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HYBRID MODELS OF OPERATIONS RESEARCH AND ARTIFICIAL
INTELLIGENCE FOR INTEGRATED OPERATING ROOM SCHEDULING AND
PERIOPERATIVE PATIENT PATHWAYS

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Abstract

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The core focus of this research is surgical activity, a key component of hospital management. Surgery involves a wide range of highly specialized human and technological resources and represents the area with the greatest impact not only on patient health outcomes but also on the hospital's economic performance.

Throughout the PhD journey, the research was directed toward the study and implementation of Operation Research (OR) and Machine Learning techniques to provide practical solutions for the management of operating rooms and outpatient surgical scheduling.

A data-driven, multi-phase approach was adopted. It began with the analysis of existing hospital information systems to map and understand the complex dynamics occurring within the healthcare setting. This phase was followed by the development of classification, forecasting, and prescriptive models aimed at optimizing surgical processes.

These models were then integrated into optimization frameworks and meta-heuristic algorithms, with their performance ultimately validated through simulation experiments.

The results demonstrated how advanced data analytics can support operational decision-making in hospitals, enabling more efficient use of surgical resources, improving planning accuracy, and ultimately contributing to higher quality and sustainability in healthcare delivery.

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Contents

Abstract	i
Acknowledgements	iii
List of Figures	ix
List of Tables	xi
List of Abbreviations	xiii
1 Introduction	1
1.1 Surgical activities management	4
1.2 Context	5
1.3 Research objectives	7
1.4 Thesis structure	9
2 Data Overview	11
2.1 Data Sources	11
2.1.1 Waiting List position	11
2.1.2 Ward transfers	13
2.1.3 Operating Room Register	13
3 Predictive Models	15
3.1 Introduction	15
3.2 Literature Review	15
3.2.1 Perioperative Path Prediction	15
3.2.2 Procedure Time Prediction	16
3.3 Methodology	17
3.3.1 Text Preprocessing	17

3.3.2	Feature Integration	18
3.3.3	Machine Learning Models	19
3.4	Evaluation Metrics for Classification Models	21
3.5	Evaluation Metrics for Regression Model	23
3.6	Results and Discussion	23
3.7	Surgical Procedure Time	26
3.8	Conclusions	26
4	Optimization Model	29
4.1	Literature review	29
4.2	Problem definition	30
4.3	Patients' Information	30
4.4	Model	31
5	Metaheuristic Algorithms	35
5.1	Introduction	35
5.2	Literature review	35
5.3	Algorithms	36
5.3.1	Greedy Algorithm	36
5.3.2	Local Search Criteria	38
5.3.3	Multiswap	39
5.3.4	Tabu	41
5.3.5	Tabu Ad	41
5.3.6	Random	43
5.3.7	Random Degrade	44
5.4	Algorithmic Details	44
6	Results	47
6.1	Introduction	47
6.2	Computational results	47
6.3	Real world application Comparison	52
7	Simulation	57
7.1	Introduction	57
7.2	Simulation Case Study	57
7.3	Objectives	58
7.4	Conceptual Simulation Framework	58

7.5	Simulation Components	59
7.5.1	Patient Component	60
7.5.2	Operating Room Component	63
7.5.3	Ward Bed Component	65
7.6	Simulation Framework Overview	65
7.7	Simulation Scenarios	66
7.8	Discussion	68
8	Conclusion	71
8.1	Summary and Findings	71
8.2	Future Work	72
	Bibliography	75
A	Appendix A — Additional figures	89
A.1	Confusion Matrices	89
A.2	ROC Curves	94

List of Figures

6.1	Score of the weekly scheduled patients	53
6.2	Number of weekly scheduled patients	53
7.1	Conceptual simulation of surgical scheduling	66
7.2	Not Scheduled Patients	67
7.3	Overrun	67
7.4	Delayed hospitalization	68
A.1	Confusion Matrices Decision Tree	89
A.2	Confusion Matrices K-Neighbors	90
A.3	Confusion Matrices Logistic Regression	91
A.4	Confusion Matrices Random Forest	92
A.5	Confusion Matrices Neural Network	93
A.6	ROC Curves Decision Tree	94
A.7	ROC Curves K-Neighbors	95
A.8	ROC Curves Logistic Regression	96
A.9	ROC Curves Random Forest	97
A.10	ROC Curves Neural Network	98

List of Tables

2.1	Summary table of the WL dataset	12
2.2	Summary table of the Ward transfer dataset	13
2.3	Summary table of the Operating room register dataset	14
3.1	Classification Models Results	24
3.2	Linear regression metrics	26
4.1	Example of Length Of Stay (LOS) Matrix	31
4.2	Notation use for the Surgical Case Assignment Problem formulation	32
6.1	Score of scheduled patients	49
6.2	Gap between metaheuristic solutions and the ILP model	50
6.3	Running Time	51
6.4	Scheduled patients	54
6.5	Waiting List state at the end of the planning horizon	55

List of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
ABS	Agent Based Simulation
BoW	Bag of Words
DES	Discrete Event Simulation
ILP	Integer Linear Programming
ICU	Intensive Care Unit
LOS	Length of Stay
ML	Machine Learning
NLP	Natural Language Processing
OR	Operationg Room
WL	Waiting List
WT	Waiting Time

1 Introduction

The organization, management, and continuous improvement of healthcare systems represent a fundamental responsibility for governments worldwide and remain a central issue of public concern. Healthcare is not only an essential pillar of social welfare but also a fundamental right that must be safeguarded and universally guaranteed.

Designing and managing healthcare services, however, is a highly complex task. This complexity arises from multiple factors. First, health systems must deliver a wide spectrum of services, ranging from primary care and preventive interventions to specialized outpatient treatment and complex surgical procedures. Second, these services require vast resources: financial, human, and technological, that must be allocated and managed efficiently.

Demographic changes, particularly the progressive aging of the population (World Health Organization [87], Sun et al. [80] and Hajizadeh et al. [40]) and the resulting increase in chronic diseases, have further amplified these challenges.

The COVID-19 pandemic, which has impacted the world since 2019, has exposed the fragility of healthcare systems and the critical consequences of resource scarcity. In many contexts, resources were diverted to manage the emergency, often leading to the suspension of essential services such as ambulatory care and elective surgery (Uimonen et al. [81], Fu et al. [34]). Several studies have quantified the scale of these disruptions, all over the world, showing that millions of elective procedures were canceled globally with repercussions on both patient outcomes and hospital finances (Mehta et al. [54], Frio et al. [33]). These disruptions generated negative repercussions not only during the peak of the pandemic but also in the subsequent recovery phases, highlighting the urgent need for more resilient and adaptable healthcare systems, and also played a crucial role in increasing surgical waiting lists, and

consequently the waiting times, as elective surgeries were significantly reduced during that period to prioritize the treatment of COVID-19 patients. Several studies have confirmed this trend, highlighting a general increase in waiting times for elective surgery during and after the pandemic, as reported in Garcia et al. [35], and the Organization for Economic Co-operation and Development (OECD) [58]. COVID-19 significantly influenced hospital admission management policies during the pandemic, leading to a reduction in elective hospitalizations and a subsequent worsening of patients' conditions, as reported by Dionisie et al. [24] and Araja et al. [4].

Nowadays, healthcare systems are under significant operational pressure, especially with regard to surgical procedures, where demand often exceeds the availability of resources.

Data science and the use of quantitative methods are essential to provide effective and efficient assistance and care services to optimize the utilization of available resources (Subrahmanya et al. [79]).

Starting from the fundamentals of data science, the use of quantitative approaches in healthcare has progressed toward more advanced techniques, like Operations Research (including mathematical modeling and simulation) and Machine Learning. These allow researchers and practitioners to go beyond descriptive data analysis, with methods to investigate complex hospital systems. By translating data into models that reflect real-world processes, healthcare professionals can make more informed decisions, effectively reducing the gap between practice and evidence.

Operations research can significantly enhance decision-making in hospital resource management by providing data driven solutions, leading to more efficient outcomes compared to traditional management approaches. This technique has been applied in different hospital areas, including:

- **Strategic planning and policy evaluation:** Strategic planning is a structured process for defining essential decisions and actions that determine the goals and direction of the public health sector. Recent literature reviews, such as those by Wongsin et al. [86] and by Pellense et al. [77], have analyzed the current state of research on this topic.
- **Resource allocation and capacity planning:** This area covers the allocation of resources such as hospital beds, healthcare personnel, and medical equipment, aimed at reducing inefficiencies and shortening wait-

ing times. Humphreys et al. (2022) [43] and Seixas et al. (2024) [74] provide comprehensive literature reviews summarizing current approaches and best practices.

- **Patient flow and scheduling optimization:** Optimization of patient admissions, operating room schedules, and outpatient appointments to reduce waiting times and enhance the efficient use of hospital facilities. To tackle this point, appointment scheduling systems are commonly used in primary care, specialty clinics, and hospitals to manage access to providers and to coordinate elective surgeries, as discussed in Gupta and Deton. [39]. Other contributions, such as Croella et al. [20], Celik et al. [17], and Doneda et al. [25], demonstrate how mathematical programming and stochastic optimization approaches can be applied to surgical scheduling to improve efficiency, reduce patient waiting times, and optimize the use of operating rooms.
- **Emergency department operations:** Examining and simulating patient movements within the emergency department to reduce overcrowding, optimize triage processes, and improve the overall emergency response, as discussed in recent studies on emergency department simulation and crowding (Doudareva & Carter [26] and Pearce et al. [65]).
- **Supply chain and inventory management:** Managing drugs, medical devices, and supplies to prevent stock out and control costs. Recent reviews highlight strategies such as multi-sourcing, and inventory sharing among healthcare hospitals or facilities to enhance resilience and efficiency (Guo et al. [38] and Atcha et al. [8]).

In this context, ensuring the rational and efficient use of resources while maintaining high quality care emerges as one of the greatest challenges facing health systems. Striking a balance between efficiency and quality is crucial to avoid difficult trade offs in the future, particularly in scenarios characterized by uncertainty.

Addressing this challenge requires the adoption of advanced methodologies that enable data driven decision making and the design of robust decision support systems. In recent years, healthcare has increasingly benefited from the application of innovative techniques such as Process Mining ([52]), as well as the growing adoption of Data Mining, Machine Learning (Bellini et al. [15]

and Merghani et al. [1]), and other analytics based methods. When integrated with traditional approaches to process management, these methods provide new opportunities for improving the performance of complex and dynamic healthcare processes.

Moreover, Operations Research (OR) techniques, such as combinatorial optimization and simulation, play a central role in transforming data into actionable insights for decision making. These methods have been widely recognized for their ability to optimize hospital operations, resource allocation, and patient flow (Priyan et al. [66], Bagherian et al. [9] and VanLent et al. [49]). By combining advanced analytics with OR methodologies, it becomes possible to design Decision Support Systems (DSS) that empower healthcare managers and policymakers to make data-driven decisions, improving both efficiency and patient outcomes (Ordu et al. [62, 61]).

Recent studies have shown that Operations research and hybrid analytical models are particularly effective to handle the complexity of healthcare systems, where uncertainty, variability, and interdependencies among resources must be considered (Wang et al. [85], Masmoudi et al. [53] and Ordu et al. [60]). The integration of forecasting, simulation, and mathematical programming has been proved to obtain benefits in hospital capacity management and staff scheduling (Goodarzian et al [37] and Rachuba et al. [67]).

