERTIME PER OT SCENARIO 1, MODEL C

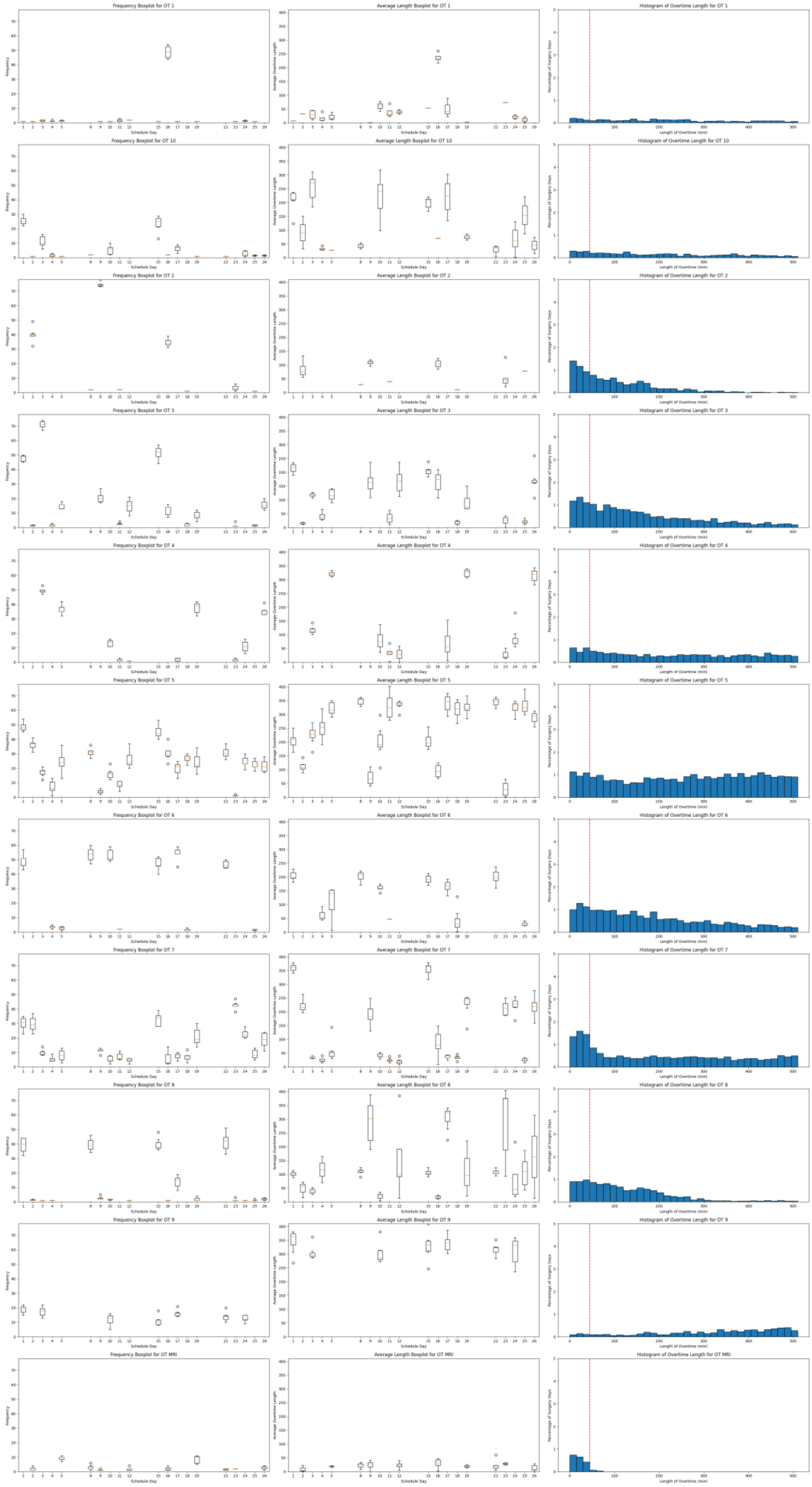


FIGURE F.28: OVERTIME PER OT SCENARIO 1, MODEL D

F.3 SCENARIO 2

F.3.1 SUMMARY TABLE

TABLE F.9: SUMMARY TABLE SCENARIO 2 , MODEL A

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	12163	1957	17384	2127	31512	835	0,95	0,67
2	12043	1987	17470	2132	31512	809	0,96	0,67
3	12228	1998	17275	2205	31512	821	0,95	0,67
4	11692	1796	18011	2027	31512	842	0,94	0,68
5	11601	1791	18111	2047	31512	830	0,93	0,68
6	12062	1936	17504	2178	31512	788	0,94	0,67
7	11921	1898	17682	2086	31512	783	0,93	0,67

TABLE F.10: SUMMARY TABLE SCENARIO 2 , MODEL B

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	11968	1708	17669	2091	31356	868	0,94	0,68
2	12310	1794	17240	2198	31356	867	0,97	0,67
3	11982	1754	17611	2132	31356	818	0,95	0,68
4	12252	1784	17313	2198	31356	849	0,96	0,67
5	12612	1840	16897	2217	31356	823	0,97	0,66
6	12135	1721	17489	2241	31356	847	0,94	0,68
7	12426	1768	17154	2151	31356	831	0,96	0,67

TABLE F.11: SUMMARY TABLE SCENARIO 2 , MODEL C

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	12998	2241	13843	2355	29094	962	0,95	0,64
2	13025	2138	13920	2375	29094	950	0,93	0,65
3	13144	2242	13693	2396	29094	934	0,94	0,64
4	13309	2348	13428	2351	29094	887	0,95	0,63
5	13127	2197	13763	2382	29094	912	0,94	0,64
6	13213	2302	13568	2420	29094	936	0,94	0,64
7	13013	2201	13871	2379	29094	941	0,94	0,65

TABLE F.12: SUMMARY TABLE SCENARIO 2 , MODEL D

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	13628	1911	13622	2331	29172	1064	0,96	0,64
2	13439	1931	13791	2334	29172	1098	0,97	0,65
3	13976	2003	13183	2396	29172	1099	0,96	0,63
4	13390	1904	13866	2299	29172	1108	0,98	0,65
5	13267	1812	14083	2272	29172	1084	0,96	0,65
6	13505	1850	13806	2279	29172	1163	0,96	0,65
7	13363	1875	13925	2257	29172	1128	0,96	0,64