Ultimately, the effective integration of these approaches represents a promising path toward sustainable and responsive healthcare systems, achieving the delicate balance between cost efficiency and service quality. This thesis is situated within this research perspective, focusing on the application of Operations Research techniques to tackle these challenges in healthcare management.

1.1 Surgical activities management

Among all the areas presented so far regarding the use of quantitative methods, this thesis focuses on investigating and proposing tools for the surgical component, providing a comprehensive approach from data analysis to patient scheduling in operating rooms and an evaluation of the proposed solution through simulation. For this reason, this important topic will be described in greater detail, highlighting the methodologies and tools used to address it.

Surgical scheduling is a fundamental and highly complex process in hospital

management, crucial for ensuring that patients receive timely surgical care while optimizing the use of limited healthcare resources. At the same time, the allocation of resources in surgical scheduling must consider a wide range of constraints and priorities, which makes it a natural target for quantitative methods and structured decision-support tools.

At its core, surgical scheduling involves the allocation of operating rooms, surgical teams, and associated resources, including specialized equipment, nursing staff, and postoperative beds (AlAmin et al. [3], Denton et al. [22]) and can also deal with emergency (Lamiri et al. [47]). The primary goal of this process is to maximize the efficiency of the hospital's surgical services while maintaining high standards of patient safety and quality of care (Beaulieu et al. [12]).

Given its complexity, surgical scheduling increasingly relies on structured methodologies and decision-support tools, including mathematical modeling, predictive analytics, and optimization algorithms. These tools can assist in balancing competing objectives, such as minimizing patient waiting time while maximizing operating room utilization and adhering to clinical priorities. By integrating data from historical patient flows, surgical durations, and hospital capacity, modern approaches aim to provide robust, flexible, and data-driven schedules that can adapt to dynamic hospital conditions and unexpected disruptions.

1.2 Context

This project was developed within the IRCCS Azienda Ospedaliero-Universitaria di Bologna – Policlinico di Sant'Orsola, a public hospital that operates under the national public healthcare system. The Italian healthcare system is regionally organized and provides universal access to medical care, primarily funded through taxation. Within this institutional framework, hospital practices are guided by *Decreti della Giunta Regionale* (DGR), official acts issued by the Regional Government to establish policies, guidelines, and organizational rules for public institutions and services. Specifically, with regard to surgical scheduling, reference is made to DGR 272/2017 [69], “Reduction of waiting lists for scheduled surgical admissions in the Emilia Romagna region” and the subsequent DGR 603/2019[21] "Regional Plan for the Governance of Waiting Lists (PRGLA) for the 2019–2021 Three-Year Period", which pro-

vide detailed guidelines and operational frameworks for the management of operating rooms and patient scheduling. These regulations form the basis for defining priority criteria, waiting times, and standardized processes, which are then applied in the operational management of the surgical schedule.

These official rules also directly impact the management of the waiting list, which is a central component of surgical scheduling. The waiting list serves as a repository of information on patients who require surgical interventions but have not yet been assigned a specific date or operating room.

Each entry typically contains detailed data such as the patient's medical condition, the type of surgical procedure required, specialty requirements, clinical priority, and any constraints related to the patient's health or treatment protocol. Patients are generally prioritized based on clinical urgency, with emergency cases taking precedence over elective procedures. Within elective cases, prioritization may also consider factors such as potential complications, length of wait, and the risk of deterioration if surgery is delayed (James et al. [44], Oliveira et al. [59]).

In accordance with the DGR 272/2017, a numerical indicator, denoted as **score** was introduced as a standardized tool to manage patients with different levels of priority. This measure allows for the comparison of patients on waiting lists by summarizing multiple parameters into a single numerical value that reflects the degree of urgency. Patients are generally classified into priority categories, each associated with a maximum waiting time depending on the severity of their condition. The **score** thus ensures transparent and consistent prioritization. In our context, patients are classified from priority A to D, with maximum waiting times of 30, 60, 180, and 365 days respectively.

The value of the **score** for each patient is evaluated as follows:

$$\text{score} = \text{WT} \times \frac{\text{Waiting time limit of the class with lowest priority (days)}}{\text{Waiting time limit of the patient class (days)}}$$

The value of WT is the number of days the patient has already spent on the waiting list, from the moment they were added to the list to the time of evaluation.

The surgical scheduling process translates the information from the waiting list into a structured timetable that specifies which patients will undergo surgery, in which operating room, and at what time. This process must ac-

count for multiple constraints, including the availability of operating rooms, surgical teams, anesthesiologists, specialized staff, and postoperative beds. In addition, considerations such as the estimated duration of each surgery, setup and cleanup times between procedures must be incorporated to prevent conflicts and ensure a smooth flow of operations.

Managing the waiting list and generating the surgical schedule is an ongoing, iterative process. Hospitals must continuously update the list to account for new patient arrivals, cancellations, changes in clinical urgency, or unexpected resource limitations. For example, a patient's condition may worsen, requiring a change of his priority class, or an operating room may become unavailable due to maintenance or emergency cases. As a result, the surgical schedule often needs to be adjusted dynamically, which requires both careful planning and the ability to respond quickly to unforeseen events.

Efficient surgical scheduling has significant implications not only for hospital operations but also for patient outcomes (Fahmy et al. [31], Oudhoff et al. [63] and Zeng et al. [92]). Optimized scheduling can reduce patient waiting times, minimize idle times for operating rooms and surgical teams, and improve overall resource utilization. It also helps prevent bottlenecks in downstream services, such as intensive care units and post-anesthesia recovery rooms, ensuring that patients receive continuous and coordinated care. Conversely, poorly managed scheduling and waiting lists can lead to extended delays, suboptimal use of resources, increased staff workload, and potential deterioration of patient health, particularly for those with conditions that are sensitive to delays.

In summary, surgical scheduling and waiting list management are critical and interrelated components of hospital operations. They require the careful coordination of personnel, facilities, and patient needs, while also addressing uncertainties inherent in healthcare delivery. As such, understanding the principles, challenges, and methodologies of surgical scheduling is essential for developing healthcare systems that are both effective and resilient.

1.3 Research objectives

The primary aim of this doctoral project is to develop advanced methodologies for optimizing surgical scheduling and hospital resource management, with

a particular focus on improving decision-making processes in complex and dynamic healthcare environments. The project seeks to integrate predictive modeling, mathematical optimization, and metaheuristic techniques to address the challenges of allocating limited resources while maintaining high standards of patient care.

The specific objectives of the project are as follows:

1. **Modeling Patient Flow and Hospital Resources:** Develop comprehensive models estimating surgical durations, and hospital occupancy to accurately represent the dynamics of hospital operations.
2. **Formulation of the Surgical Assignment Problem:** Define a mathematical framework for the assignment of patients to operating rooms and surgical times, incorporating constraints such as operating room availability, bed capacity, and clinical priorities.
3. **Application of Optimization and Metaheuristic Techniques:** Explore and implement both exact and approximate solution methods, including combinatorial optimization, simulation, and metaheuristic algorithms, to efficiently solve the surgical scheduling problem in realistic, large-scale scenarios.
4. **Integration of Predictive Models with Optimization:** Combine predictive analytics with optimization approaches to create data-driven DSS.
5. **Evaluation and Validation of Proposed Methods:** Conduct computational experiments and simulation studies to assess the effectiveness, efficiency, and robustness of the proposed methodologies. Performance metrics will include waiting times, resource utilization, and the ability to adapt to unexpected changes in hospital demand.

By achieving these objectives, this doctoral research aims to bridge the gap between advanced analytical methods and practical hospital management, offering innovative solutions for one of the most critical and challenging areas in healthcare operations.

1.4 Thesis structure

The remainder of this thesis is organized into six chapters, each focusing on a specific aspect of the research on surgical case assignment, predictive modeling, and metaheuristic optimization in healthcare systems:

- **Chapter 2 – Data Overview:** This chapter presents the information assets that will be used for the development of the thesis, from the preparation of the inputs to their use within the models and simulations.
- **Chapter 3 – Predictive Models:** This chapter presents the development of a predictive models aimed at forecasting surgical durations, and hospital occupancy. It describes the data collection and pre-processing steps, as well as machine learning techniques used to generate accurate predictions that inform the optimization process.
- **Chapter 4 – Optimization Model:** Here, the Surgical Case Assignment Problem is formalized as a mathematical model. Sets, parameters, decision variables, and constraints are defined, and the objective function is presented. This model provides a framework for assigning patients to operating rooms and days while respecting hospital resources and capacity limitations.
- **Chapter 5 – Metaheuristics Algorithms:** Given the computational complexity of the assignment problem, this chapter explores metaheuristic methods for obtaining high-quality solutions efficiently.
- **Chapter 6 – Results:** This chapter presents the results obtained by applying the proposed models and metaheuristic methods. Computational experiments, performance evaluation, and comparisons with alternative approaches are discussed to demonstrate the effectiveness and efficiency of the proposed solutions.
- **Chapter 7 – Simulation:** Simulation techniques are employed to evaluate the robustness of the scheduling and predictive models under realistic hospital scenarios. Different scenarios have been tested to provide insights into the system's behavior under varying conditions.

- **Chapter 8 – Conclusion:** The final chapter summarizes the main findings, discusses the implications for healthcare management, and outlines potential directions for future research.

This structured organization guides the reader through a logical progression from predictive modeling to optimization, evaluation, and final conclusions, providing a comprehensive view of the research contributions of this thesis.

2 Data Overview

2.1 Data Sources

This chapter describes the datasets used to develop the models in this thesis. All data used came from IRCCS Azienda Ospedaliero-Universitaria di Bologna - Policlinico di Sant’Orsola, and are pseudonymized so that no patient could be identified, in accordance with the General Data Protection Regulation (EU) 2016/679 [70].

2.1.1 Waiting List position

This data set contains information on the patients included in the Waiting List (WL). The moment of insertion in the waiting list represents the first step in planning a surgical procedure.

There are two main types of information:

1. **Structured data** – demographic characteristics (age, gender), clinical indicators (diagnosis, surgical procedure, priority class, etc.), and hospital related variables (surgical specialty, list, etc.)
2. **Unstructured textual notes** – free text annotations written by clinicians at the time of patient inclusion on the waiting list, containing information on symptoms, clinical history, and subjective assessments

The notes field, where healthcare professionals enter details they consider useful, will be the focus of this chapter. The final piece of information (Hospitalization code) is used to link the patient’s position on the waiting list to both the hospital admission and to the surgical procedures performed.

Table 2.1: Summary table of the WL dataset

Column name	Type
Waiting List ID	<i>String</i>
Age	<i>Int</i>
Gender	<i>String</i>
Health State	<i>Int</i>
Insertion Date	<i>DateTime</i>
Priority Class	<i>String</i>
Setting	<i>String</i>
Specialty	<i>String</i>
List	<i>String</i>
Sub-List	<i>String</i>
Pathology	<i>String</i>
Procedure	<i>String</i>
Note	<i>String</i>
Hospitalization code	<i>String</i>

2.1.2 Ward transfers

This dataset contains information on patient hospitalizations. Each record corresponds to an individual patient transfer, so if a patient was moved across multiple wards during a single admission, a separate row is recorded for each transfer. In this study, the intensive care unit (ICU) is considered as a ward in its own right.

Table 2.2: Summary table of the Ward transfer dataset

Column name	Type
Hospitalization code	<i>String</i>
Progressive transfer number	<i>Int</i>
Transfer start date	<i>DateTime</i>
Transfer end date	<i>DateTime</i>
Insertion Date	<i>DateTime</i>
Ward	<i>String</i>
Specialty	<i>String</i>

2.1.3 Operating Room Register

This dataset contains information on the surgical procedures performed. It also includes all intermediate steps that occur in the operating room, but for simplicity, we have considered only the moments of entry and exit from the operating room, as these best reflect the utilization of the room.

Table 2.3: Summary table of the Operating room register dataset

Column name	Type
Hospitalization code	<i>String</i>
Procedure ID	<i>String</i>
Operating Room	<i>String</i>
Start Date	<i>DateTime</i>
End Date	<i>DateTime</i>
Operating unit	<i>String</i>

The contents of this table will be necessary for predicting the duration of surgical procedures for patients currently in the WL.

3 Predictive Models

3.1 Introduction

Forecasting **surgical times** and LOS upon patient admission to the waiting list provides a powerful decision support tool for health administrators because it allows them to optimize scheduling, utilization of resources, and bed utilization.

We propose in this chapter a group of predictive models that combine both structured (such as age, sex, diagnosis codes, priority class, etc.) and unstructured data from text notes documented during patient registration. The textual component is processed using NLP techniques, with a particular focus on the BoW technique, which transforms free-text medical notes into numerical features in structured format for machine learning.

The final objective is to train and evaluate a collection of predictive models, comparing their performance in forecasting surgical times and LOS through quantitative metrics.

3.2 Literature Review

3.2.1 Perioperative Path Prediction

Intensive Care Unit(ICU) resource utilization is one the most critical health-care challenges. Choosing which patients will use the ICU can improve both patient safety and hospital workflow.

Emerson et al. [30] analyzed ICU utilization after elective surgery showing the importance of balancing safety and resource efficiency. O’Grady et al. [57] categorized patients based on postoperative needs, finding that a subset of them may safely recover outside the ICU, while Vourc’h et al. [84] supported

a policy of selective admission. Ribeiro et al. [71] emphasized the value and importance of predictive approaches in this specific case with limited ICU resources.

Li et al. [50] trained different machine learning models for ICU admission prediction comparing different techniques like logistic regression, random forests, SVM, and neural networks. These models can support physician's prediction for real time decision making.

Machine learning in medicine has been widely reviewed by Deo [23] and Choi et al. [18], illustrating how heterogeneous clinical data can be integrated to build robust predictive paradigms.

The literature supports the need for effective predictive systems to condense ICU allocation and reduce unnecessary admissions.

3.2.2 Procedure Time Prediction

Accurate prediction of surgery duration is essential to the improvement of operating room (OR) efficiency and resource allocation. Early works emphasized the unreliability of accurate estimates; Rogers et al. [73] indicated that surgeons correctly predicted operative times only 26% of the time. To address this, statistical and data driven and statistical models were proposed: Eijkemans et al. [29] combined patient, team, and surgeon into a linear mixed-effects model, while Hosseini et al. [42] utilized data mining techniques, and Stepaniak et al. [78] used conventional regression techniques.

Machine learning and optimization methods have further improved predictions. Gomes et al. [36] integrated data mining with optimization in scheduling, ShahabiKargar et al. [75, 76] developed models for elective procedures using procedural and historical data, Zhao et al. [93] focused on robot-assisted procedures, and Zabardast [91] applied supervised learning to predict durations with few data. Riekert et al. [72] emphasized improved process efficiency by means of predictive modeling.

In later research, large clinical datasets were utilized to identify significant predictors of operative time. Passias et al. [64] cited surgeon, surgical approach, age, and frailty as significant predictors for surgery in spinal deformity, while Costa [19] and Yuniartha et al. [90] presented evidence that even simple models based on procedural parameters can drastically reduce significant variability and make OR scheduling easier.

Collectively, these works illustrate how combining statistical, optimization, and machine learning approaches yield increased predictability of surgical duration so that the OR as well as resources can be better managed.

3.3 Methodology

In order to predict patient care pathways, we developed machine learning models designed to estimate the likely course of hospitalization. What we mean by hospitalization pathway in this thesis is an ordered list of departments, each associated with its own length of stay. A preliminary analysis showed that the distribution of patient flows is as follow: approximately 54% of patients experience a single transit within their specialty ward, 44% require ICU admission in the middle of their hospital stay resulting in two transits within the specialty ward and the remaining 2% follow other, less common pathways. Thanks to this information, we decided to focus the pathway prediction on whether or not the patient will require the intensive care unit (ICU). In this way, the model aims to predict whether the patient will follow a single transit pathway or a triple one, with the latter including an intermediate stay in the intensive care unit. Once the ICU utilization is predicted, the patient is assigned a care pathway sequence according to the predicted ward transitions. The duration of each transit, whether a single transit or the three-transit sequence including ICU, is defined based on the average duration observed in patient classes with similar structured characteristics (specialty, waiting list, diagnosis, and procedure).

For the prediction of surgical procedure duration, the estimation is performed in a single step, directly predicting the total duration from the patient's entry into the operating room to their exit.

3.3.1 Text Preprocessing

Since clinical notes are unstructured and often contain noisy information, a preprocessing pipeline was applied before feature extraction. Several steps are included in the pipeline:

1. **Tokenization:** Splitting the text smaller components called tokens, which in our case are the single words

2. **Lowercasing:** Converting all characters to lowercase. The normalization can reduce the vocabulary size, treat words with different cases as the same token
3. **Stopword removal:** Eliminating frequent words that have no or barely any semantic content to remove noise
4. **Stemming:** Reducing words to their base or root form by removing suffixes and prefixes
5. **Vocabulary construction:** Building a set of unique tokens that defines all the tokens that the model is able to recognize and use, which is the basis for text representation, feature extraction and embedding generation

For the creation of the dictionary, not only the set of single words (or base words) was considered, but also the version where tokens consist of word pairs. This was done to ensure that certain keywords could be captured together with the negation that precedes or follows them. By performing this operation and considering patients over 8 years of hospitalization, the size of the dictionaries became very large. To ensure that this information could be used in the next phases of the project, not all of the dictionary contents were considered, but only a portion using the most frequent words and word pairs. The predictive models used in the following sections were tested with different dictionary sizes.

3.3.2 Feature Integration

Once the dictionary of single words and word pairs was obtained, the next step was to prepare the input file to test different predictive models and identify the most effective one for forecasting patients' hospitalization pathways.

We used one-hot encoding to all structured features. This encoding represents categorical variables as a binary vector. In this technique, every category of variables is coded as a vector of zeros with only one position marked by one, representing the presence of that specific category.

For some variables, preliminary transformations were carried out before applying one-hot encoding. For instance, in the case of patient age, 5-year age groups were created to provide a more compact and informative representation.

The same procedure was applied to the dictionaries: for each record, if a given word was present in the notes field, the corresponding attribute was assigned a value of 1, otherwise 0. To avoid having an input that is too large and not meaningful, subsets of words were then selected according to their frequency in the historical data. Each word is assigned its absolute frequency, indicating how many times it appears and then ordered from the most to the least frequent. After that, the percentage of each word relative to the total occurrences is calculated, followed by a coverage percentile that shows how much of the total occurrences are covered by summing them in order of frequency. In this study, the 0th, 25th, and 50th percentiles were considered for each of the two dictionaries, as well as all possible combinations derived from them. For the first dictionary, the 25th and 50th percentiles correspond to 35 and 142 words, while for the second dictionary, they correspond to 422 and 2874.

The textual features were concatenated with the structured clinical and demographic variables, generating a hybrid feature set. This integration allows models to exploit both explicit patient information and hidden patterns in the unstructured notes.

3.3.3 Machine Learning Models

Several machine learning algorithms have been tested and compared. The following models will be evaluated using the k-fold cross validation technique. This technique divides the dataset into K folds and trains the model the same number of times, and each one of these folds is used as a test set while the remaining K-1 folds are used for training, while the final performance metrics are computed as the average across all folds. Here, they are presented with some implementation details and parameters:

- **Logistic Regression:** It is a machine learning algorithm used to predict a categorical output, by estimating the probability of the class by modeling the relationship between the predictors as a linear combination. The search for the best parameters is carried out iteratively through an optimization algorithm for a certain number of times, with the goal of minimizing the loss function. In the implementation, the number of iterations (*max_iter*) was set to 1000, and it represents the maximum number of iterations that the model can perform to converge.

- **Decision Tree Classifier:** A decision tree is a non-parametric supervised learning algorithm, which is utilized for both classification and regression tasks. It has a hierarchical tree structure, which consists of a root node, branches, internal nodes and leaf nodes. It is a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. The aim is to divide samples into leaves and assign them a class trying to reduce impurity, meaning how mixed the classes are within a node..
- **Random Forest:** This model that builds multiple decision trees on random subsets of the data and features, combining them to improve the accuracy and reduce overfitting. In the implementation, the *n_estimators* parameter was set to 500, and it represents the number of decision trees to be built in the forest.
- **K-Neighbors Classifier:** It is is a non-parametric supervised learning method which uses proximity to make classifications. The output value is the average of the values of k nearest neighbors. It assign weights to the contributions of the neighbors, so that nearer neighbors contribute more to the average than distant ones. In our case *n_neighbors* that represent *k* was set to 100.
- **Neural Network:** It is a computational model inspired by a biological neural network. It is composed of interconnected nodes called neurons grouped in layer trying to learn non linear relationship between features. In our case study the structure of the Neural network is as follow: a fully connected neural network composed of five hidden layers with 1024, 512, 256, 128, and 64 neurons respectively, each layer use the Rectified Linear Unit (*ReLU*) as activation function and followed by a *Dropout* of 0.4. The output layer has a single neuron with a *sigmoid* activation function for binary classification. The solver used is *Adam* optimizer with a learning rate of 0.00005 and a weight decay of 0.00001, *binary cross-entropy* loss, and *Sparse Categorical Accuracy* as the evaluation metric, for 10 epochs with a batch size of 128.

The key parameters and design decisions of the Neural Network will be explained in detail. The hidden layers make use of *ReLU* activation function

to address the vanishing gradient (gradients that are very small in backpropagation), while the output layer makes use of *sigmoid* activation function to normalize predictions into probabilities suitable for binary classification. Regularization is applied through *Dropout*, which disables a random subset of neurons during training to prevent overfitting. The network is trained with the *Adam* optimizer with a specified *learning rate* to control the step size of gradient descent and a *weight decay* to penalize large weights and improve generalization.

3.4 Evaluation Metrics for Classification Models

The evaluation of the models is performed by using a group of well known metrics described in detail in Rainio et al. [68] and Miller et al. [55]. Before defining the evaluation metrics, we first introduce the basic classification outcomes: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). They are defined as follows:

- **True Positives (TP)**: predictions correctly predicted as positive.
- **False Positives (FP)**: predictions incorrectly predicted as positive.
- **True Negatives (TN)**: predictions correctly predicted as negative.
- **False Negatives (FN)**: predictions incorrectly predicted as negative.

For the prediction of the care pathway, which is a classification task aimed at predicting the correct category, the following metrics will be used:

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

It measures the proportion of correctly classified instances among all samples.

Precision:

$$Precision = \frac{TP}{TP + FP}$$

It indicates the proportion of positive predictions that are actually correct.

Recall:

$$Recall = \frac{TP}{TP + FN}$$

It represents the ability of the model to correctly identify all actual positive instances.