F.3.2 OT UTILSIATION ACROSS SCHEDULE CYCLE

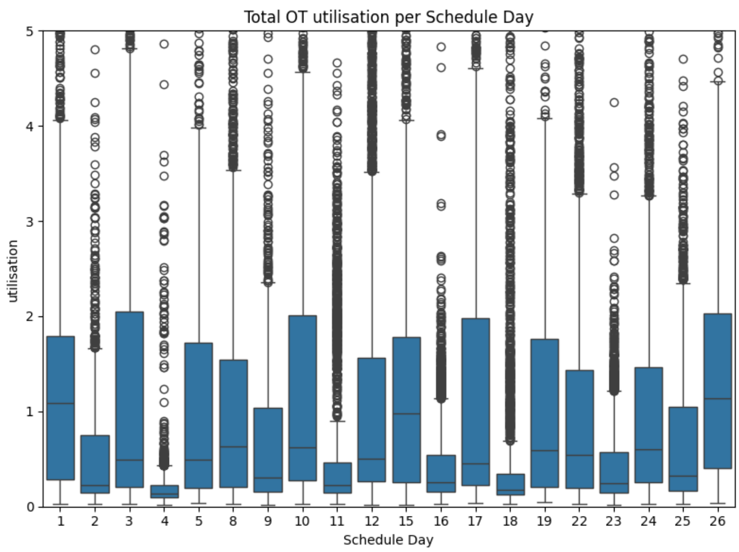


FIGURE F.29: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 2, MODEL A

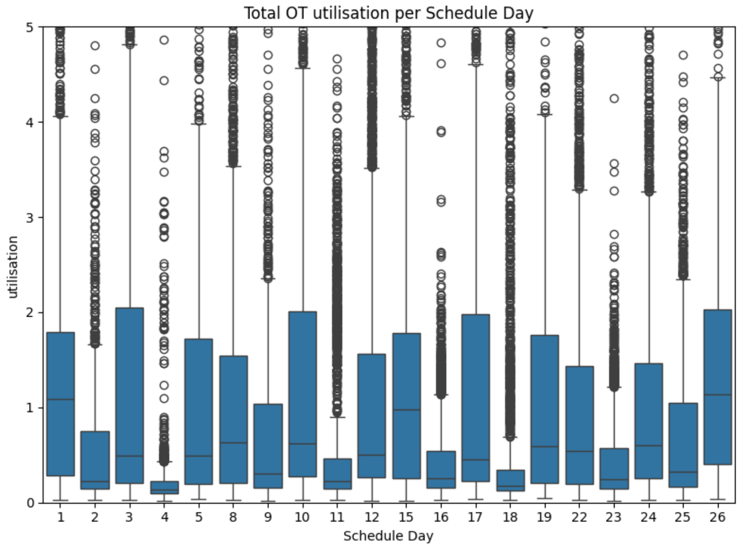


FIGURE F.30: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 2, MODEL B

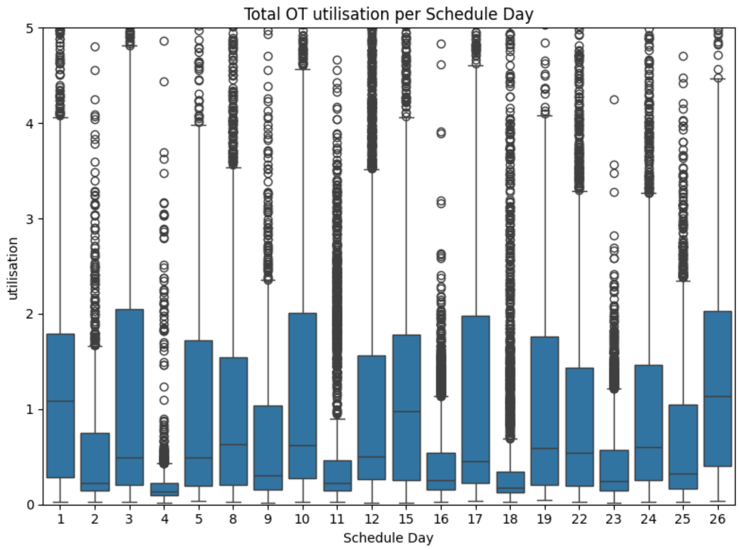


FIGURE F.31: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 2, MODEL C

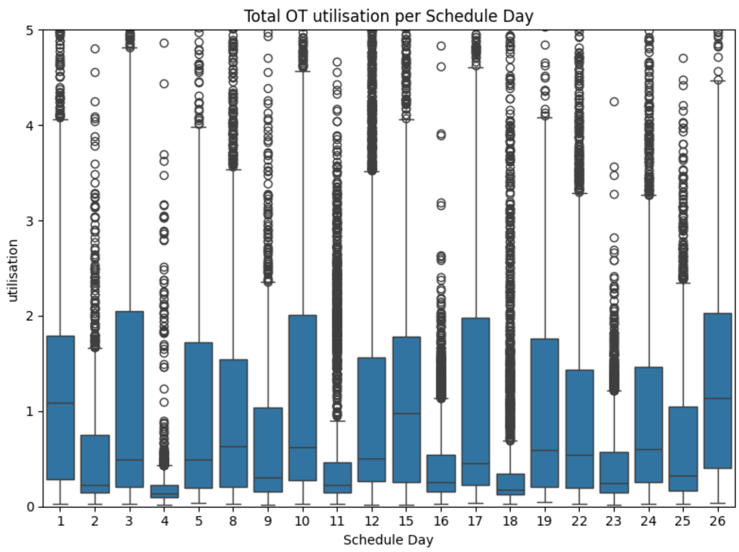


FIGURE F.32: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 2, MODEL D

F.3.3 WARD UTILSIATION ACROSS SCHEDULE CYCLE

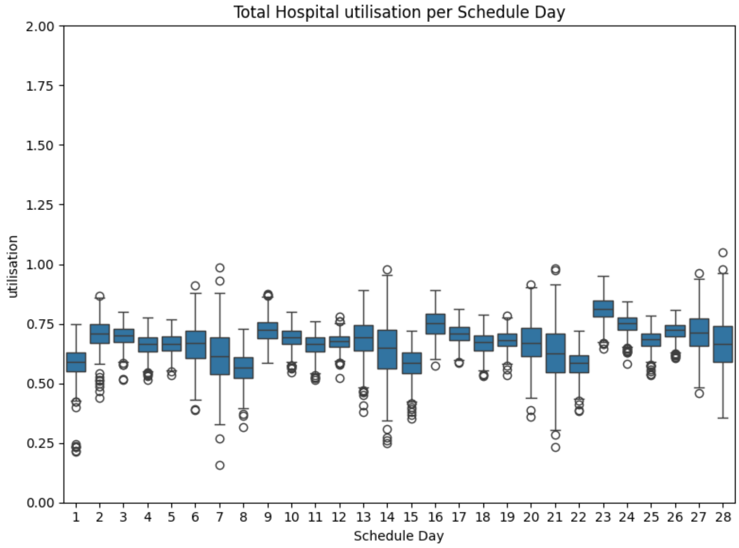


FIGURE F.33: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 2, MODEL A

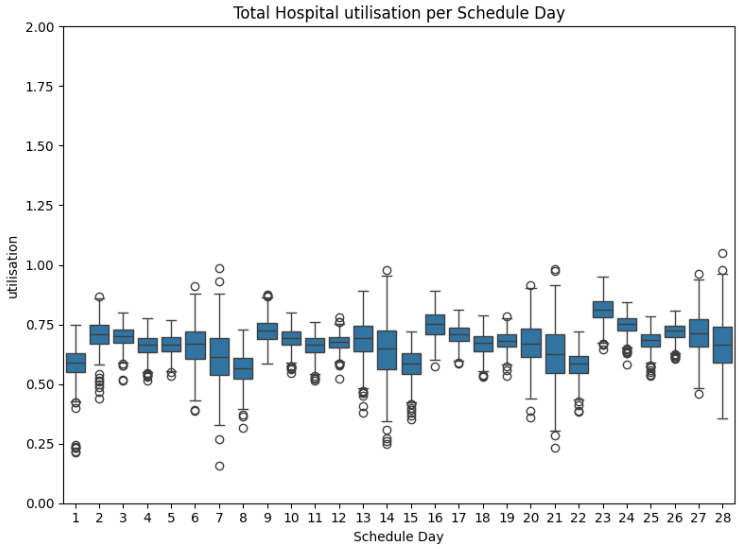


FIGURE F.34: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 2, MODEL B

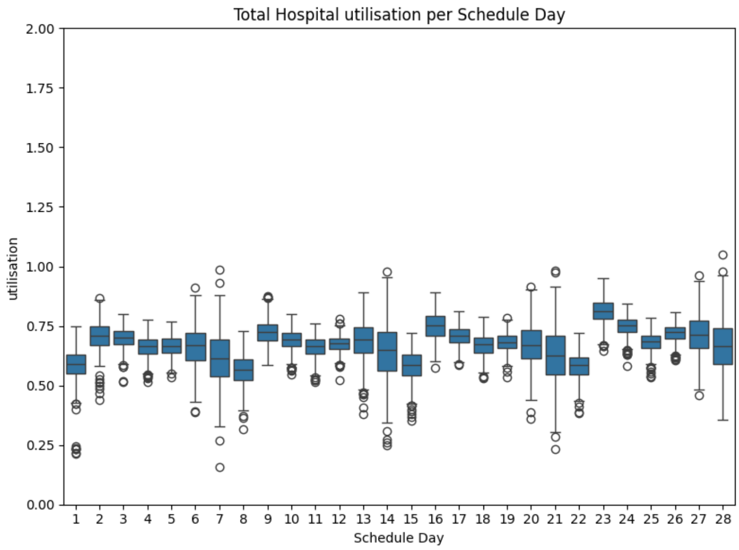


FIGURE F.35: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 2, MODEL C

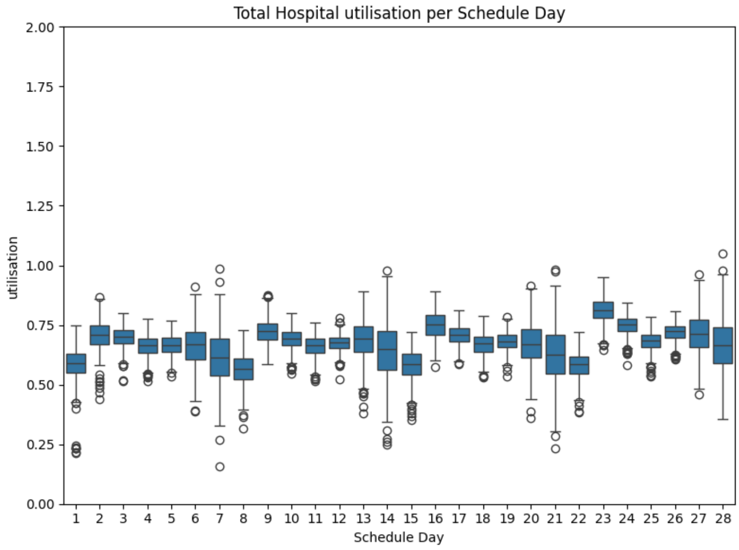


FIGURE F.36: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 2, MODEL D

F.3.4 TOTAL OVERTIME

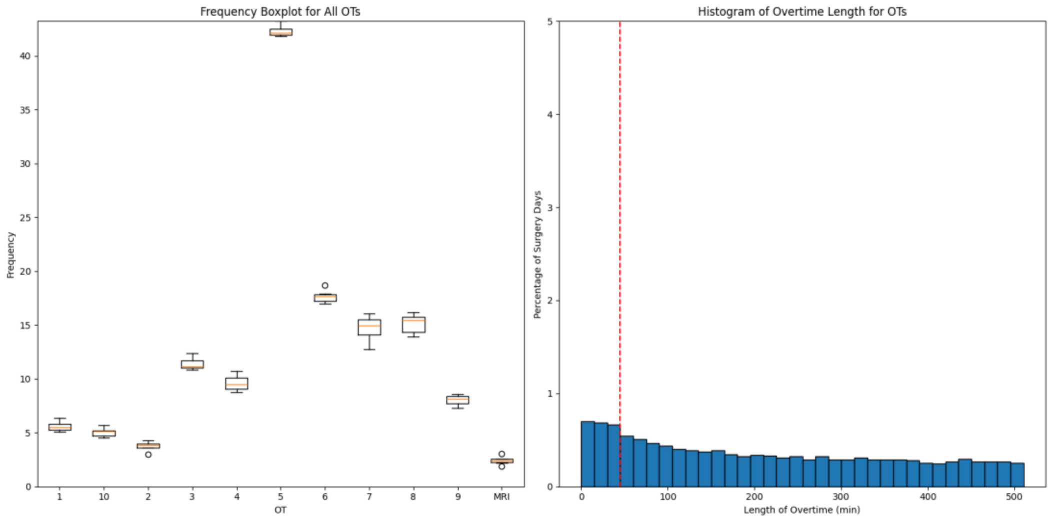


FIGURE F.37: TOTAL OVERTIME SCENARIO 2, MODEL A

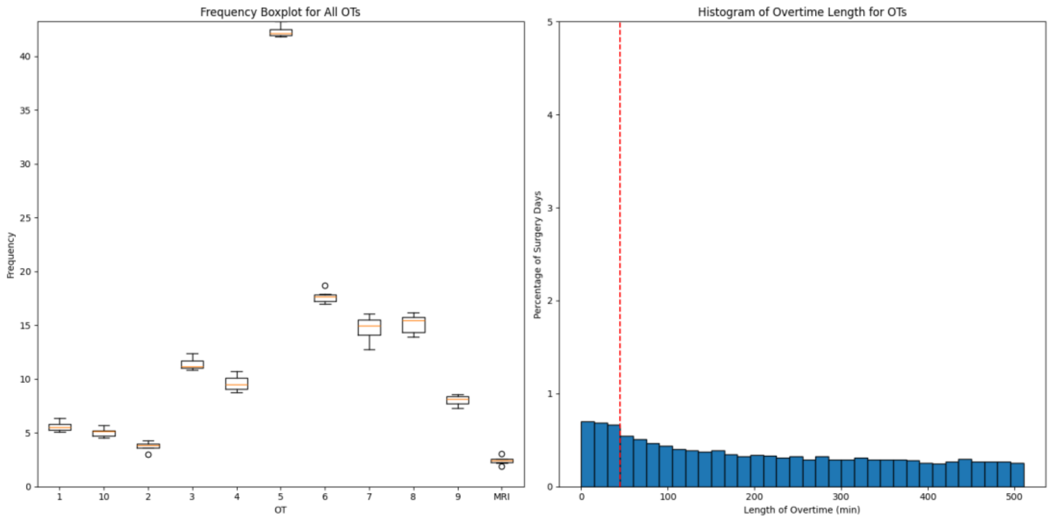


FIGURE F.38: TOTAL OVERTIME SCENARIO 2, MODEL B

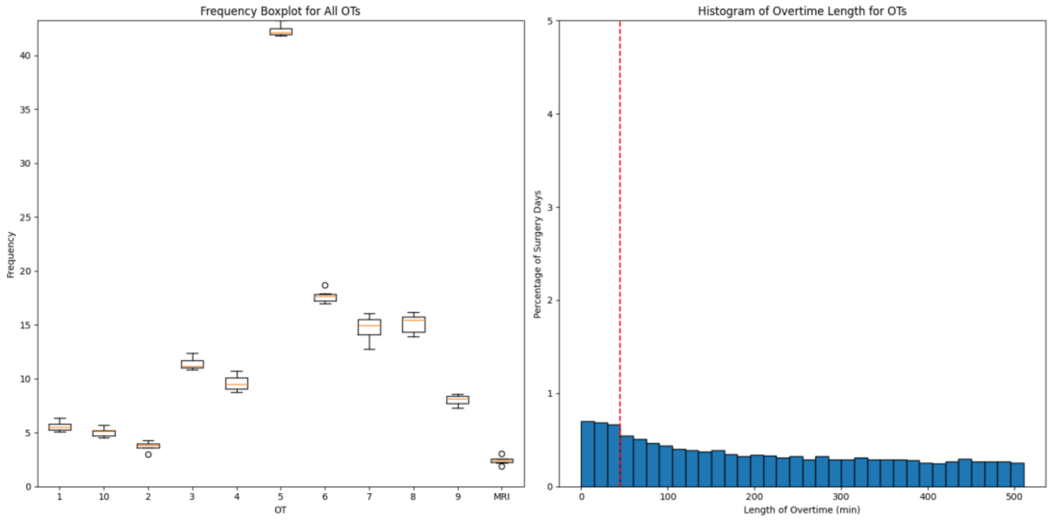


FIGURE F.39: TOTAL OVERTIME SCENARIO 2, MODEL C

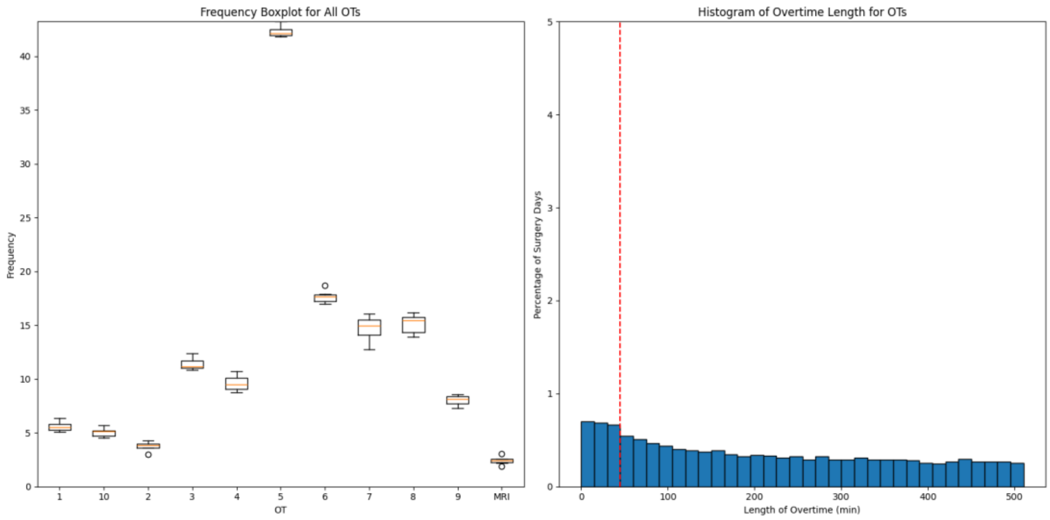


FIGURE F.40: TOTAL OVERTIME SCENARIO 2, MODEL D

F.3.5 OVERTIME PER OT

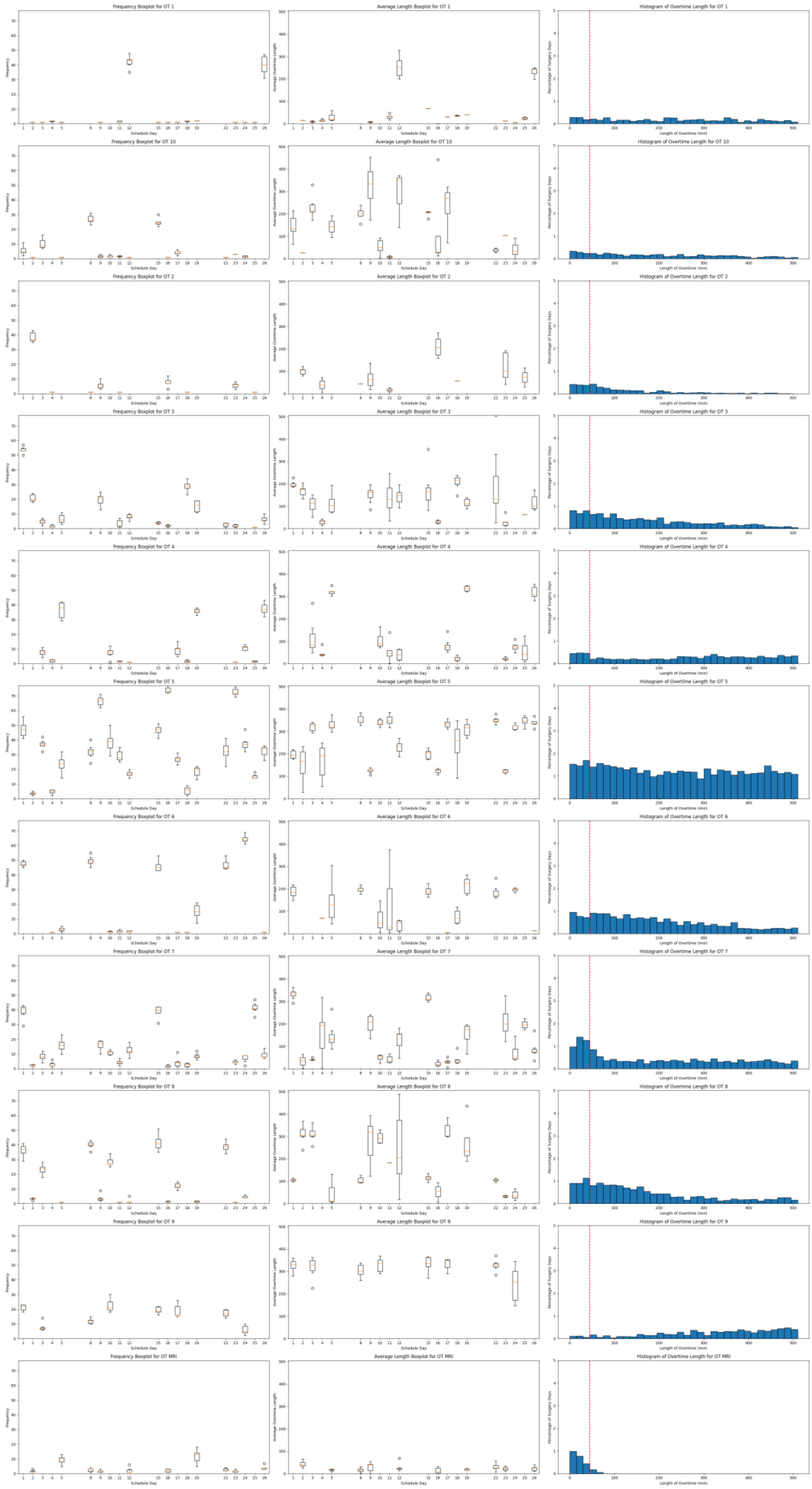


FIGURE F.41: OVERTIME PER OT SCENARIO 2, MODEL A

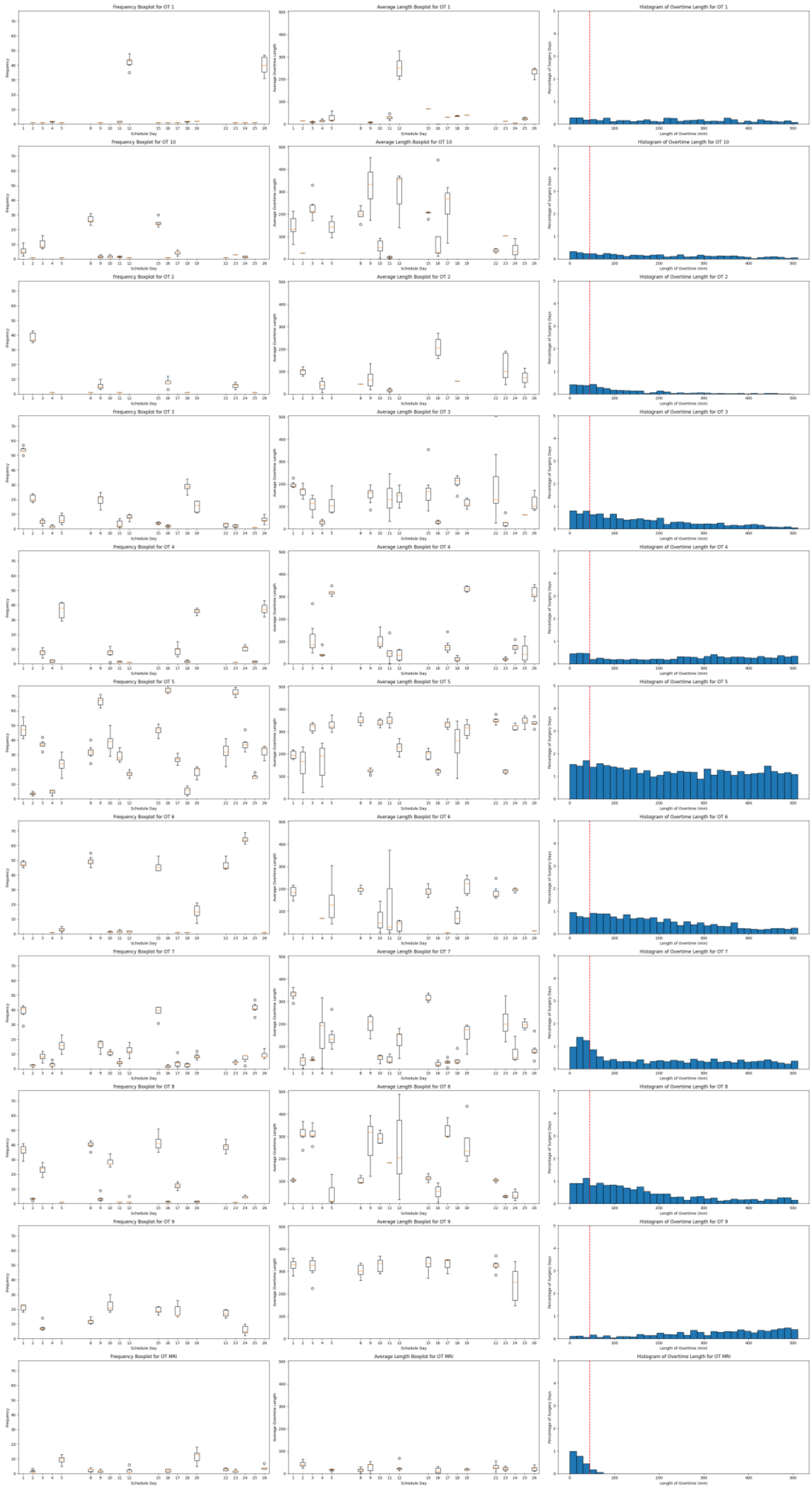


FIGURE F.42: OVERTIME PER OT SCENARIO 2, MODEL B

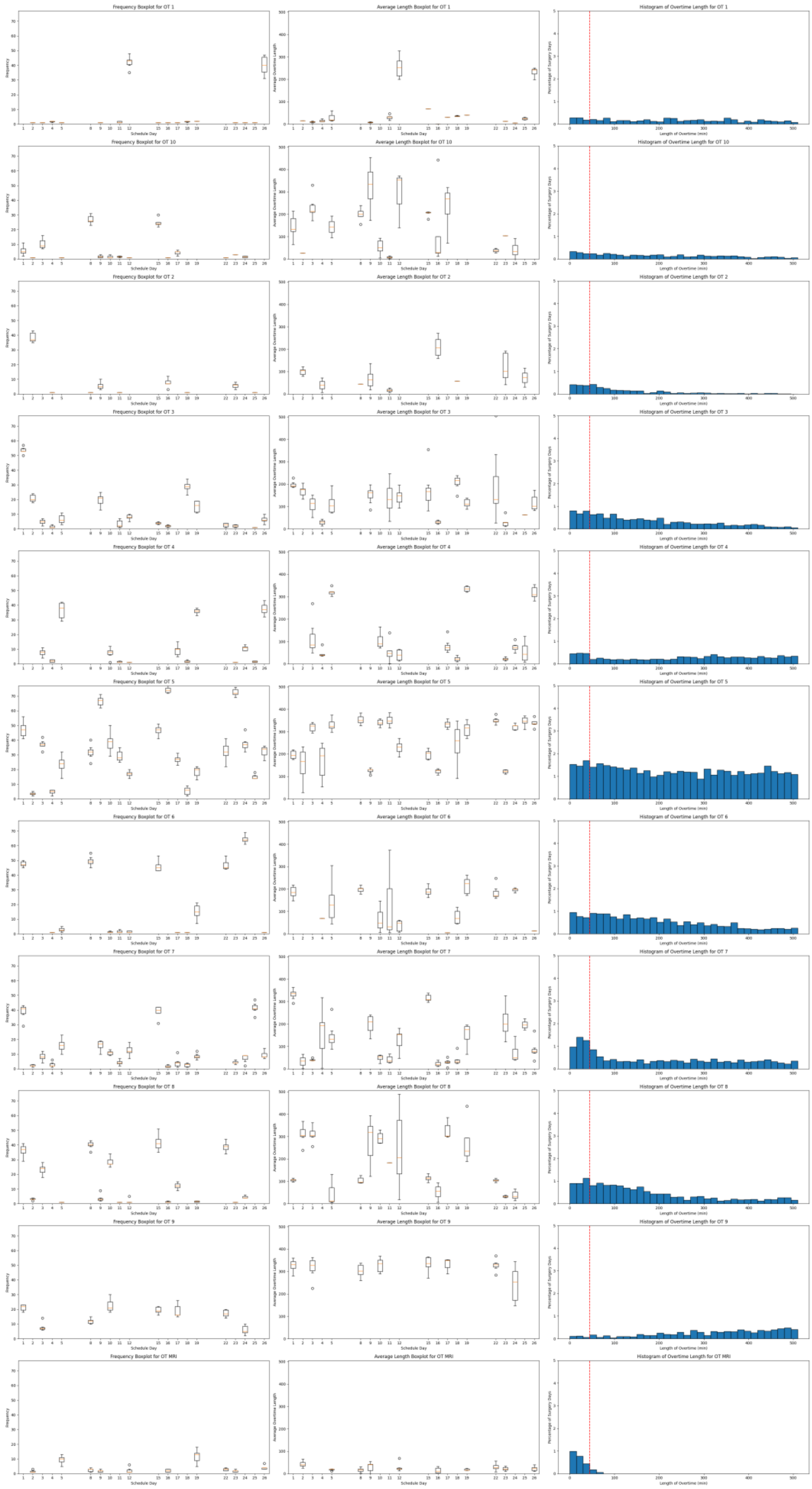


FIGURE F.43: OVERTIME PER OT SCENARIO 2, MODEL C