F1 Score:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

It is the harmonic mean of *Precision* and *Recall*, balancing both metrics in a single value.

ROC Curve: (Receiver Operating Characteristic) is a parametric curve defined as:

$$\begin{cases} TPR = \frac{TP}{TP + FN} \\ FPR = \frac{FP}{FP + TN} \end{cases}$$

where *TPR* is the *True Positive Rate* and *FPR* is the *False Positive Rate*. It shows the trade off between the true positive rate and the false positive rate across different classification thresholds.

AUC (Area Under the Curve): L'AUC measure the area under the ROC Curve:

$$AUC = \int_0^1 TPR(FPR) d(FPR)$$

It quantifies the overall performance of the model, where a higher value indicates better discrimination ability.

Confusion Matrix:

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

It is a table that summarizes the classification results, showing the number of correct and incorrect predictions for each class.

3.5 Evaluation Metrics for Regression Model

For the model used to predict the duration of surgical procedures, which is a regression task aimed at estimating a numerical value, the following metrics will be employed:

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

Measures the average absolute difference between the observed values y_i and the predicted values $\hat{y}_i$. Lower values indicate better predictive accuracy.

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

Provides the square root of the average squared differences between observed and predicted values. RMSE penalizes larger errors more heavily than MAE.

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

Indicates the proportion of variance in the observed data explained by the model. Values closer to 1 represent better model performance, while values near 0 or negative indicate poor predictive ability.

3.6 Results and Discussion

For testing the models we utilized the historical data of the last 9 years of three different specialties. The number of considered patients is 21977. The ratio between patients who used intensive care and those who did not is 55% vs

Table 3.1: Classification Models Results

Model	Accuracy	Precision	Recall	F1 Score	AUC	Dict. 1	Dict. 2
DecisionTree	0.655	0.620	0.564	0.591	0.660	0	0
DecisionTree	0.647	0.603	0.588	0.595	0.642	0	25
DecisionTree	0.658	0.616	0.600	0.608	0.653	0	50
DecisionTree	0.635	0.588	0.577	0.583	0.633	25	0
DecisionTree	0.645	0.600	0.588	0.594	0.643	25	25
DecisionTree	0.655	0.613	0.592	0.602	0.651	25	50
DecisionTree	0.654	0.610	0.599	0.605	0.653	50	0
DecisionTree	0.656	0.613	0.599	0.606	0.652	50	25
DecisionTree	0.663	0.620	0.613	0.617	0.660	50	50
KNeighbors	0.688	0.643	0.659	0.651	0.765	0	0
KNeighbors	0.677	0.674	0.516	0.585	0.760	0	25
KNeighbors	0.660	0.680	0.435	0.530	0.746	0	50
KNeighbors	0.672	0.664	0.522	0.584	0.755	25	0
KNeighbors	0.669	0.670	0.494	0.569	0.753	25	25
KNeighbors	0.665	0.675	0.465	0.551	0.744	25	50
KNeighbors	0.676	0.675	0.513	0.583	0.760	50	0
KNeighbors	0.672	0.674	0.497	0.572	0.754	50	25
KNeighbors	0.668	0.676	0.479	0.561	0.747	50	50
LogisticRegression	0.707	0.668	0.671	0.669	0.780	0	0
LogisticRegression	0.714	0.681	0.664	0.672	0.787	0	25
LogisticRegression	0.699	0.663	0.646	0.654	0.762	0	50
LogisticRegression	0.712	0.676	0.668	0.672	0.787	25	0
LogisticRegression	0.714	0.682	0.662	0.672	0.788	25	25
LogisticRegression	0.699	0.662	0.647	0.655	0.762	25	50
LogisticRegression	0.717	0.685	0.667	0.676	0.795	50	0
LogisticRegression	0.716	0.684	0.665	0.674	0.791	50	25
LogisticRegression	0.701	0.666	0.648	0.657	0.764	50	50
NeuralNetwork	0.711	0.656	0.726	0.689	0.783	0	0
NeuralNetwork	0.721	0.667	0.734	0.699	0.796	0	25
NeuralNetwork	0.717	0.674	0.698	0.686	0.778	0	50
NeuralNetwork	0.711	0.654	0.735	0.692	0.790	25	0
NeuralNetwork	0.720	0.664	0.740	0.700	0.796	25	25
NeuralNetwork	0.718	0.667	0.720	0.692	0.785	25	50
NeuralNetwork	0.717	0.659	0.743	0.699	0.799	50	0
NeuralNetwork	0.723	0.664	0.755	0.706	0.799	50	25
NeuralNetwork	0.719	0.671	0.711	0.691	0.790	50	50
RandomForest	0.675	0.635	0.620	0.627	0.729	0	0
RandomForest	0.705	0.672	0.648	0.660	0.777	0	25
RandomForest	0.713	0.686	0.645	0.665	0.790	0	50
RandomForest	0.698	0.667	0.630	0.648	0.776	25	0
RandomForest	0.709	0.680	0.642	0.661	0.789	25	25
RandomForest	0.712	0.689	0.634	0.660	0.794	25	50
RandomForest	0.715	0.688	0.649	0.668	0.798	50	0
RandomForest	0.720	0.692	0.658	0.674	0.799	50	25
RandomForest	0.721	0.696	0.653	0.674	0.803	50	50

45%. Using the k-fold technique (with the value of $k = 10$) for a fair evaluation of the models, the values of the analyzed metrics will be the average values obtained across each fold, as performed in Jung et al.[45]. Table 3.1 summarizes the performance of the mean **accuracy** over the 10 folds. The **NeuralNetwork** achieves the highest accuracy (0.711–0.723), followed by **RandomForest** (0.675–0.721) and **LogisticRegression** (0.699–0.717). Simpler models like **DecisionTree** have lower performance (0.635–0.658), and **K-Neighbor** shows

intermediate accuracy (0.660–0.688).

A similar results is obtained if we look to the other metrics like the **F1 Score** or **AUC**, where the **NeuralNetwork** is overall the best performing algorithm.

The following are some observations on the performance of the different classification models, with respect to the variation in the dictionary percentiles used:

- **DecisionTree:** The model yields acceptable results, but accuracy is generally lower than all the other models in every metrics. Increasing the percentiles of the dictionaries does not significantly improve performance, suggesting that Decision Tree is relatively insensitive to these features.
- **K-Neighbor:** Accuracy is slightly higher than Decision Tree, but interestingly, increasing the usage of the dictionaries tends to decrease performance. This is likely because the features extracted from text are less effective than the structured features in identifying similar patients.
- **Logistic Regression:** Performance improves as the percentiles of the dictionaries increase, especially when only the one word dictionary percentiles is at the maximum value, and the two word dictionary is not used. This suggests that linear combinations of first dictionary features provide additional predictive power, while the second introduces noise. Overall, this model appears to be the most performative in many scenarios, despite being conceptually one of the simplest.
- **Random Forest:** Consistently achieves the high accuracy with high dictionary percentiles, with a noticeable improvement as dictionary coverage increases. Both dictionaries contribute to improving accuracy, making this model one of the most robust among the tested approaches.
- **Neural Network:** The neural network over performs compared to the other models, showing higher and less variable accuracy. Its performance is highly sensitive to the dictionary percentiles, indicating that the features extracted from text are fully exploited. The use of the second dictionary has beneficial effects only up to the 25th percentile, after which it begins to introduce noise and degrades performance.

The Confusion Matrices and ROC Curves are shown in Appendix A. The reported confusion matrices were obtained as the average of the matrices from each fold, while the ROC curve plots show all 10 curves and their average.

3.7 Surgical Procedure Time

To predict the duration of surgical procedures, we employed a **Linear Regression** model. This model estimates the target variable (surgery time) as a linear combination of the coefficients minimizing the sum of squared errors between predicted and observed values.

In this analysis, we tested different percentile values for both dictionaries using the same dataset employed for ICU prediction in the previous section, and the resulting performance metrics are summarized in Table 3.2.

Table 3.2: Linear regression metrics

Model	MAE	RMSE	R^2	Perc. Dictionary 1	Perc. Dictionary 2
LinerRegression	23.574	40.467	0.7374	0	0
LinerRegression	23.905	40.262	0.7401	0	25
LinerRegression	25.282	41.342	0.7259	0	50
LinerRegression	23.647	40.381	0.7385	25	0
LinerRegression	23.954	40.326	0.7393	25	25
LinerRegression	25.348	41.380	0.7254	25	50
LinerRegression	23.102	38.652	0.7605	50	0
LinerRegression	23.337	38.803	0.7586	50	25
LinerRegression	25.123	40.839	0.7326	50	50

From the results, it appears that Dictionary 1, containing single words, is positively correlated with R^2 : as its percentile increases, the predictive performance of the linear regression model improves. On the other hand, Dictionary 2, which contains word pairs, seems to introduce noise, resulting in a decrease in model performance and a less accurate prediction of surgical procedure duration.

3.8 Conclusions

This chapter explored the application of linear regression models to predict surgical procedure durations based on various input features, including single word and word pair dictionaries. The results indicate that the inclusion of single word dictionaries positively correlates in both categorical and regression models with improved model performance, as evidenced by higher metric val-

ues. On the other hand, the use of the second dictionary seems useful only up to the 25th percentile, beyond this threshold it tends to introduce noise and negatively affect model performance across all approaches, reducing predictive **accuracy**, **F1 Score** and **AUC**.

These findings demonstrate the potential benefit of feature selection in predictive modeling for surgical planning. Future work can involve attempting more sophisticated feature engineering techniques and exploring additional modeling approaches to enhance the accuracy of predictions.

4 Optimization Model

4.1 Literature review

As anticipated in the introductory section, the surgical case assignment problem has been extensively studied in the literature through various approaches. The Surgical Scheduling Problem has been investigated by distinguishing three decision levels: strategic, tactical, and operational, depending on the considered time horizon. The focus at strategic level (long-term) is to determine how many operating rooms (ORs) will be needed and to assign them to the different specialties, in order to match the overall demand for surgical procedure time, see, e.g. in Ma et al. [51]. At the tactical and operational levels, the planning of operating rooms is typically based on the use of time slots known as blocks, which usually group procedures from the same specialty. At the tactical decision level (medium term), the problem is commonly referred to as the Master Surgical Schedule Problem, which aims to assign specialties to OR blocks over a defined cyclic period, typically a week or a month, as shown by Belien et al. [13] and Ebrahimi et al. [28]. Scheduling at the operational level (short-term) involves two subproblems, denoted as Advanced Scheduling and Allocation Scheduling. The first assigns patients to OR blocks, while the second determines the detailed sequencing of patients within each block. Scheduling has been extensively studied at the operational level, in some cases by also considering the use of specific resources in the post-procedural phase, but without including the complete patient pathway, see Hamid et al. [41] and Latorre et al. [48]. By applying such methodologies, excellent results can be obtained when compared to real-world data, as demonstrated by Barbagallo et al. [11].

The Integrated Surgical Scheduling Problem refers to the challenge of coordinating both the allocation of operating room (OR) blocks to specialties

(Master Surgical Schedule Problem) and the assignment of individual surgical cases to these blocks (Surgical Case Assignment Problem). In some cases, the Integrated Surgical Scheduling Problem is tackled by jointly considering the tactical and operational levels, simultaneously solving the Master Surgical Schedule Problem and the Surgical Case Assignment Problem; see. e.g. Agnetis et al. [2], Aringhieri et al. [6] and Duran et al. [27]. Several studies have addressed these problems considering different objectives, such as the maximization of patient prioritization, which will also be considered in this study, as well as the maximization of resource utilization. In some cases, both objectives have been addressed simultaneously, as in Aringhieri et al. [7].

4.2 Problem definition

The problem under study involves scheduling surgeries for a set of patients across different surgical specialties, where each specialty has been allocated a specific number of operating room (OR) slots. The objective is to determine, within a defined planning horizon, the surgery date, the assigned operating room, and the associated patient pathway for each patient.

The primary aim is to create a feasible schedule that minimizes patient delays, optimizes the use of operating room (OR) resources, and respects all relevant constraints. Planning decisions must take into account several resource constraints, including the duration of OR time blocks, the allocation of OR time blocks to each surgical specialty, and the daily availability of ward beds for each specialty.

The objective of the optimization is to maximize equity compliance, which will be assessed using a metric called **score**, representing the scheduling profit for each individual patient.

4.3 Patients' Information

In order to be applied, the model requires some input information, two of which were the subject of the previous chapter. The first is the duration of surgical procedures, and the second is the patient care pathway. The care pathway is defined as the sequence of hospital wards in which the patient will be admitted, together with the duration of each transit. This pathway can

Table 4.1: Example of Length Of Stay (LOS) Matrix

Day	General Surgery	Intensive Care Unit
1	0.5	0.5
2	0	1
3	0.4	0.6
4	1	0
5	1	0
6	1	0
7	0.5	0

be transformed into a matrix representation, which we will refer to as the LOS matrix (Length of Stay matrix). This matrix is defined as follows: each row represents a day starting from the patient's hospitalization, each column corresponds to a specialty, and the value in each cell indicates the amount of time the patient will spend in that specialty on that day.

In the example of Table 4.1, the patient spends 0.5 days in the General Surgery ward and after surgery is transferred to the Intensive Care Unit for 2.1 days. The patient then returns to the General Surgery ward, where she stays for 3.9 days before being discharged.

4.4 Model

We propose a linear programming model that considers a pre-assigned Master Surgical Schedule, in which operating room slots are already allocated to surgical specialties. Furthermore, the model assumes that patient admission occurs on the same day as the scheduled surgery.

We now introduce some necessary notation. Let us denote by I the set of patients, by S the set of operating rooms, by T the set of days considered in the scheduling and by J the set of specialties. The set I_t represents the subset of patients who are still present on day t . The set T_t represents the subset of days prior to day t . For each patient $i \in I$ we have the length of stay $d_{ij\tau}$ which represent the total time spent by patient i in ward of specialty j on day τ . For each patient i , w_i represents the surgical procedure time and p_i denotes the profit associated with scheduling patient i , where the profit value in the model is represented by the **score**, the numerical value presented in the definition

Table 4.2: Notation use for the Surgical Case Assignment Problem formulation

Problem notation	
Sets	
I	Set of patients
S	Set of operating rooms
T	Set of days
J	Set of specialties
I_t	Set of patients that are still inside the hospital at day t
T_t	Set of days prior to day t
Parameters	
$d_{ij\tau}$	Length of stay of patient i in a ward of specialty j on day τ
w_i	Time for the surgical procedure of patient i
p_i	Profit for scheduling patient i
C_{jt}	Bed capacity of specialty j at day t
A_{st}	Time capacity of operating room s at day t
a_{ist}	1 if patient i can be scheduled in operating room s on day t , 0 otherwise
Decision variables	
x_{ist}	1 if patient i is assigned in operating room s on day t , 0 otherwise

of the previous section. In our problem an initial master surgical schedule is provided as input, specifying the assignment of the operating theater to the different specialties. A binary parameter, denoted as a_{ist} takes value one if patient i can be assigned to OR s on day t . This same parameter is also used to prevent the assignment of patients to rooms that lack certain requirement needed for their surgery (e.g. robotic equipment). The parameter a_{ist} also embeds the information linking the patient's specialty to the one assigned to the operating room, and takes the value 0 whenever they differ. Finally, we denote by A_{st} the time capacity of operating room s on day t , and C_{jt} the bed capacity of the ward of specialty j on day t . The model uses binary variables x_{ist} which take the value of 1 if patient i is scheduled in operating room s on day t , and 0 otherwise.

$$\begin{aligned}
& \max \sum_{i \in I} \sum_{s \in S} \sum_{t \in T} p_i x_{ist} \quad (\text{obj}) \\
& \text{s.t.} \\
& \sum_{s \in S} \sum_{t \in T} x_{ist} \leq 1 \quad \forall i \in I \quad (4.1) \\
& \sum_{i \in I} w_i x_{ist} \leq A_{st} \quad \forall s \in S, \forall t \in T \quad (4.2) \\
& x_{ist} \leq a_{ist} \quad \forall i \in I, \forall s \in S, \forall t \in T \quad (4.3) \\
& \sum_{\tau \in T_i} \sum_{i \in I_t} \sum_{s \in S} d_{ij(t-\tau+1)} x_{is\tau} \leq C_{jt} \quad \forall j \in J, \forall t \in T \quad (4.4) \\
& x_{ist} \in \{0, 1\} \quad \forall i \in I, \forall s \in S, \forall t \in T \quad (4.5)
\end{aligned}$$

The objective function (obj) seeks to maximize the profit generated by the scheduled patients. Each patient's profit is evaluated with reference to the starting day of the planning horizon.

Constraints (4.1) ensure that each patient is scheduled at most once. Constraints (4.2) ensure that the operating room time slot duration is respected. Constraints (4.3) ensure the compatibility of the patient for assignment to the room. Constraint (4.4) ensures that the bed occupancy in each specialty ward on day $t \in T$ does not exceed its capacity. Bed occupancy for ward of specialty j on day t is evaluated by considering the time spent in the ward by all patients scheduled on previous days that are still in the hospital. In particular for a patient i who had surgery on day τ , the value $t-\tau+1$ denotes time elapsed since surgery, which allows to retrieve the proper figure from the length of stay matrix. Finally, constraints (4.5) restrict the decision variables to be binary.

5 Metaheuristic Algorithms

5.1 Introduction

In the Surgical Case Assignment Problem, the objective is to schedule patients in operating rooms while satisfying multiple resource constraints, such as room availability, surgical durations, and postoperative ward capacities. The Surgical Case Assignment Problem is a complex problem and is proved to be NP-Hard in Aringhieri et al. [6]. The combinatorial nature of these problems causes the solution space to grow exponentially with the number of patients and resources, making exact methods computationally infeasible in real time hospital operations. In this context, ILP optimization models may encounter difficulties when solving large scale instances, often requiring excessive computation times to obtain optimal solutions. For this reason, metaheuristic approaches are often preferred. This techniques does not guarantee an optimal solution, but can produce high quality feasible solutions. In this chapter will be presented a set of different metaheuristics to solve the Surgical Case Assignment problem described in the previous one.

5.2 Literature review

In real world hospital settings, decision makers have to create surgical schedules in a reasonable amount of time. To obtain good feasible solutions within acceptable computational times, metaheuristic algorithms are often employed. Metaheuristics do not guarantee optimality but can explore vast solution spaces and provide high quality, near optimal solutions (Belkhamisa et al. [14], Vieira et al. [83] and Moosavi et al. [56]). This makes them extremely suitable for this problem, where efficient and timely decision-making is key to improving resource utilization and patient care Because of the nature of metaheuristics,

they can be also applied to more complex problem settings, like operating room staff constraints, as in Farsi [32].

5.3 Algorithms

In this work, we propose several algorithms for the allocation of patients to operating rooms, aimed at optimizing surgical scheduling in a hospital setting.

5.3.1 Greedy Algorithm

The first algorithm is the simplest one, based on a greedy logic. It produces the solution in very short time, although the quality of the result is not always sufficient. The solution obtained by this algorithm can be a good starting point for applying a local search, with the aim of improving the initial solution. This rationale forms the foundation of the subsequent algorithms.

The algorithm begins by ordering patients according to their assigned **scores**, in decreasing order, ensuring that those with the highest priority are considered first. The operating rooms are then sequentially iterated and for each available time slot, the algorithm examines only the patients eligible for that specific slot based on clinical and logistical constraints.

To decide whether a patient can be assigned to the operating room that day, two key factors are considered: the duration of the surgery and the capacity of the relevant hospital departments (e.g. post operative intensive care unit units) to accommodate the patient during the entire hospital stay. If both the operating room and ward capacity constraints are satisfied, the patient is assigned to that operating room and time slot. The procedure continues in an iterative manner, progressing through the remaining patients in the priority list until every possible assignment is completed or no feasible matches are left.

The greedy approach guarantees that, at each iteration, the algorithm selects locally optimal actions by giving precedence to patients with higher **scores**, while simultaneously respecting operational constraints such as surgical time and hospital bed capacity. Although global optimality cannot be assured, the method is both efficient and well-suited to real-time scheduling in hospital environments characterized by rapidly changing patient priorities and resource availability. The Greedy Algorithm is presented in Algorithm 1.

Algorithm 1 Greedy Patient Scheduling in Operating Rooms

Input:

- Patients I with surgical procedure time w_i , **scores** p_i , and perioperative path $d_{ij\tau}$
- Operating rooms S , each with a time capacity A_{st}
- Assignability of patients a_{ist}
- Capacity of wards C_{jt} for each ward $j \in J$ and each time period $t \in T$

Ensure: Schedule patients into operating rooms while respecting the capacity constraints of operating rooms and wards**for** $t \in T$ **do** **for** $s \in S$ **do** $A_{residual} \leftarrow A_{st}$ $P \leftarrow \{i \in I \mid a_{ist} = 1 \text{ e } x_{ist} = 0\}$ $P \leftarrow \text{sort}(P, \text{key} = p_i)$ **for** $i \in P$ **do** **if** $w_i \leq A_{residual}$ and $d_{ij\tau} < C_{jt}, \forall j \in J, \forall t \in [d, d + D_i]$ **then** $x_{ist} \leftarrow 1$ $A_{residual} \leftarrow A_{residual} - w_i$ Reduce bed capacity C_{jt} accordingly **end if** **end for** **end for****end for**

5.3.2 Local Search Criteria

The Greedy algorithm was then modified by introducing policies allowing scheduled patients to be removed from the plan and replaced with others not yet scheduled.

All the following algorithms are based on the Ruin and Recreate logic. Starting from a given solution, it is partially destroyed (Ruin) by removing some of the already scheduled patients, and then reconstructed using different criteria (Recreate). The procedure used to remove patients is described in Algorithm 2.

Algorithm 2 Remove patients from schedule in Operating Rooms

Input:

- Greedy solution
- Specialty j
- Day τ
- Parameter k

Ensure: Removing subset of patients from schedule

for $t \in [\tau - k, \tau]$ **do**

for $s \in S$ **do**

for $i \in I$ **do**

if $x_{ist} = 1$ **then**

$x_{ist} \leftarrow 0$

 Update bed capacity C_{jt} accordingly

 Update OR capacity A_{st} accordingly

end if

end for

end for

end for

The idea behind this algorithm is to select a specialty and a specific day, and then remove from the schedule all patients belonging to that specialty who were assigned to that day and the k preceding days. After that, the patients are reinserted into the schedule using a different criterion from the one previously applied. To reconstruct the partially destroyed solution, three policies were tested for selecting the patient to be removed, and two for choosing their replacements, creating different versions of the algorithm. In these three policies, instead of using only the original patient **scores**, two additional criteria inspired by Dantzig's algorithm were also explored: one where the **scores** is weighted by the duration of the surgery in the operating room, and another

where the **scores** is weighted by the number of hospitalization days.