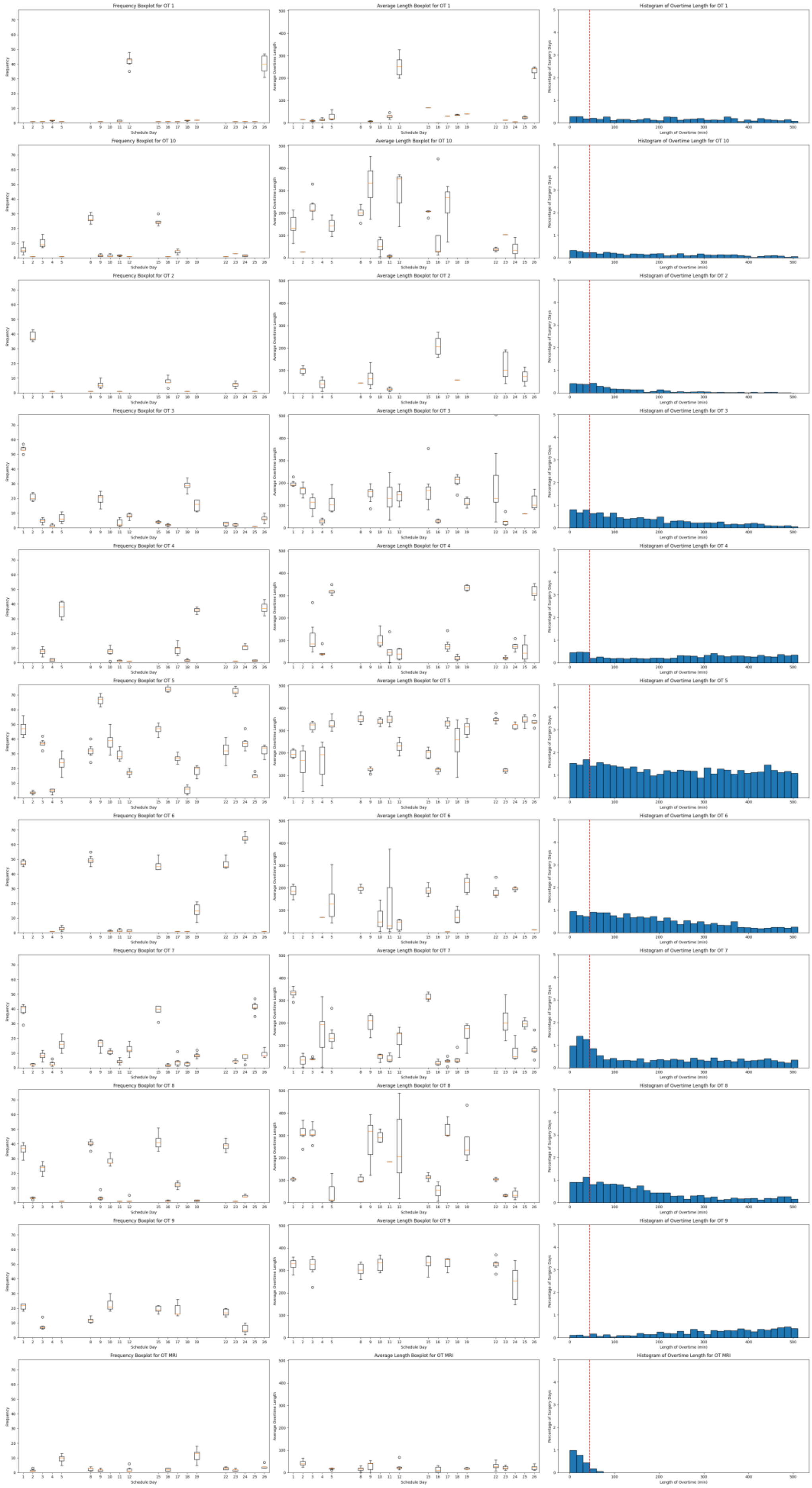


FIGURE F.44: OVERTIME PER OT SCENARIO 2, MODEL D

F.4 SCENARIO 3

F.4.1 SUMMARY TABLE

TABLE F.13: SUMMARY TABLE SCENARIO 3, MODEL A

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	15327	2934	13233	2569	31512	768	1,02	0,63
2	15514	3003	12980	2643	31512	761	1,04	0,62
3	15686	3103	12702	2700	31512	747	1,04	0,62
4	15834	3200	12455	2743	31512	743	1,06	0,62
5	15300	2931	13267	2609	31512	772	1,02	0,63
6	15519	3009	12969	2655	31512	743	1,03	0,62
7	15712	3063	12716	2651	31512	723	1,03	0,62

TABLE F.14: SUMMARY TABLE SCENARIO 3, MODEL B

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	15477	2807	13053	2624	31356	753	1,03	0,62
2	15861	2963	12513	2671	31356	783	1,02	0,61
3	16556	3191	11590	2778	31356	690	1,06	0,61
4	16372	3125	11840	2707	31356	740	1,05	0,62
5	16450	3117	11771	2704	31356	724	1,05	0,60
6	16738	3288	11317	2826	31356	710	1,07	0,60
7	16308	2996	12036	2767	31356	729	1,05	0,61

TABLE F.15: SUMMARY TABLE SCENARIO 3, MODEL C

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	17246	3845	7985	2977	29094	632	1,00	0,58
2	17040	3725	8310	2905	29094	637	1,00	0,58
3	16783	3683	8608	2874	29094	695	0,99	0,59
4	16838	3640	8601	2843	29094	717	0,99	0,58
5	16589	3511	8982	2888	29094	727	1,00	0,59
6	16894	3700	8482	2895	29094	706	1,00	0,59
7	17494	3909	7674	2979	29094	681	1,01	0,58

TABLE F.16: SUMMARY TABLE SCENARIO 3, MODEL D

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	18121	3550	7487	2971	29172	841	1,04	0,57
2	17817	3410	7929	2917	29172	829	1,04	0,58
3	17746	3472	7937	2856	29172	831	1,05	0,58
4	18151	3606	7396	2958	29172	844	1,04	0,58
5	17490	3258	8409	2875	29172	830	1,04	0,59
6	17508	3282	8367	2780	29172	901	1,04	0,58
7	17845	3405	7904	2848	29172	876	1,04	0,57