After an extensive testing phase, the value of k was set to 5 days. Since bed availability is typically one of the most restrictive constraints, this choice is also supported by the observation that over 95% of patients have a length of stay shorter than five days. Given that the criterion used to empty the operating rooms is based on the identification of the most crowded departments, it makes sense to adopt this threshold, as it ensures that nearly all patients impacting that department during its peak occupancy are included. Moreover, this approach allows the algorithm to reassign almost the entire workweek, since bed occupancy generally peaks on Thursday and Friday. In the following subsections, the algorithms constructed based on these components are presented and discussed in detail.

5.3.3 Multiswap

The **Multiswap** algorithm is designed to improve an initial greedy solution. Starting from this initial solution, the algorithm keeps track of the best solution found and uses a Tabu list to prevent recently modified operating rooms from being reconsidered immediately.

The method iteratively attempts to modify the schedule through a series of removal and reinsertion steps, using different prioritization criteria to explore alternative solutions. The algorithm consists of three consecutive phases, each comprising N iterations. The criteria chosen to select the subset of patients to remove from the schedule is to use the specialty and the day of the most crowded ward. The patients assigned to the operating rooms of the selected specialty, within the period including the chosen day and the preceding k days, are removed from the solution. At every iteration, this combination is selected and added to the Tabu list. Then, this subset of operating rooms is refilled according to a criterion that changes across the three phases. The first phase prioritizes patients according to **scores** weighted by the duration of the surgery, the second phase uses the **scores** weighted by the total length of stay, and the third phase considers only the **scores**. At each iterations, only improving solutions are taken. The pseudocode of the algorithm is presented in Algorithm 3.

Algorithm 3 Multiswap scheduling in Operating Rooms

Input:

- Greedy solution

Ensure: Schedule patients into operating rooms while respecting the capacity constraints of operating rooms and wards $z^* := z_{Greedy}$ $k := 5$ Tabu := $\emptyset$ **for** $iter = 1$ to N **do** Select Most full ward (j, τ) Tabu = Tabu $\cup (j, \tau)$ Empty Algorithm (j, τ, k) Apply Greedy on subset of OR (p_i/w_i) **if** $z \geq z^*$ **then** Update z^* Update all x_{ist} **end if****end for**Tabu = $\emptyset$ **for** $iter = 1$ to N **do** Select Most full ward (j, τ) Tabu = Tabu $\cup (j, \tau)$ Empty Algorithm (j, τ, k) Apply Greedy on subset of OR (p_i/D_i) **if** $z \geq z^*$ **then** Update z^* Update all x_{ist} **end if****end for**Tabu = $\emptyset$ **for** $iter = 1$ to N **do** Select Most full ward (j, τ) Tabu = Tabu $\cup (j, \tau)$ Empty Algorithm (j, τ, k) Apply Greedy on subset of OR (p_i) **if** $z \geq z^*$ **then** Update z^* Update all x_{ist} **end if****end for****return** z^*

5.3.4 Tabu

The **Tabu** algorithm is an evolution of the **Multiswap** and instead of performing the three different exchange criteria sequentially, all three possibilities are evaluated at each iteration, and the best one is chosen if it improves the current solution.

The criterion for selecting the subset of patients to remove remains the same: those belonging to a single specialty on the day of maximum bed occupancy, as these patients are typically the most constraining. In this version as well, only improving solutions are accepted. The pseudocode of the algorithm is presented in Algorithm 4.

Algorithm 4 Tabu scheduling in Operating Rooms

Input:

- Greedy solution

Ensure: Schedule patients into operating rooms while respecting the capacity constraints of operating rooms and wards

$z^* := z_{Greedy}$

$k := 5$

Tabu := $\emptyset$

for $iter = 1$ to N **do**

 Select Most full ward (j, τ)

 Tabu := Tabu $\cup (j, \tau)$

 Empty Algorithm (j, τ, k)

 Apply Greedy on subset of OR (p_i)

 Apply Greedy on subset of OR (p_i/w_i)

 Apply Greedy on subset of OR (p_i/D_i)

 Take best z

if $z \geq z^*$ **then**

 Update z^*

 Update all x_{ist}

end if

end for

return z^*

5.3.5 Tabu Ad

In this version of the algorithm, called **Tabu Ad**, which is very similar to the **Tabu** version, an additional element has been introduced: the duration of the swap period.

In the previous version, this duration was fixed at five days to include an entire week. Here, it initially starts at five days, but after a y number of iterations without any improvement in the objective function, this parameter is reduced by one, and the tabu list is cleared. This mechanism is inspired by the concept of temperature in the Simulated Annealing algorithm, although it is applied differently. The criterion for selecting patients remains the same, as does the rule that accepts a new solution only if it represents an improvement. The pseudocode of the algorithm is presented in Algorithm 5.

Algorithm 5 Tabu Ad scheduling in Operating Rooms

Input:

- Greedy solution

Ensure: Schedule patients into operating rooms while respecting the capacity constraints of operating rooms and wards

$z^* := z_{Greedy}$

$k := 5$

$q := 0$

Tabu := $\emptyset$

for $iter = 1$ to N **do**

Select Most full ward (j, τ)

Tabu := Tabu $\cup$ (j, τ)

Empty Algorithm (j, τ, k)

Apply Greedy on subset of OR (p_i)

Apply Greedy on subset of OR (p_i/w_i)

Apply Greedy on subset of OR (p_i/D_i)

Take best z

if $z \geq z^*$ **then**

Update z^*

Update all x_{ist}

$q := 0$

else

$q += 1$

end if

if $q \geq y$ and $k \geq 1$ **then**

$k := k-1$

$q = 0$

Tabu := $\emptyset$

end if

end for

return z^*

5.3.6 Random

In the **Random** algorithm, randomness is also included. In metaheuristics, randomness is used to diversify the search process and reduce the risk of the algorithm becoming trapped in local optima. In our problem, randomness is used to select the specialty and the day on which to clear the operating room, instead of considering the ward with highest utilization. The criterion for selecting improving solutions is maintained. The pseudocode of the algorithm is presented in Algorithm 6.

Algorithm 6 Random scheduling in Operating Rooms

Input:

- Greedy solution

Ensure: Schedule patients into operating rooms while respecting the capacity constraints of operating rooms and wards

$z^* := z_{Greedy}$

$k := 5$

$q := 0$

$Tabu := \emptyset$

for $iter = 1$ to N **do**

Select random ward (j, τ)

$Tabu := Tabu \cup (j, \tau)$

Empty Algorithm (j, τ, k)

Apply Greedy on subset of OR (p_i)

Apply Greedy on subset of OR (p_i/w_i)

Apply Greedy on subset of OR (p_i/D_i)

Take best z

if $z \geq z^*$ **then**

Update z^*

Update all x_{ist}

$q = 0$

else

$q += 1$

end if

if $q \geq y$ and $k \geq 1$ **then**

$k := k-1$

$q := 0$

$Tabu := \emptyset$

end if

end for

return z^*

5.3.7 Random Degrade

The final algorithm presented is called **Random Degrade**. This algorithm synthesizes all the features of the previous approaches, with the addition of the ability to accept solutions that are worse than the current solution. Specifically:

- The selection of operating room slots to be emptied is randomized.
- The use of the tabu list for previously used wards and days remains valid.
- When refilling the emptied subset of operating rooms, all three criteria are evaluated simultaneously, and the best option is selected.
- After a certain number of iterations y in which the solution does not improve the value of the best found objective function so far, the parameter k is decreased by one.

Whenever k is reduced, the tabu list is cleared, and the algorithm continues iterating from the best solution found so far, rather than from the current solution. After a testing phase, the acceptance threshold for worse solutions was set to 0.95. The pseudocode of the algorithm is presented in Algorithm 7.

5.4 Algorithmic Details

In practice, certain specialties, such as the ICU (Intensive Care Unit), do not have any assigned operating rooms, as these are typically used by other specialties.

If the ICU ward happens to be the most saturated (in the case of the first three algorithms) or is selected randomly (as in the last two algorithms), it would not be possible to empty its associated operating rooms, since it has none. To overcome this problem, and since all the other specialties can contribute to filling the ward, operating room of all disciplines are cleared and then refilled simultaneously.

All the swaps are performed only if they improve the Objective Function, defined as the sum of the scheduled patients' **scores**, except for the **Random Degrade** algorithm.

Algorithm 7 Random Degrade scheduling in Operating Rooms

Input:

- Greedy solution

Ensure: Schedule patients into operating rooms while respecting the capacity constraints of operating rooms and wards $z^* := z_{Greedy}$ $z_{best} := z_{Greedy}$ $k := 5$ $q := 0$ Tabu := $\emptyset$ **for** $iter = 1$ to N **do** Select random ward (j, τ) Tabu := Tabu $\cup (j, \tau)$ Empty Algorithm (j, τ, k) Apply Greedy on subset of OR (p_i) Apply Greedy on subset of OR (p_i/w_i) Apply Greedy on subset of OR (p_i/D_i) Take best z **if** $z \geq (0.95) z^*$ **then** Update z^* Update all x_{ist} **if** $z_{best} < z^*$ **then** $z_{best} := z^*$ $q := 0$ **else** $q += 1$ **end if** **end if** **if** $q \geq y$ and $k \geq 1$ **then** $k := k-1$ $q := 0$ Tabu := $\emptyset$ $z^* := z_{best}$ **end if****end for****return** z_{best}

The last two versions of the metaheuristic algorithm differ from the previous ones as they introduce an element of randomness. Both are based on the **Tabu Ad** algorithm, but the selection of the operating rooms to be emptied is made randomly, while still respecting the Tabu list.

In the next chapter, the results will be presented, in which the different versions of the metaheuristics are compared in terms of performance, specifically by comparing the obtained objective function values and execution times.

6 Results

6.1 Introduction

This chapter presents the results of applying the model and the algorithms introduced in the previous chapter, defining two different types of analyses.

- In the first part, the results of the performance comparison across different instances are presented, with the aim of identifying which of these algorithms performs best.
- In the second part, a study is conducted in which the scheduling generated by the optimization model was compared with actual real world scheduling implemented by the physicians, in order to assess the potential impact of using these techniques. Further analyses were then conducted to assess the impact of the resulting outputs on the equity of treatment for patients awaiting surgery, as well as on waiting times and the size of the waiting list.

6.2 Computational results

This section reports the performance obtained from the model runs compared with the metaheuristics. A subset of algorithms (Greedy, Multiswap, Tabu, Tabu AD) are deterministic, which means that the result obtained in terms of the final solution is always the same. In contrast, the other two algorithms (Random and Random Degrade), being inherently stochastic, produce different solutions each time they are run. To enable a fair comparison with the deterministic algorithms, the random algorithms were executed 30 times, and the average values obtained are reported in Table 6.1 and Table 6.3.

For completeness of the analysis, the maximum values of the objective function

obtained and the minimum running time are also reported, since in some cases they can yield better solutions than any other algorithm presented. This could also help in real-world applications, as running them multiple times within a reasonable execution time can produce both better results and a variety of solutions. Presenting multiple solutions to physicians provides greater choice and can facilitate the adoption of these tools in practice.

The test set consists of instances of increasing size, all defined over the same planning horizon. The experimental setup includes nine medical specialties and ten operating rooms, analyzed over a 60-day period. The instances are defined by a number, which represents the number of patients per specialty. The instances range from the smallest, with 10 patients per specialty (totaling 90 patients), to the largest, with 1000 patients per specialty (totaling 9000 patients). Small instances (10–40 patients per specialty) include a limited number of cases, medium-sized instances (50–200 patients per specialty) involve a moderate workload for a surgical operating theater, while large instances (400–1000 patients per specialty) represent full-scale hospital scenarios. The results show a progressive improvement in both efficiency and quality of solutions obtained with the different algorithms implemented. Metaheuristic approaches, such as Tabu Ad, have proven particularly effective in reducing computation times compared to the other algorithms. In terms of objective function values, these metaheuristic algorithms closely approximate the solutions provided by the ILP model, finding near-optimal solutions in significantly shorter times.

If we look at Table 6.2, which shows the gap between the ILP model and the metaheuristic solutions, we notice that it is negligible for small instances, slightly increases for medium-sized instances, and becomes more noticeable for large instances. Despite this, metaheuristics remain near-optimal across all instance sizes, offering high accuracy for small and medium instances and acceptable precision for large ones, while significantly reducing computation time. This makes them particularly suitable for solving large-scale instances, where the exact optimization model encounters difficulties in achieving optimality within a reasonable time due to the high computational complexity. While the optimization model generates optimal solutions for small and medium sized instances, it begins to encounter difficulties in solving problems from instance 200 and above (i.e., with almost 2000 patients). Therefore, the meta-

Table 6.1: Score of scheduled patients

Instance	O.F.				Rand(mean)	Rand(max)	Rand Deg(mean)	Rand Deg(max)	Model
	Greedy	Multiswap	Tabu	Tabu Ad					
10	45330	45330	45330	45330	45330	45330	45330	45330	45330
20	92449	93877	93877	93877	93877	93877	93877	93877	94329
40	154602	157842	158080	158080	159524	160678	159576	160644	161326
50	183665	189926	191254	191628	191584	193517	190994	192388	193947
100	295505	306181	306388	309658	310320	312983	309900	312935	316078
200	381233	401976	402572	402614	406239	408689	406192	408390	416857
400	470565	505735	512203	512653	519034	521779	518596	521661	534972
500	509181	546994	545861	550030	556602	560864	556615	562152	577517
800	599774	648819	648861	650665	655065	659560	654046	660504	681057
1000	618962	680437	681459	683216	687726	692856	685594	691711	713409

Table 6.2: Gap between metaheuristic solutions and the ILP model

Instance	Greedy	Multiswap	Tabu	Tabu Ad	Rand(mean)	Rand(max)	Rand Deg(mean)	Rand Deg(max)
10	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
20	1,99%	0,48%	0,48%	0,48%	0,48%	0,48%	0,48%	0,48%
40	4,17%	2,16%	2,01%	2,01%	1,12%	0,40%	1,08%	0,42%
50	5,30%	2,07%	1,39%	1,20%	1,22%	0,22%	1,52%	0,80%
100	6,51%	3,13%	3,07%	2,03%	1,82%	0,98%	1,95%	0,99%
200	8,55%	3,57%	3,43%	3,42%	2,55%	1,96%	2,56%	2,03%
400	12,04%	5,47%	4,26%	4,17%	2,98%	2,47%	3,06%	2,49%
500	11,83%	5,29%	5,48%	4,76%	3,62%	2,88%	3,62%	2,66%
800	11,93%	4,73%	4,73%	4,46%	3,82%	3,16%	3,97%	3,02%
1000	13,24%	4,62%	4,48%	4,23%	3,60%	2,88%	3,90%	3,04%

Table 6.3: Running Time

Instance	Time (second)		Tabu Ad	Random(mean)	Random(min)	Radom Deg(mean)	Radom Deg(min)	Model
	Greedy	Multiswap						
10	0.339	12.316	11.782	3.536	7.345	6.056	7.021	5.946
20	0.39	7.422	6.79	5.826	11.811	10.903	13.787	11.715
40	0.536	14.289	13.952	11.435	33.694	26.725	29.112	24.301
50	0.609	24.831	16.795	12.456	34.077	30.019	34.729	30.025
100	0.911	45.364	35.092	34.3	98.279	80.467	83.638	71.815
200	1.504	113.962	71.124	64.698	155.07	131.716	163.717	134.506
400	2.723	208.276	140.398	120.744	335.029	287.715	350.159	281.695
500	2.676	279.487	173.89	154.748	452.143	371.984	479.431	411.883
800	4.395	417.095	271.267	232.297	809.549	737.935	756.962	684.063
1000	4.898	513.277	329.195	278.669	906.174	810.987	823.786	684.788

heuristic approach proves to be a valid alternative when dealing with larger problems. However, there remains a slight difference in objective function values, as heuristics converge towards near optimal solutions but not always reach the exact optimum. In conclusion, while the MILP model remains the best tool for ensuring optimal solutions for smaller instances, the algorithms demonstrate to be a better approach for large scale problems getting good solutions in a smaller period of time, offering a balance between precision and execution time. Overall, the slight gap between heuristics and the exact model is an acceptable compromise, providing near-optimal results with considerable computational savings.

6.3 Real world application Comparison

This section presents the numerical results obtained by comparing the schedules generated by the optimization model with those implemented in the hospital by physicians and nurses. The analysis covers 28 weeks (9 January to 31 July 2023), involving 286 operating spaces in three operating rooms and 1,959 patients from three specialties. In our analysis, we excluded patients who were removed from the waiting list during this period. The analysis relies on a snapshot of the waiting lists taken at the time of planning. This implies that the model considered only the patients listed at that specific moment, without accounting for fluctuations due to new entries or removals. To align with real-world practice, where planning is carried out weekly, we applied the model using a rolling-horizon logic. At the beginning of each week, the waiting list was updated by removing patients who had already been scheduled and including any new entries that occurred in the meantime. Patient profit was computed on the first day of each weekly planning period and kept fixed during the period. This profit definition served for evaluating both the model solution and the real world solutions designed by practitioners. The profit chosen to evaluate the solutions is the **score**, which, as a reminder, was defined as follows:

$$\text{score} = \text{WT} \times \frac{\text{Waiting time limit of the class with lowest priority (days)}}{\text{Waiting time limit of the patient class (days)}}$$

A similar approach for evaluating the quality of different planning strategies

has been addressed in previous studies, such as Aringhieri et al. [5]. By defining fixed profits within a period, we avoid undesired model behavior, where urgent patients would be scheduled later in the week to increase their **scores**. To enrich the analysis, the model was run with two different inputs: once using estimated surgery times (Model E.T.) and once using actual surgery times, i.e., real times observed ex post (Model R.T.). This approach allowed for a more nuanced assessment of the model's performance under both ideal assumptions and real-world conditions. To fairly evaluate the scheduling produced by the model using estimated times as input, we replaced the estimated times with actual times after the scheduling decisions were made. In other words, the scheduling was carried out based on estimated durations, but its performance was assessed using the actual surgery times, which were unknown at the time of planning. This allowed for a proper evaluation of critical issues, including operating room overtime and real bed capacity. Analytically, the best we can do is to register and evaluate the amount of overtime introduced by uncertainty, while the practical effect (i.e. delay, postponement or cancellation of the procedure) depends on the medical decision and cannot be estimated a priori. We compare the solutions produced by the model with those of the practitioners using two metrics: the overall weekly **score** and the number of hospitalized patients, whose trends are depicted in Figures 6.1 and 6.2, respectively.

From Figure 6.1, we can observe that the weekly **score** obtained by Model R.T. and Model E.T. exhibits a very similar trend. However, when compared to the actual scheduling performed by practitioners, we notice that the model's prescription and performance differ significantly from the implemented practitioner solution. In the initial weeks, the models achieve significantly higher

Figure 6.1: Score of the weekly scheduled patients

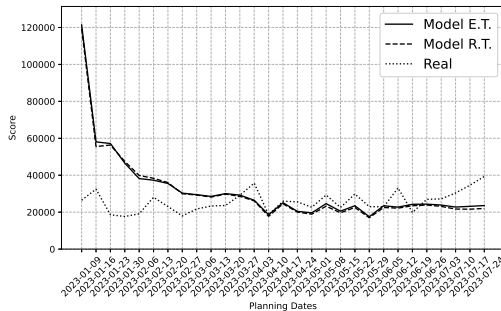
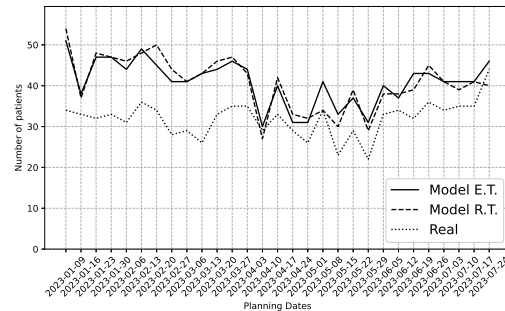


Figure 6.2: Number of weekly scheduled patients



score as they prioritize urgent patients, a practice that is not always strictly adhered to in reality. Over time, the gap gradually narrows until the implemented scheduling achieves higher **scores** in the last weeks. This outcome is not surprising, as the model's scheduling would have already treated high **score** patients in earlier weeks. Additionally, the better performance of the model scheduling in the early weeks leads to a lower average waiting time for patients still on the list. This, in turn, results in a subsequent reduction in the **score** of selected patients when their scores are updated. From Figure 6.2, we observe that the difference in the number of patients scheduled weekly is larger in the initial weeks and then gradually decreases over time. This phenomenon can be explained by the fact that, given a group of patients with similar **score**, the model tends to prioritize those requiring fewer resources, allowing more patients to be processed in the initial weeks. Over the observation period, the curve obtained by the optimized scheduling dominates the curve representing the practitioners scheduling, highlighting that, although the model prioritizes certain patients, the optimized schedule achieves a better throughput.

The numerical values for the number of patients scheduled by both the models and the practitioners, and the corresponding average **score**, are presented in Table 6.4.

In addition, an analysis was performed on the status of the waiting list at the end of the observation period to assess its size and the average **score** of the remaining patients. This analysis aimed to evaluate the equity of patient treatment, which was one of the initial objectives. The results are shown in Table 6.5.

From Table 6.5 we observe that, for both the Model R.T. and Model E.T., the average **score** of patients is lower compared to reality, and, more importantly, it is balanced across different priority classes. This outcome aligns with the primary objective of the model, which is to ensure equity in patients treat-

Table 6.4: Scheduled patients

Priority Class	Number of Patients			Average score		
	Real	Model R.T.	Model E.T.	Real	Model R.T.	Model E.T.
A	39	35	36	278.6	527.4	524.2
B	345	444	453	1060.6	966.3	960.4
C	347	520	513	738.3	682.2	700.1
D	196	182	184	590.4	596.7	615.5
Total	927	1181	1186	807.6	771.2	781.0

Table 6.5: Waiting List state at the end of the planning horizon

Priority Class	Number of Patients			Average score		
	Real	Model R.T.	Model E.T.	Real	Model R.T.	Model E.T.
A	1	5	4	584.0	489.2	380.3
B	213	114	105	948.7	337.0	297.7
C	584	411	418	466.0	324.4	314.5
D	234	248	246	300.6	324.7	307.4
Total	1042	778	773	523.2	327.4	310.3

ment. When solving Model E.T., potential issues arising from the scheduling process were evaluated for both bed and operating room (OR) capacities. This resulted in 73 cases out of 784 (approximately 9.31%) where the actual capacity of a ward was insufficient to accommodate all scheduled patients. In these cases, where the ward capacity was exceeded, the average excess was 6%, with a peak of 20%. If this event occurs, the planned intervention may be canceled and will need to be rescheduled in the following days. Concerning the OR, we evaluated how many times the procedures exceeded the times slot, resulting in 109 cases over 286 (approximately 38.18 %) with an average overrun of 15.8% of the slot duration. This situation is not ideal, but it can be managed as overtime without the need to reschedule the procedure to the following days. For the Model E.T., the results are therefore highly dependent on the accuracy of the predictions for surgical durations and patient length of stay.