F.4.2 OT UTILSIATION ACROSS SCHEDULE CYCLE

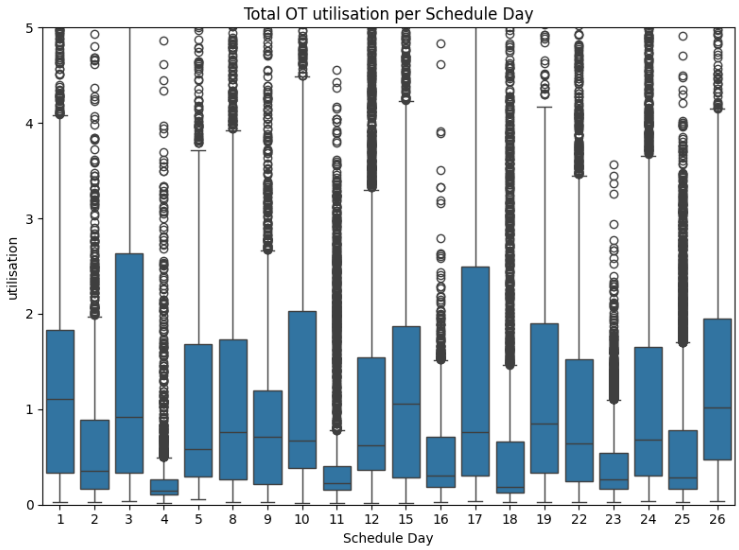


FIGURE F.45: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 3, MODEL A

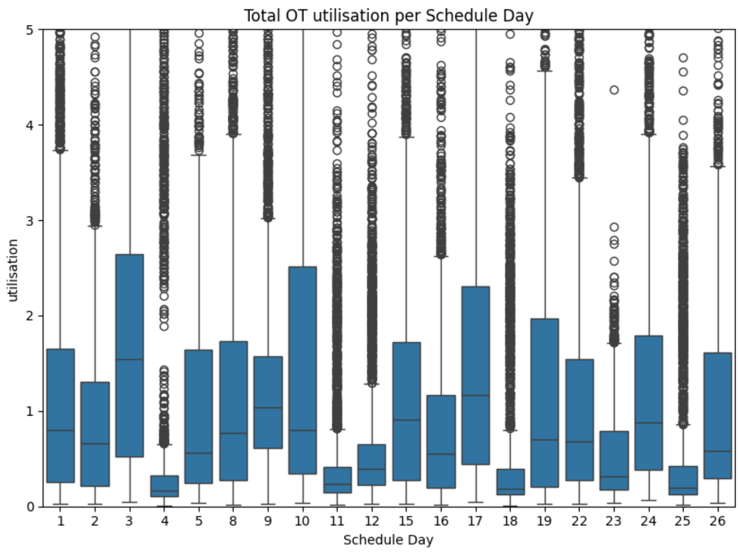


FIGURE F.46: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 3, MODEL B

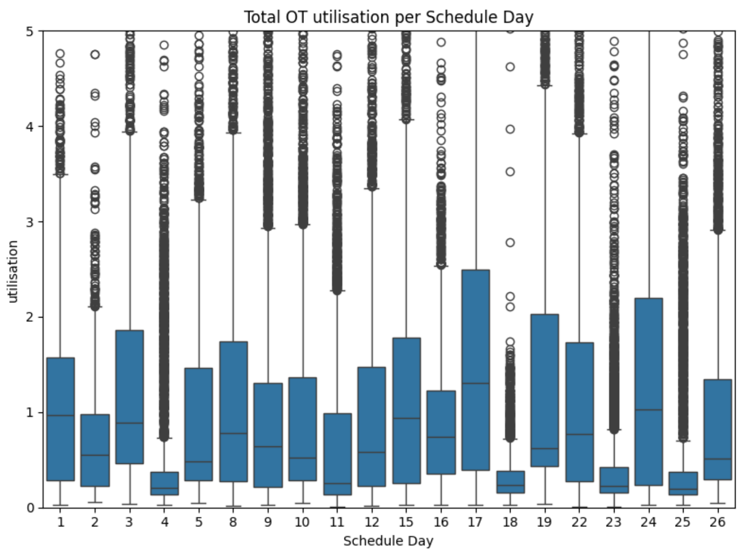


FIGURE F.47: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 3, MODEL C

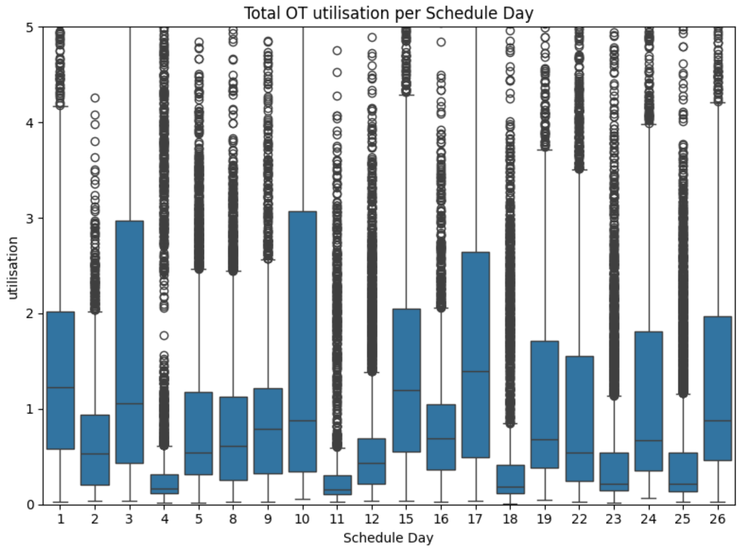


FIGURE F.48: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 3, MODEL D

F.4.3 WARD UTILSIATION ACROSS SCHEDULE CYCLE

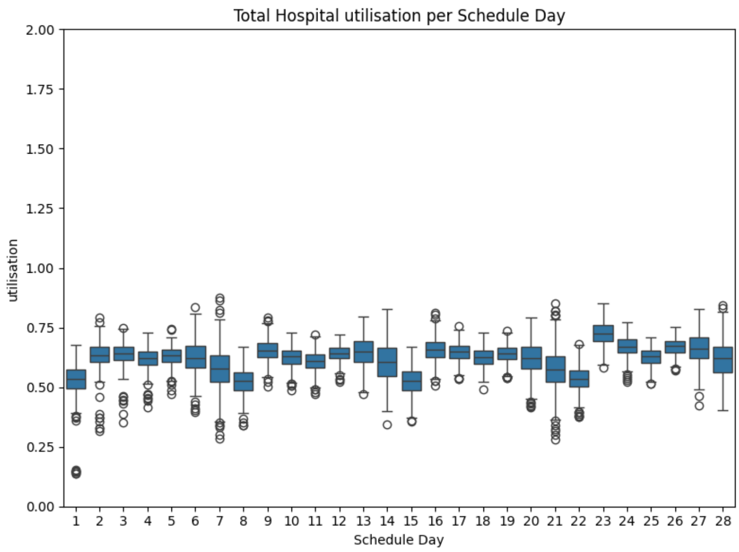


FIGURE F.49: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 3, MODEL A

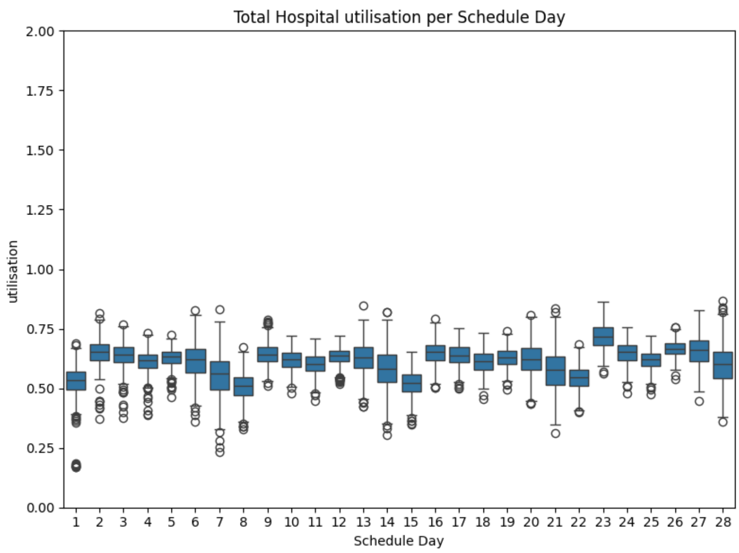


FIGURE F.50: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 3, MODEL B

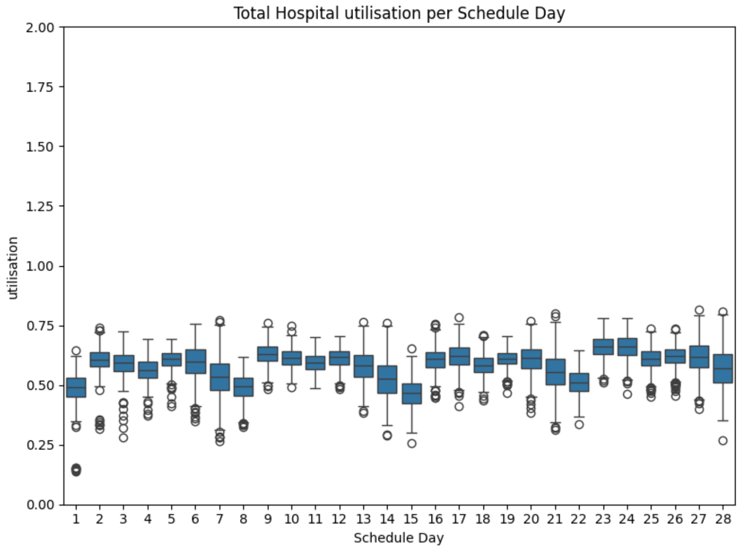


FIGURE F.51: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 3, MODEL C

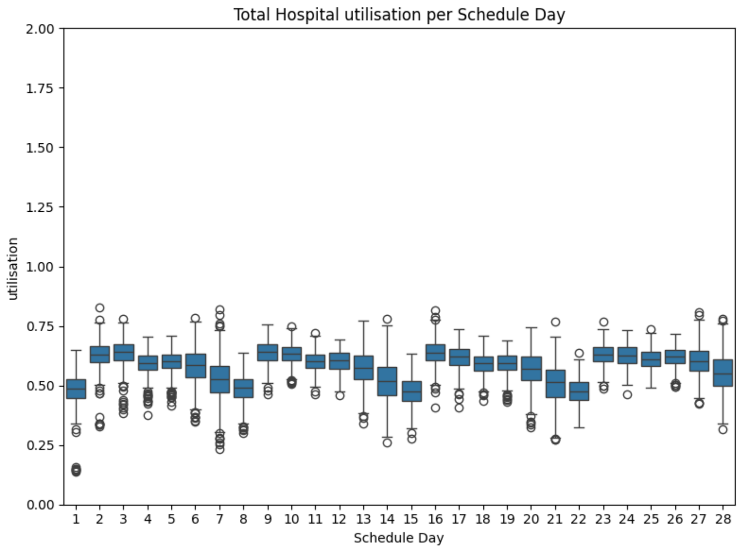


FIGURE F.52: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 3, MODEL D

F.4.4 TOTAL OVERTIME

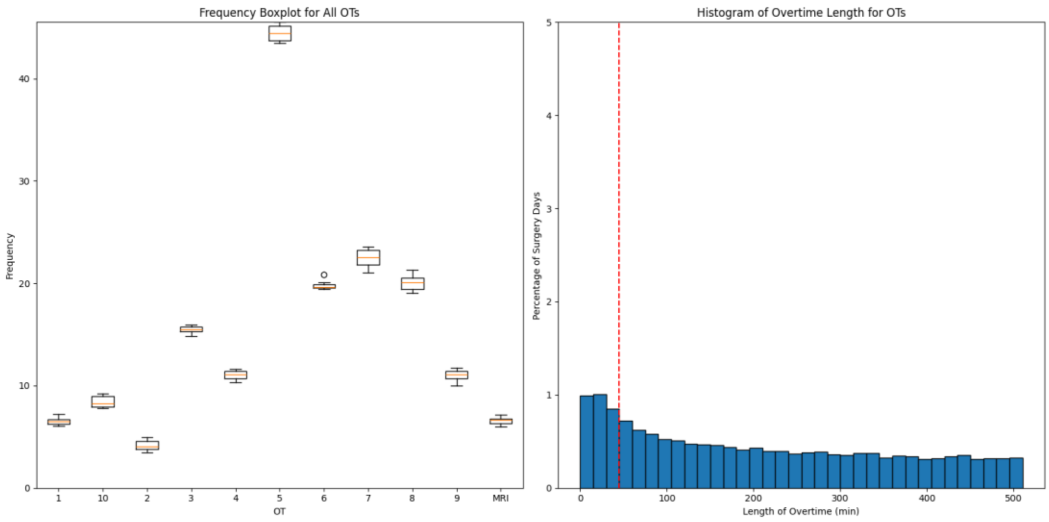


FIGURE F.53: TOTAL OVERTIME SCENARIO 3, MODEL A

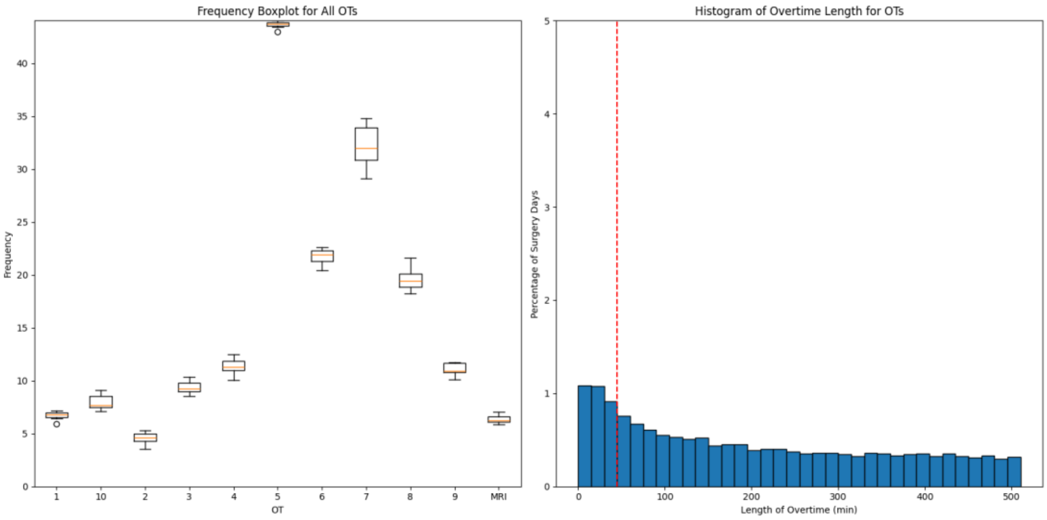


FIGURE F.54: TOTAL OVERTIME SCENARIO 3, MODEL B

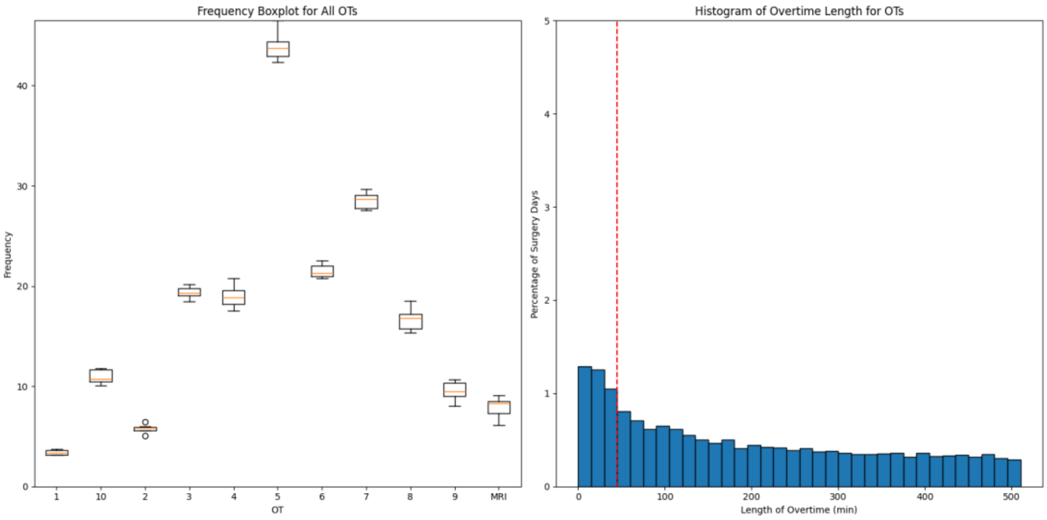


FIGURE F.55: TOTAL OVERTIME SCENARIO 3, MODEL C

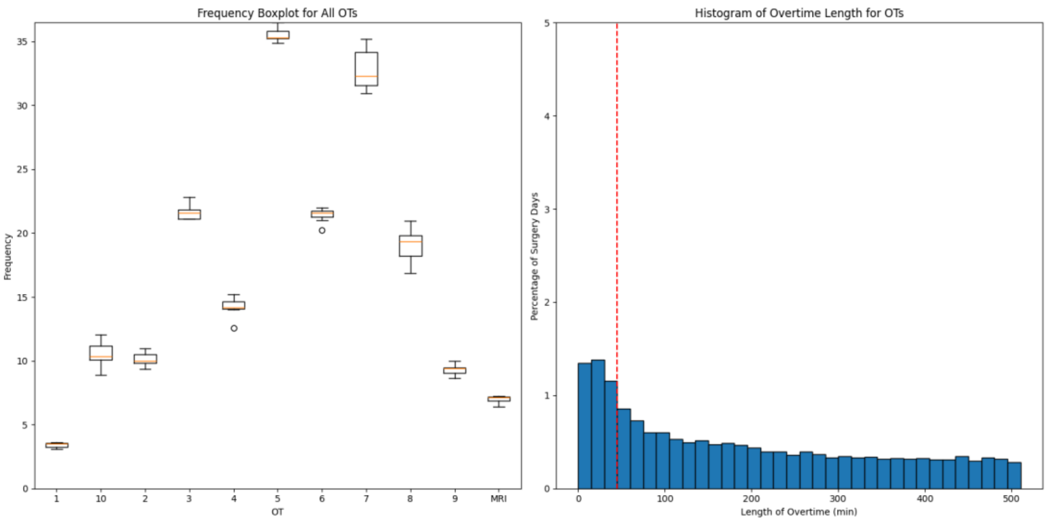


FIGURE F.56: TOTAL OVERTIME SCENARIO 3, MODEL D

F.4.5 OVERTIME PER OT

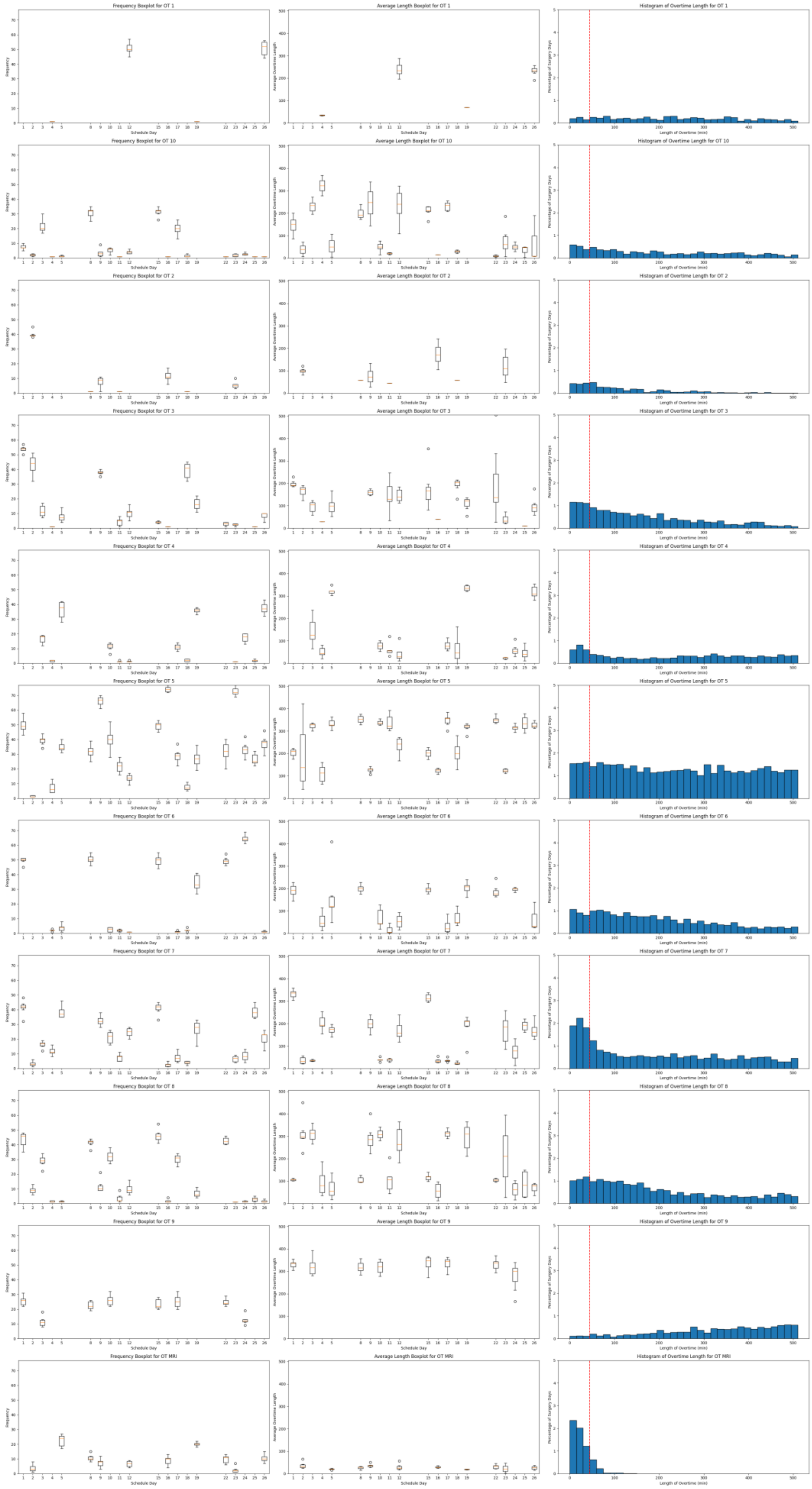


FIGURE F.57: OVERTIME PER OT SCENARIO 3, MODEL A

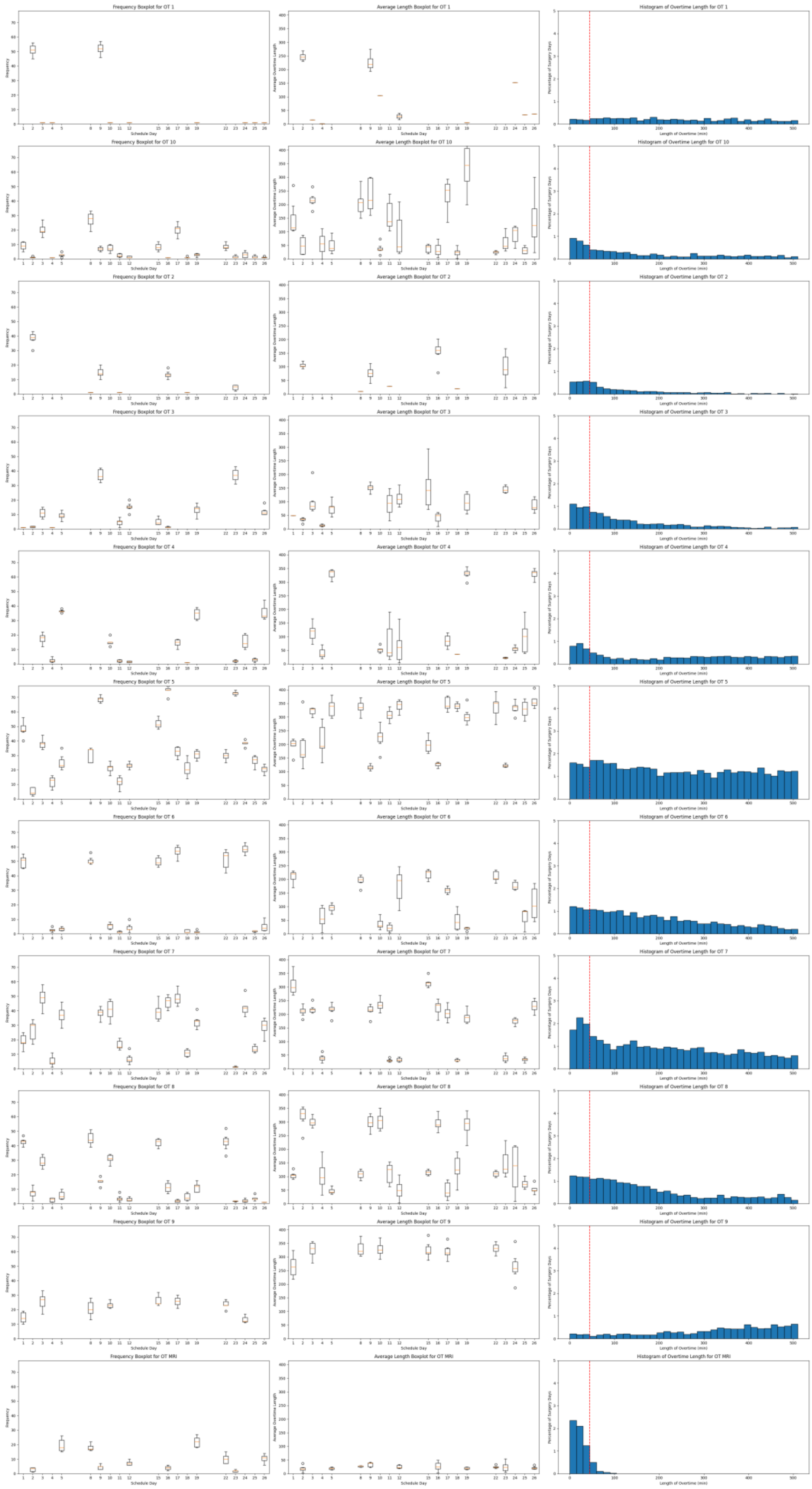


FIGURE F.58: OVERTIME PER OT SCENARIO 3, MODEL B

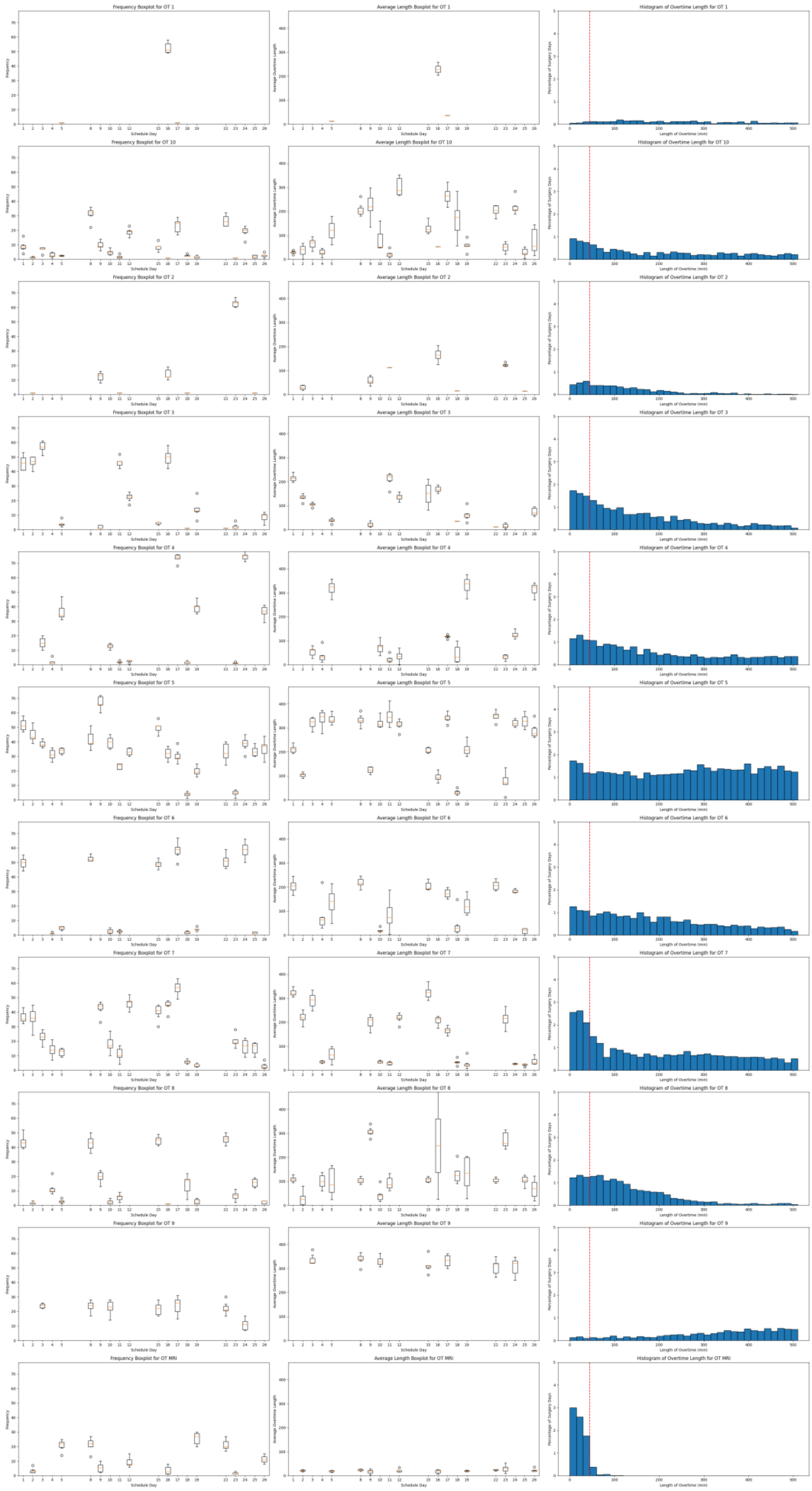


FIGURE F.59: OVERTIME PER OT SCENARIO 3, MODEL C

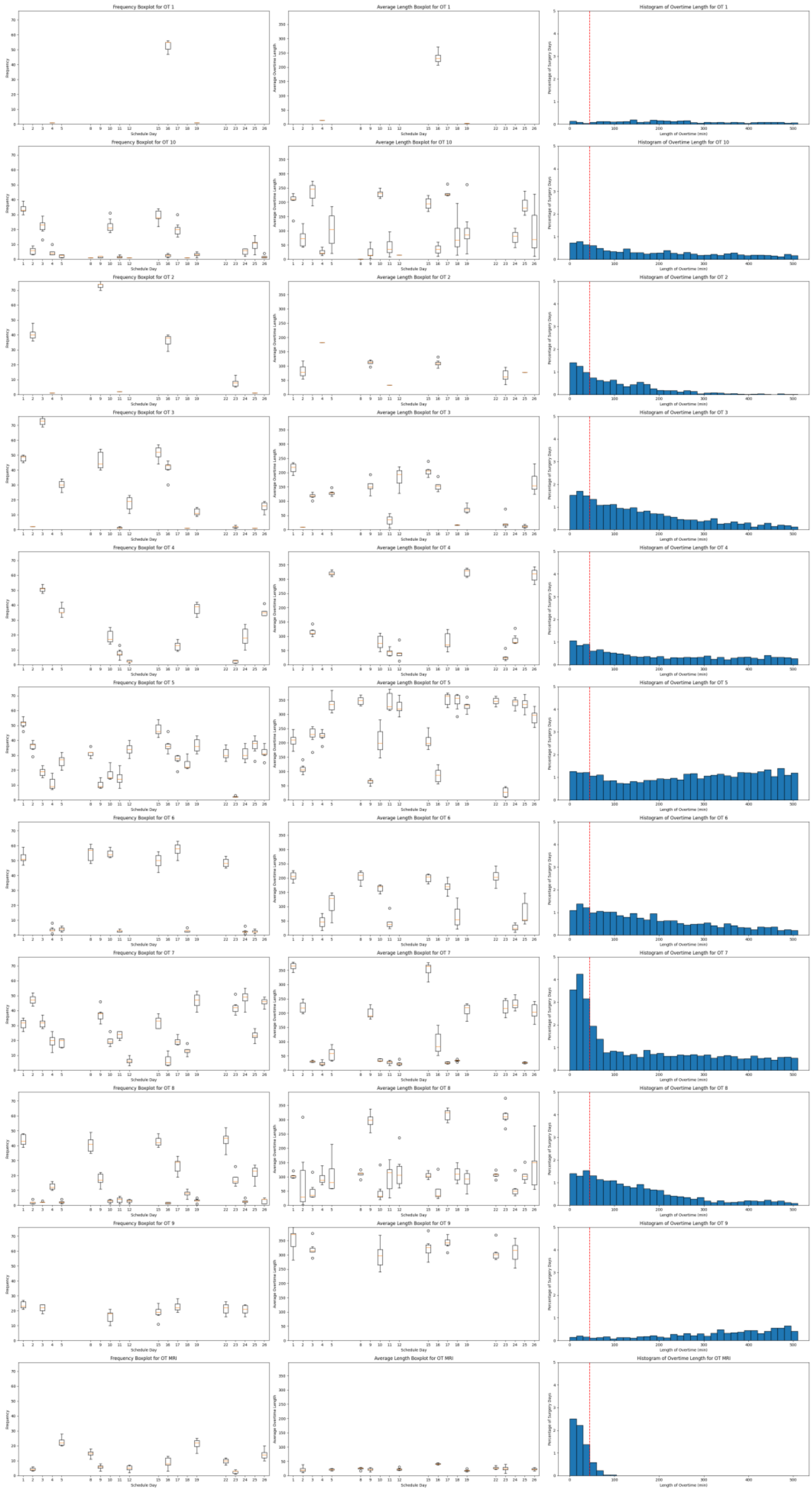


FIGURE F.60: OVERTIME PER OT SCENARIO 3, MODEL D

F.5 SCENARIO 4

F.5.1 SUMMARY TABLE

TABLE F.17: SUMMARY TABLE SCENARIO 4, MODEL A

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	17006	3469	11019	2853	31512	783	1,06	0,58
2	17849	4018	9627	3050	31512	699	1,09	0,56
3	17615	3778	10099	3018	31512	738	1,07	0,57
4	17764	3819	9913	3015	31512	697	1,08	0,56
5	17316	3612	10567	2921	31512	711	1,06	0,57
6	17310	3654	10536	2961	31512	721	1,06	0,58
7	17836	3923	9737	3020	31512	687	1,07	0,56

TABLE F.18: SUMMARY TABLE SCENARIO 4, MODEL B

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	17984	3847	9508	2998	31356	727	1,07	0,56
2	18179	3838	9324	3008	31356	699	1,08	0,57
3	17362	3559	10423	2916	31356	750	1,06	0,58
4	18679	4182	8479	3118	31356	686	1,11	0,56
5	18214	3842	9287	3037	31356	717	1,09	0,56
6	18083	3719	9540	3058	31356	726	1,08	0,56
7	18390	4008	8946	3117	31356	719	1,09	0,56

TABLE F.19: SUMMARY TABLE SCENARIO 4, MODEL C

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	18938	4577	5561	3209	29094	563	1,02	0,53
2	18935	4571	5571	3139	29094	613	1,02	0,52
3	18706	4418	5952	3134	29094	621	1,02	0,54
4	18364	4218	6497	3064	29094	638	1,01	0,54
5	19232	4697	5151	3203	29094	586	1,03	0,52
6	18561	4305	6217	3134	29094	668	1,02	0,54
7	18552	4375	6155	3080	29094	636	1,02	0,54

TABLE F.20: SUMMARY TABLE SCENARIO 4, MODEL D

Run	Successful Surgeries	Canceled Surgeries (OT Unavailability)	Canceled Surgeries (Ward Unavailability)	Overtime Occurrences	Total number of surgeries	Times a ward had to exceed capacity	Average utilisation OT	Average utilisation ward
1	19648	4429	5079	3140	29172	774	1,06	0,53
2	19666	4446	5042	3111	29172	747	1,08	0,52
3	19891	4482	4783	3215	29172	767	1,06	0,51
4	19198	4109	5851	3111	29172	780	1,07	0,54
5	19020	4082	6057	3052	29172	825	1,06	0,54
6	19734	4459	4964	3106	29172	780	1,07	0,52
7	19361	4197	5602	3101	29172	810	1,06	0,53

F.5.2 OT UTILSIATION ACROSS SCHEDULE CYCLE

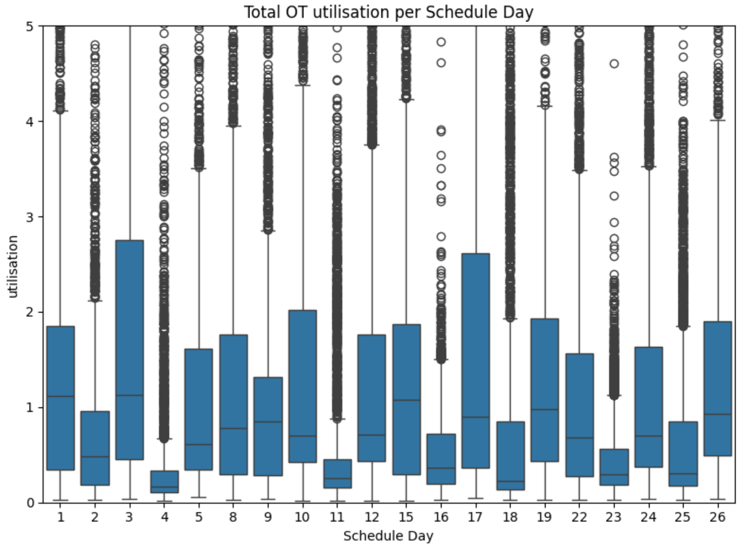


FIGURE F.61: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 4, MODEL A

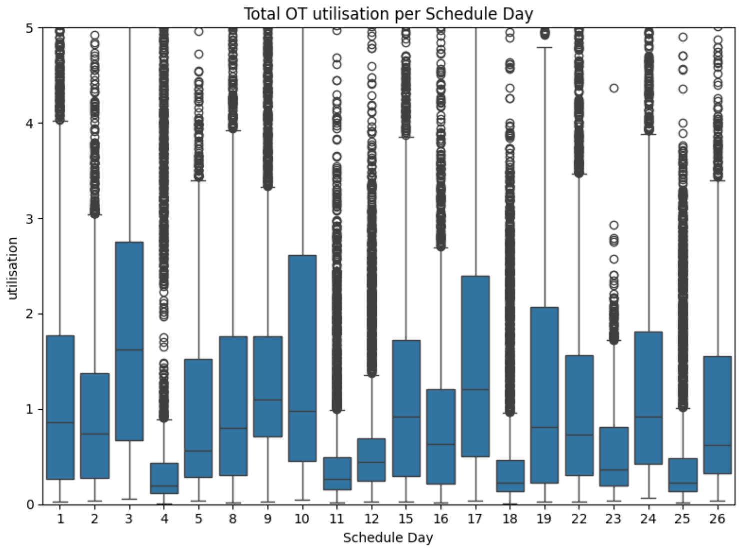


FIGURE F.62: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 4, MODEL B

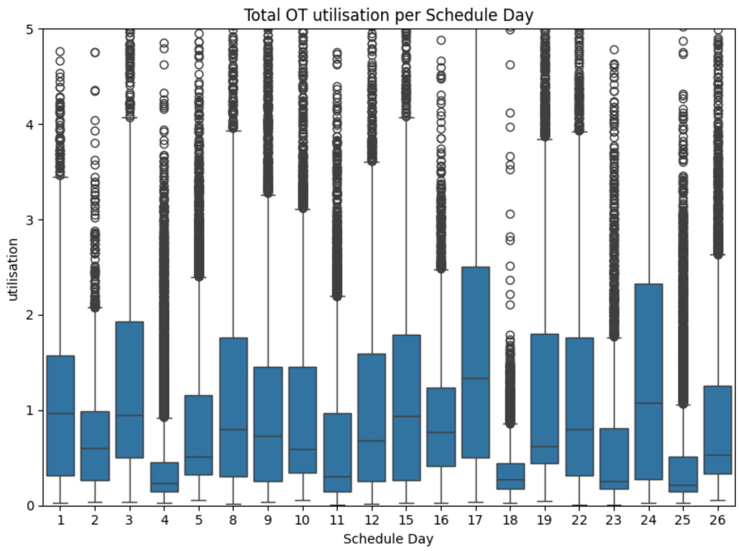


FIGURE F.63: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 4, MODEL C

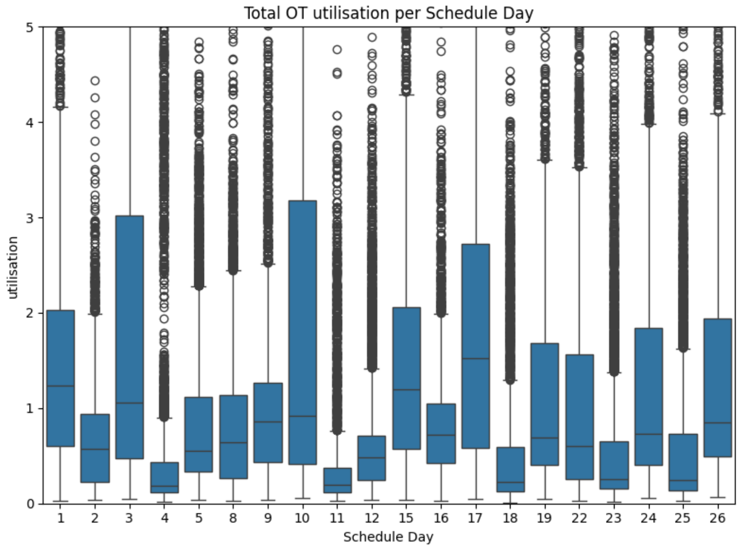


FIGURE F.64: OT UTILISATION ACROSS 28 DAY CYCLE SCENARIO 4, MODEL D

F.5.3 WARD UTILSIATION ACROSS SCHEDULE CYCLE

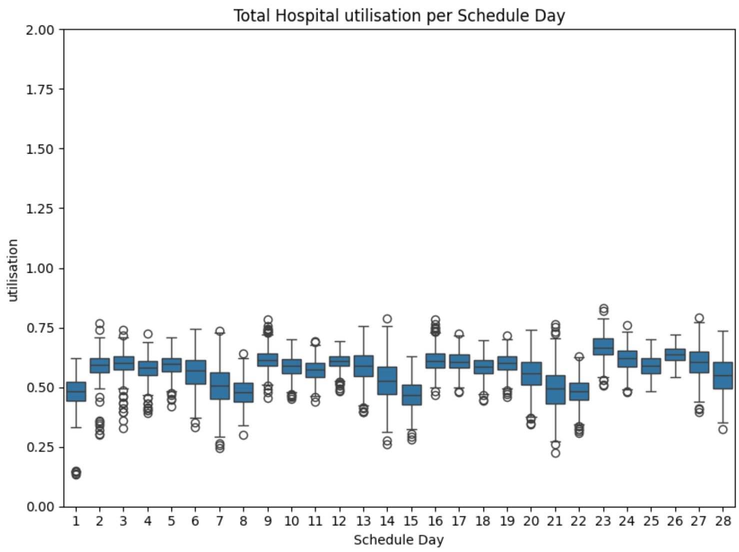


FIGURE F.65: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 4, MODEL A

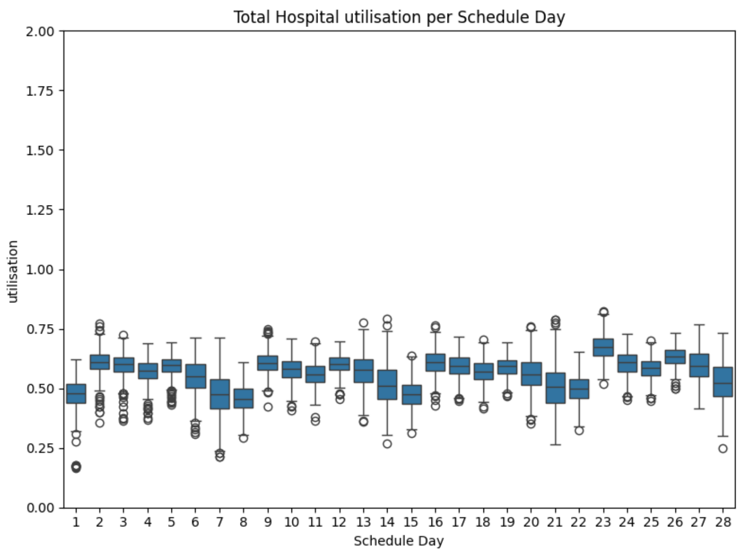


FIGURE F.66: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 4, MODEL B

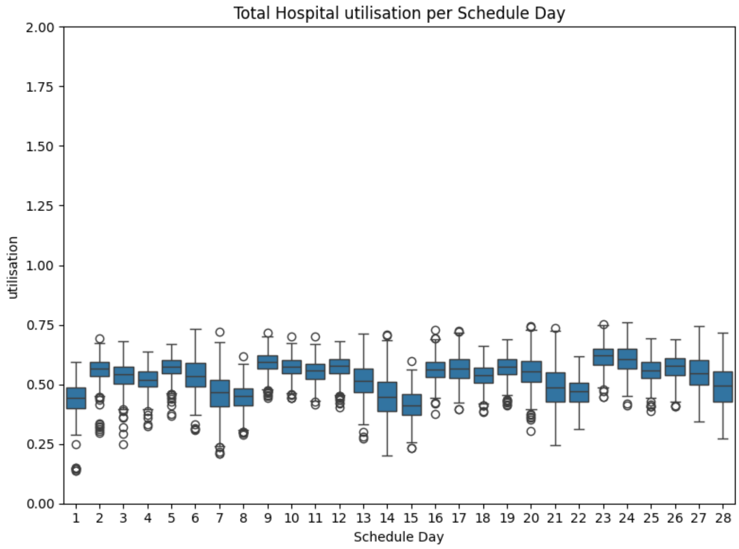


FIGURE F.67: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 4, MODEL C

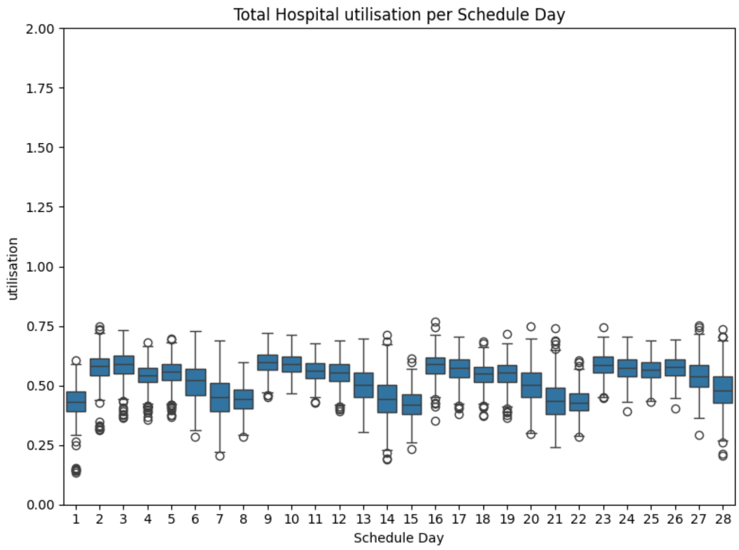


FIGURE F.68: WARD UTILISATION ACROSS 28 DAY CYCLE SCENARIO 4, MODEL D

F.5.4 TOTAL OVERTIME

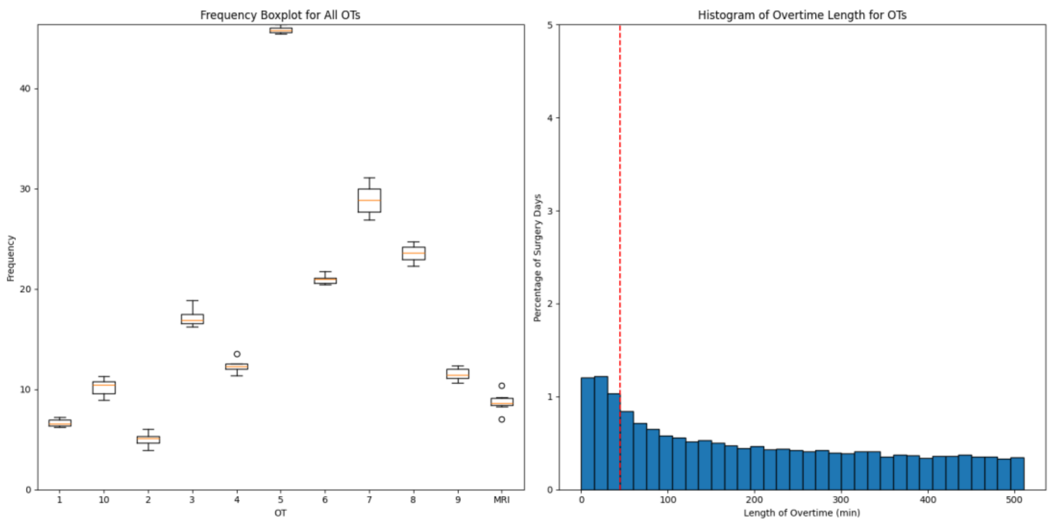


FIGURE F.69: TOTAL OVERTIME SCENARIO 4, MODEL A

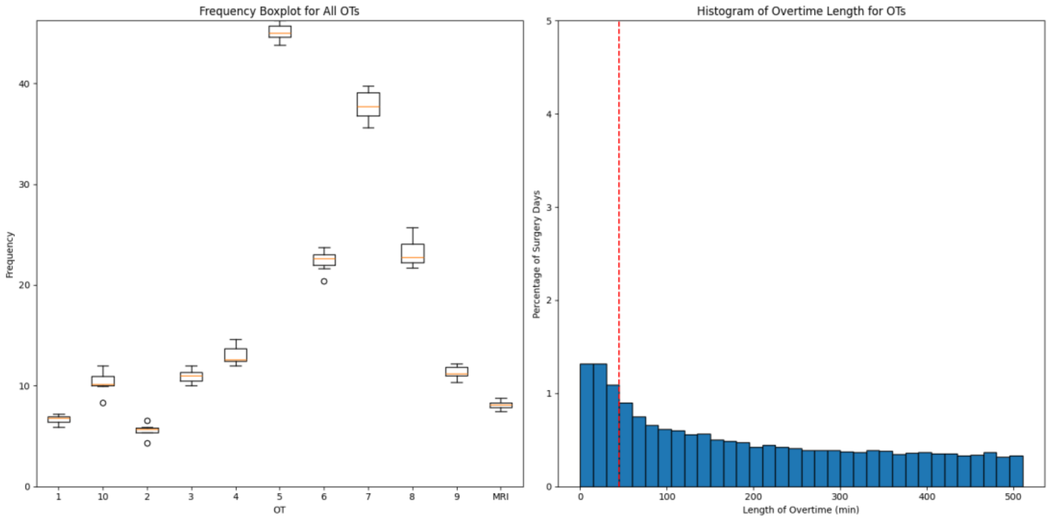


FIGURE F.70: TOTAL OVERTIME SCENARIO 4, MODEL B

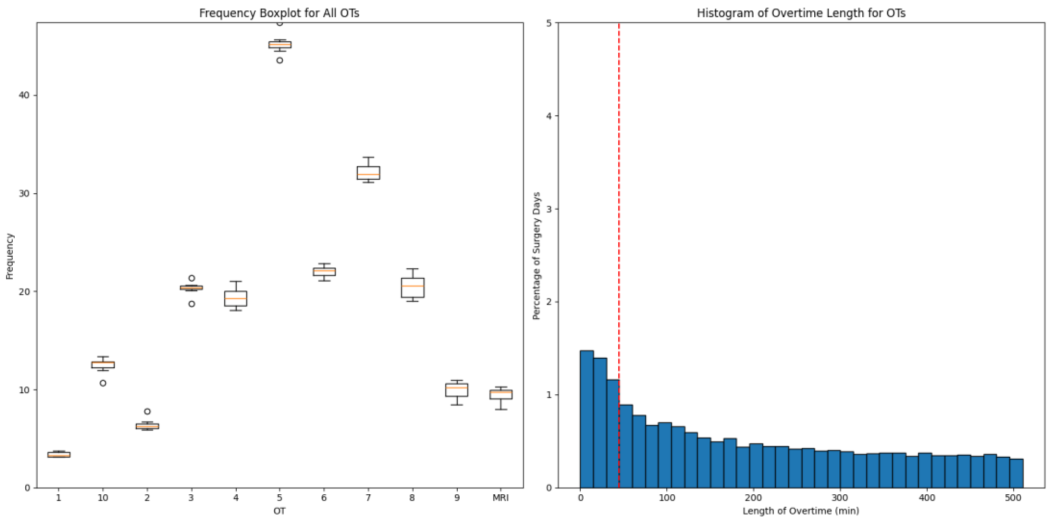


FIGURE F.71: TOTAL OVERTIME SCENARIO 4, MODEL C

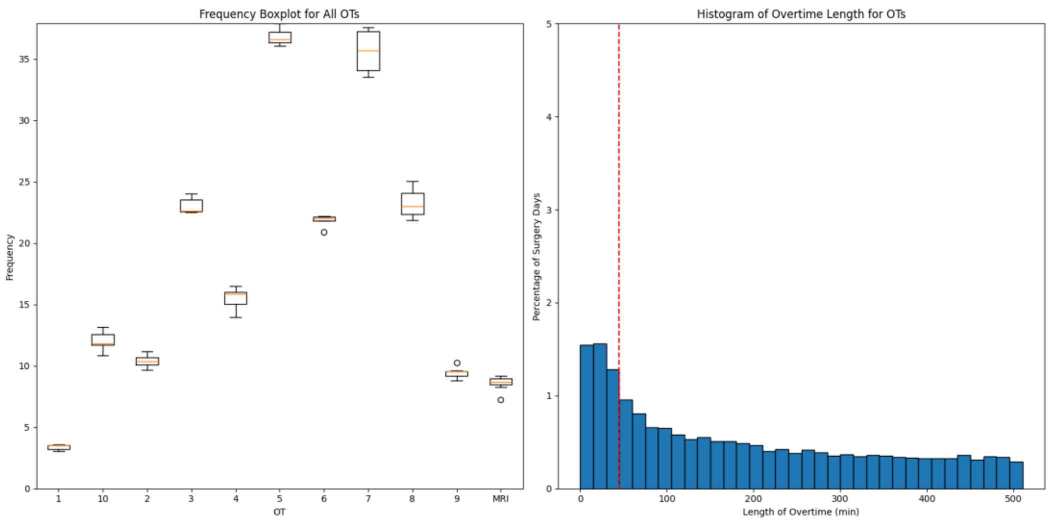


FIGURE F.72: TOTAL OVERTIME SCENARIO 4, MODEL D

F.5.5 OVERTIME PER OT

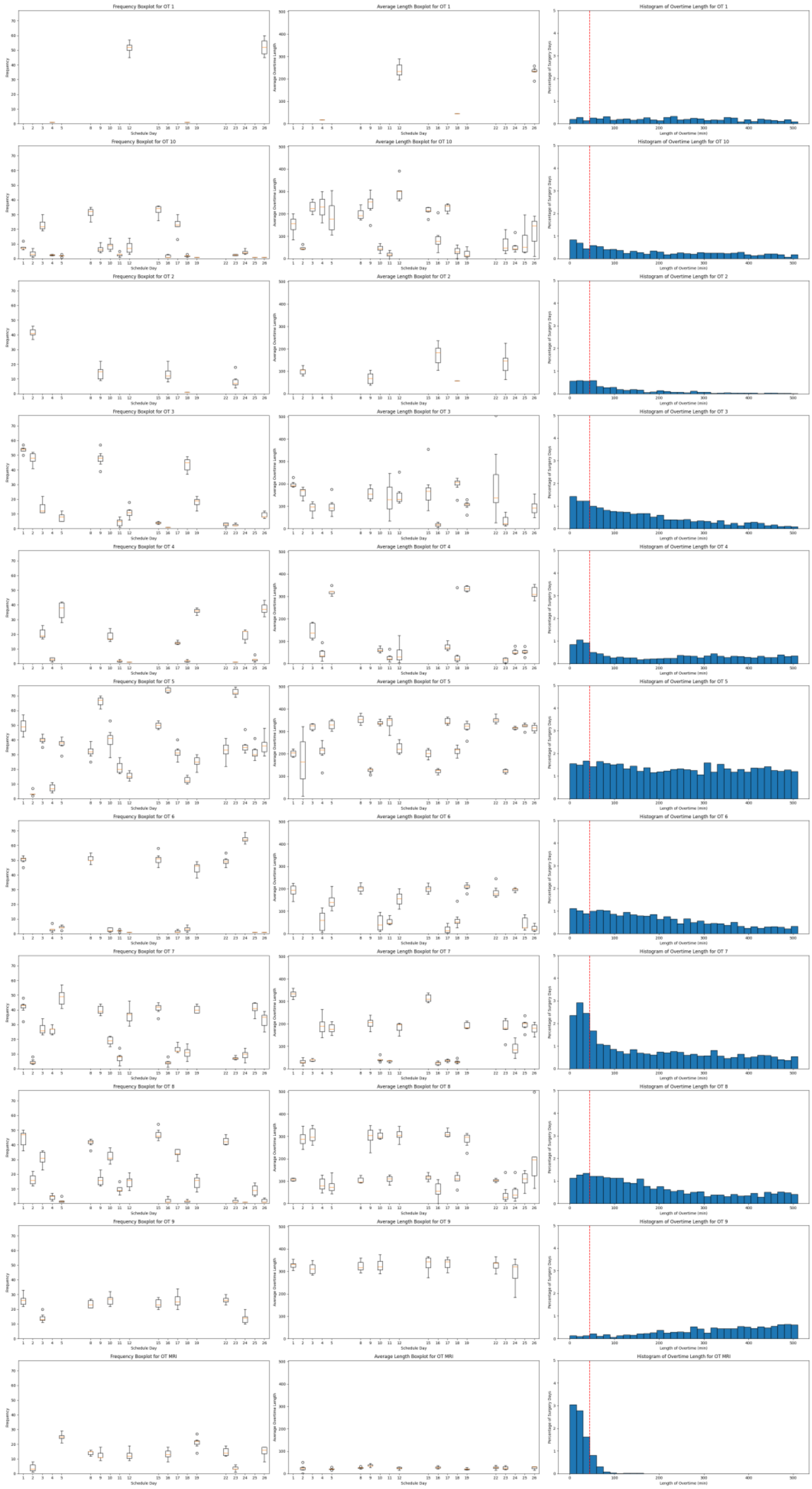


FIGURE F.73: OVERTIME PER OT SCENARIO 4, MODEL A

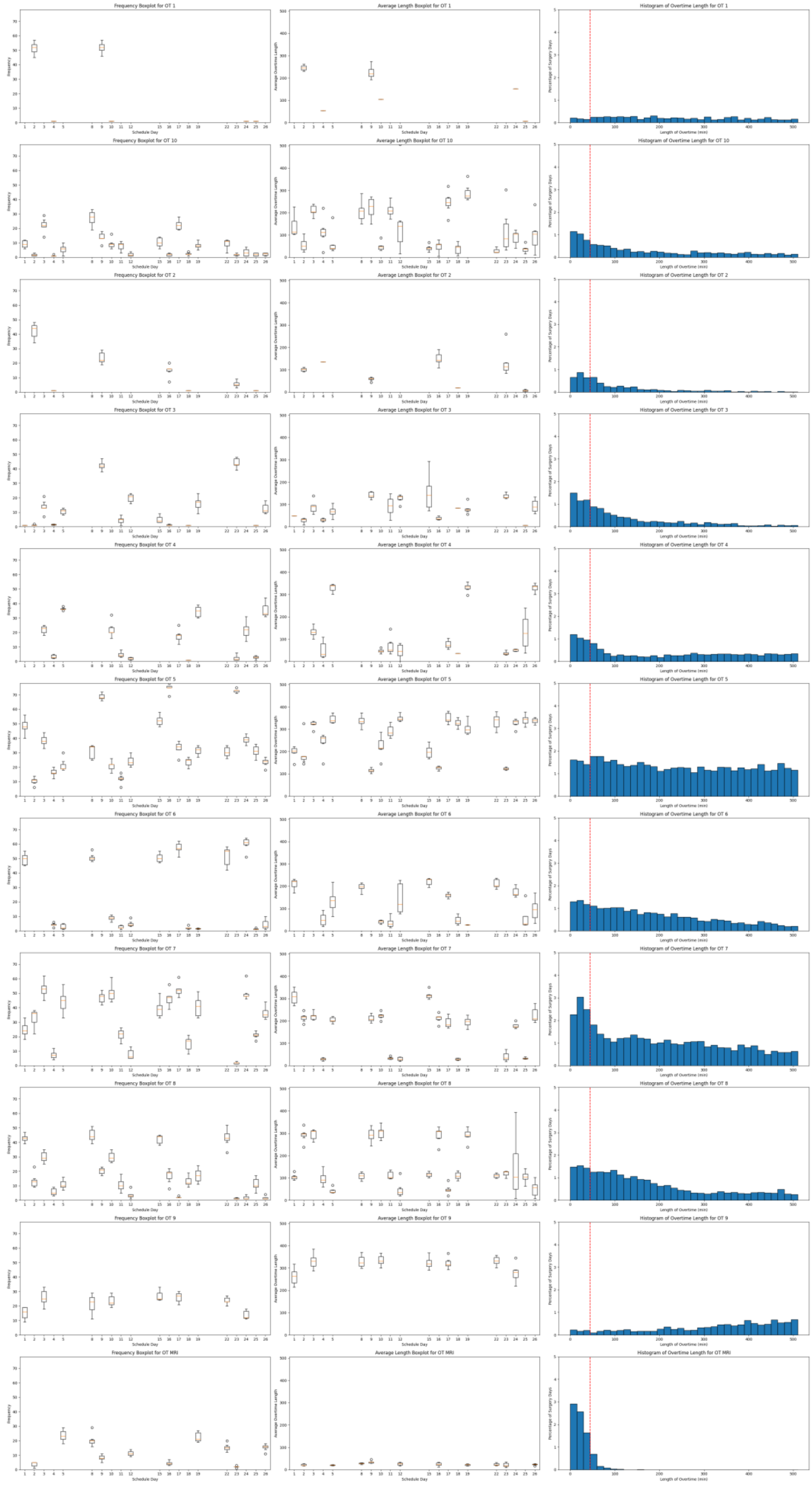


FIGURE F.74: OVERTIME PER OT SCENARIO 4, MODEL B

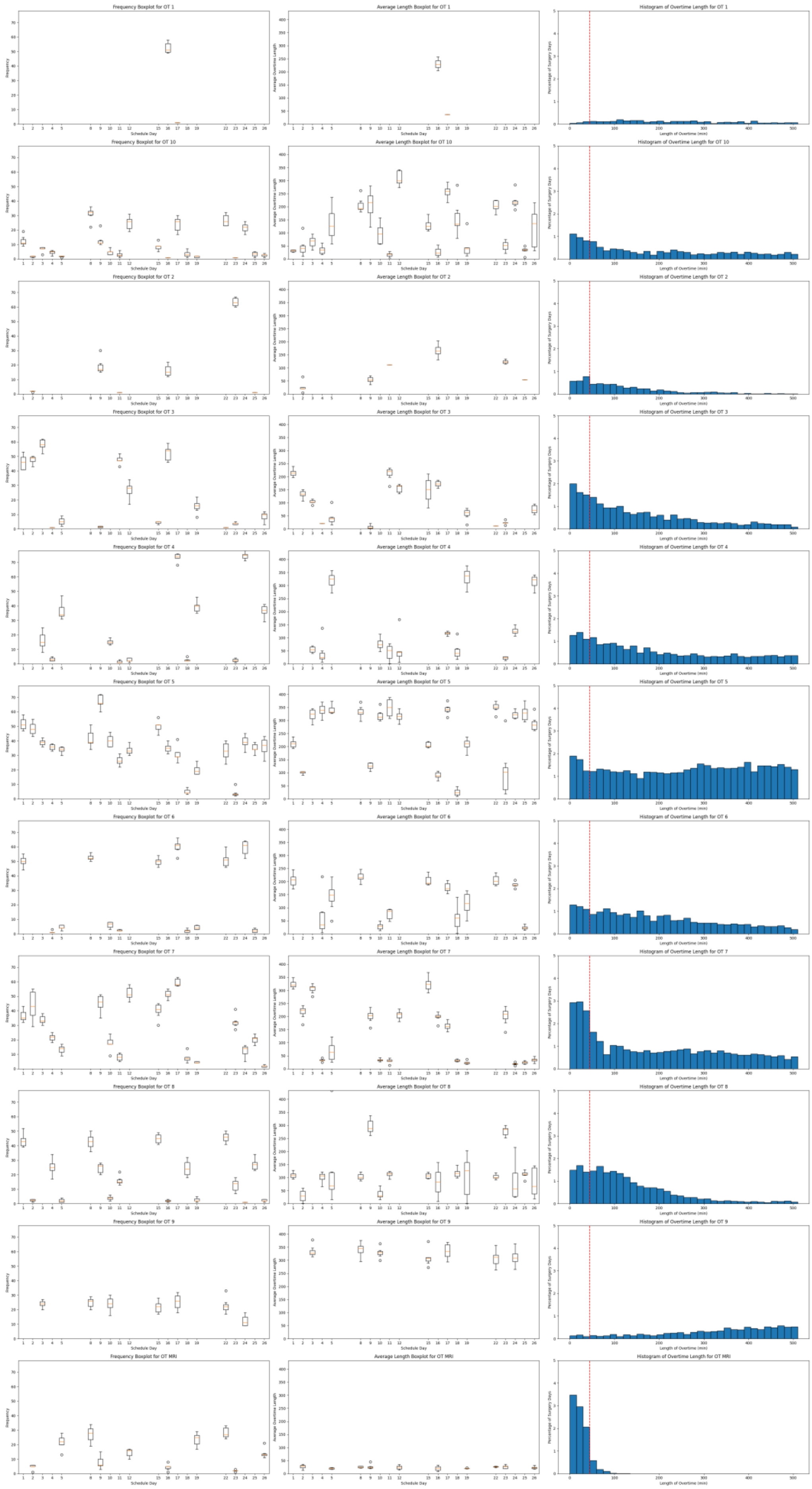


FIGURE F.75: OVERTIME PER OT SCENARIO 4, MODEL C

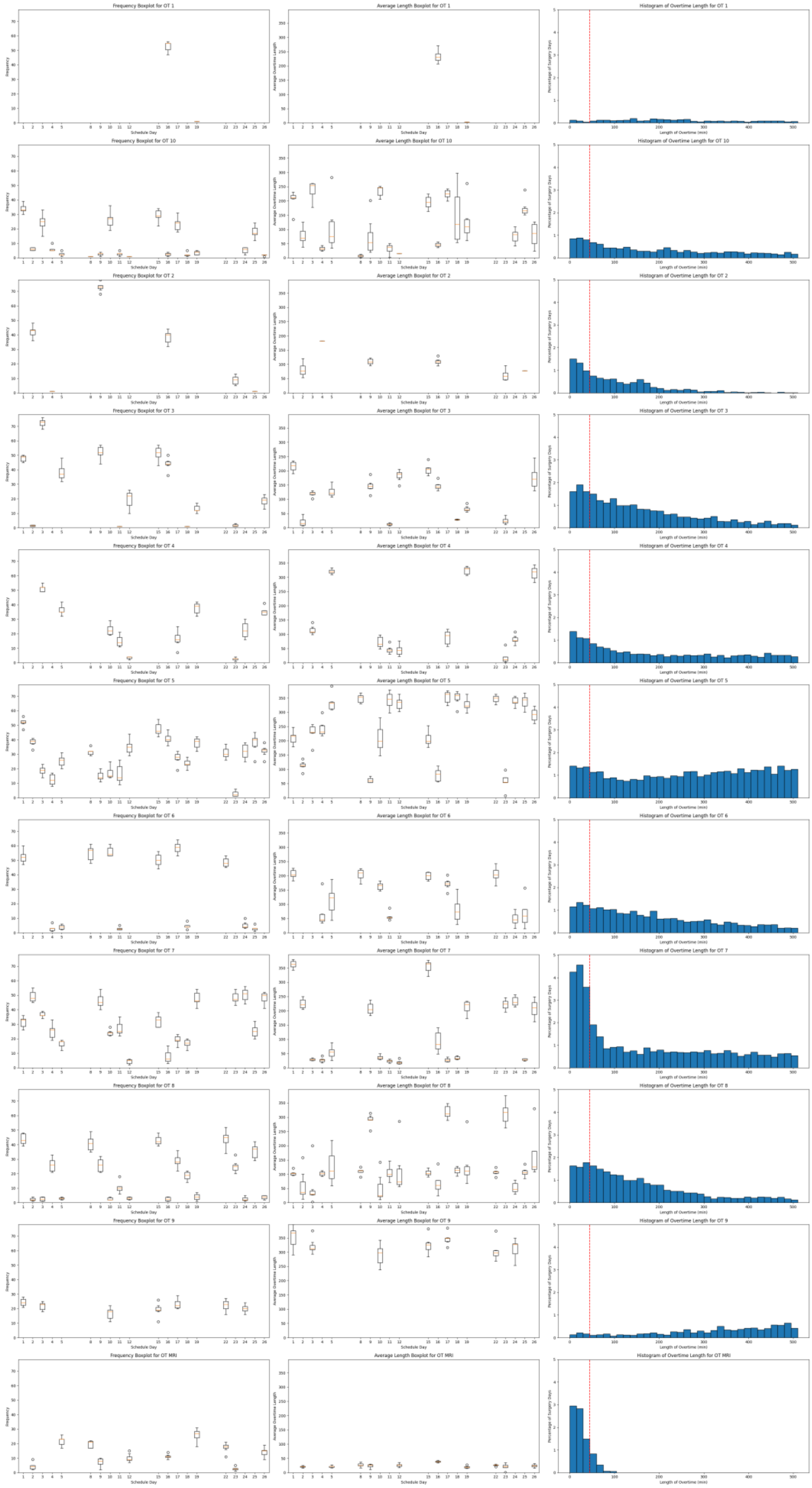


FIGURE F.76: OVERTIME PER OT SCENARIO 4, MODEL D