7 Simulation

7.1 Introduction

The use of simulation in healthcare is widely use across various areas, including operating room scheduling (Xue et al. [89]). For the surgical scheduling, it can be used to help define the Master Surgical Schedule as in Cappanera et al.[16]. It is often combined with optimization models, sometimes fully integrated into the model itself, but mainly used to assess the robustness of the proposed solution (Banditori et al. [10], Kougias et al. [46] and Xiao et al. [88]). A similar approach to those described so far will be used in this chapter.

7.2 Simulation Case Study

In this chapter, we design a simulation-based framework that models the operating room environment and the entire hospital stay of patients.

The simulator is used to test different scheduling strategies under varying conditions, allowing the analysis of delays, cancellations, and bottlenecks in the surgical pathway. Special attention is given to the effect of inaccurate predictions of surgery durations, modeled by increasing variance in procedure times.

This simulation based approach takes as input the assignment of patients to operating rooms from the ILP Model, and then proceeds to an actual scheduling phase, in which patients are temporally ordered within the operating slots. The use of this approach is due to a limitation that arises from the definition of the LOS matrix itself, as presented in Table 4.1. In this representation, for each day the value reported in each cell corresponds to the percentage of the day that the patient is expected to spend in a given ward. Unfortunately, this does not provide any information about the specific time of day. For example, if the value is 0.5, it means that the patient will spend half a day (i.e., 12

hours) in that ward, but it is not possible to determine whether this will occur in the morning or in the afternoon.

Due to this characteristic, and given that in the model's constraints these percentages are simply summed in order to remain within ward capacity, a potential issue may arise if patients overlap in the same ward at the same time of day. To mitigate this problem, the simulation framework becomes essential, as it allows us to test different criteria for ordering patients into operating room slots, to reduce the likelihood of such overlaps.

7.3 Objectives

The simulation aims to:

- Evaluate the effectiveness of different scheduling strategies in ordering patients within surgical slots
- Explore the impact of variability in surgical and recovery times on hospital operations.

To measure the effectiveness of the different scenarios, several performance indicators will be employed. These indicators capture both the frequency and the impact of undesired events, such as delays in admission or ward transfer, as well as the use of operating room resources beyond the expected time horizons. In particular, the following indicators will be considered:

- Number of canceled surgeries
- Number of delayed hospitalizations and surgeries,
- Operating room overruns

7.4 Conceptual Simulation Framework

The simulation in this study was performed using the Salabim library, an Object Oriented Environment for DES (van der Ham, 2016 [82]). Salabim is a Discrete Event Simulation Python framework designed to enable modeling of complex and dynamic systems whose development is marked by the occurrence of discrete events. It combines object oriented design with a process oriented

simulation paradigm enabling modeling of real world systems as collections of interacting entities such as processes, resources, and queues each defined by specific behaviors, and event triggered interactions.

In the simulation environment, objects are implemented as components. Each component, once instantiated, executes its own process governing his behavior, doing things, and interfacing with other objects within the system. Such interactions may involve waiting for events or intervals, and interfacing with shared resources that can be acquired, held, and released as per the rules defined within the simulated world.

This make it a useful tool for research as well as decision making in real life, particularly where scheduling strategy, resource policy, or process redesign programs have to be analyzed under uncertainty.

7.5 Simulation Components

This section presents the components that form the simulation model. A quick overview of their roles and activities is provided:

- **Patient:** This component represents the patients in the system that originates from the optimization model and its process defines which resources each patient will use and for how long
- **Operating Room:** This component represents an operating room within the hospital. It could have been modeled as a resource, but it was implemented as a component to achieve more flexibility in managing the queue of patients awaiting surgery. This approach also gives the component the capacity to check if the duration of the next scheduled procedure is expected to exceed the planned closing time of the operating room.
- **Operating Room Scheduler:** This component is responsible for opening and closing the operating room according to the slots defined in the Master Surgical Schedule
- **Ward Bed:** This last component represents a hospital bed, like the operating rooms it was modeled as a component rather than a resource. This component manages the movement of patients between wards by activating and passivating them, handling transfer requests, to patient care pathways, and bed availability.

Each of these components will be described in detail in the following sub-sections, except for the Operating Room Scheduler, which is straightforward and does not require a dedicated section. The behavior of this component is defined by a process, which is illustrated in the pseudo-code presented in Algorithm 8.

Algorithm 8 Operating Room Scheduler Component

```

Input: comp_or, moment, action, duration
if action = 'open' then
  Set comp_or.open = 1
  if comp_or is passive then
    Activate comp_or
    comp_or.estimated_end = actual_time + duration
  end if
else if action = 'close' then
  Set comp_or.open = 0
  if comp_or is active then
    passivate comp_or
  end if
end if

```

7.5.1 Patient Component

The Patient component represents an individual patient that is assigned by the ILP Model. To simplify the implementation of the model, the length of stay is defined using two arrays: the first contains the specialties included in the patient's pathway, while the second specifies the duration of stay in each corresponding unit. Each patient is instantiated with specific attributes:

- arrival time: it is the date on which the patient is scheduled
- duration: it is the time of the surgical procedure
- or_id: it is the id of the operating room in which it is scheduled
- patient_id: it is the id of the patient
- list: it is the list of wards, that the patient will visit during his hospitalization
- length_path: it is the length of array *list*, it is usually 1 or 3 (if the patient need ICU)

- `time_path`: it is the list of hospital stay's duration

When a patient is created, their process starts and searches for the index of the ward of their first transfer list. If the corresponding ward has available capacity, they are immediately admitted; otherwise, they join a waiting queue, where they remain passivated until capacity becomes available. Every ward has two types of queues: admission queue `queue_pl_ric`, used before initial hospitalization, and transfer queue `queue_pl`, used when the patient needs to move to another unit but no bed is currently free.

Once admitted, the patient must undergo a surgical procedure as part of their path. They join the operating room queue, waiting for the assigned operating room to become available. At this point, two scenarios may occur: either the operating room is open, meaning it is available according to the master surgical schedule, and the room is empty, in which case they activate the operating room and begin their procedure; or the room is closed or still occupied with a previous patient, in which case they remain in the queue waiting to be called. In both scenarios, when they leave the queue, they wait for the specified `duration` and then set their parameter `procedure_done` to 1 indicating that the procedure has been performed and will not need to be repeated during any subsequent transfer. After that, they remain in the ward for the duration of the corresponding `time_path`. In the case where the patient has undergone surgery, their length of stay starts being counted from that moment. This is because, if they had waited several days before being called due to schedule disruptions, those days should not be included in the length of stay. Therefore, inpatient stay is considered to start from the time of the intervention. However, this value is then adjusted by a few hours, representing the theoretical time that should elapse between the patient's admission and their entry into the operating room, since, in our model, this portion of time is already accounted for in the patient pathway.

At the end of the current transfer, if it is not the last one, before leaving the ward they check the next ward in the path; if no beds are available, they join the transfer queue `queue_pl` for that ward while still occupying their current bed. When they are reactivated from the queue, or if the next ward was already available, they free their current bed and restart the cycle, without repeating the surgical procedure step. If it is their final transfer, at the end of the transfer period, they are discharged, thus freeing their bed.

Algorithm 9 Patient Component

Input: arrival_time, duration, or_id, patient_id, list, length_path, time_path

Initialize procedure_done = 0

for i in length_path **do**

 id_bed $\leftarrow$ ID of the WardBed component such that

 Ward Bed.specialty = list[i] transfer= i

if WardBed[id_bed].capacity_res > 0 **then**

 WardBed[id_bed].capacity_res -= 1

else if i == 1 **then**

 Enter WardBed[id_bed].queue_pl_ric

 Wait activation

 Leave WardBed[id_bed].queue_pl_ric

else

 Enter WardBed[id_bed].queue_pl

 Wait activation

 Leave WardBed[id_bed].queue_pl

end if

if procedure_done == 0 **then**

 Enter OperatingRoom[id_or].queue_or

if (OperatingRoom[id_or] is passive &

 OperatingRoom[id_or].open == 1 &

 OperatingRoom[id_or].patient_call == 0) **then**

 OperatingRoom[id_or].patient_call = 1

 Activate OperatingRoom[id_or]

 Wait activation

else

 Wait activation

end if

 Leave OperatingRoom[id_or].queue_or

 Wait for duration

 procedure_done = 1

 Wait max(time_path[i] - 8 hours, 0)

else

 Wait time_path[i]

end if

if i < length_path **then**

 next_id_bed $\leftarrow$ ID of the WardBed component such that

 Ward Bed.specialty = list[i+1]

if WardBed[next_id_bed].capacity_res <= 0 **then**

 Enter WardBed[next_id_bed].queue_pl

 Wait activation

 Leave WardBed[next_id_bed].queue_pl

end if

end if

 WardBed[id_bed].capacity_res += 1

 Activate WardBed[id_bed]

end for

7.5.2 Operating Room Component

The Operating Room components are instantiated at the beginning of the simulation and require only the room `id_or` as input. At the time of their creation, they are set as closed, meaning they are not currently available to admit patients, and their `estimated_end` time is set to zero. A request queue `queue_or` associated with the room is created, along with the `patient_call` parameter, which is used to manage the calls of patients from the `queue_or` in the case that the room is open but passive due to an empty queue. This ensures that the arrival of a new patient triggers the start of their procedure.

The opening and closing of the Operating Rooms are managed by the Operating Room Scheduler component, which, based on the Master Surgical Schedule, opens and closes the operating rooms. At the time of opening, it sets the `estimated_end` time of the slot, which is necessary when calling a new patient, allowing the system to verify that the procedure can be performed within the available time frame.

The Operating Room process begins once the room is open. Its `patient_to_activate` attribute is initialized with a dummy patient. Then, if its queue `queue_or` is not empty, the room searches, in the order patients were added to the queue, for those who meet specific criteria: that the end of the patient's procedure does not exceed the slot's `estimated_end` by more than 20 minutes, and that, if the patient requires a bed in the subsequent ward, this bed is available.

If a patient meets these criteria, they are selected and stored in the `patient_to_activate`. If no suitable patient is found, the room becomes passive, waiting to be triggered by a new incoming patient.

If the patient call attribute is zero, meaning the room itself determines which patient to operate on. the selected patient is activated, and the room remains busy for the duration of the procedure. Otherwise, if the activation was triggered by a new patient, that patient is already active and does not need to be reactivated. In this case as well, the room waits for the duration of the patient's procedure and then resets its `patient_to_activate` attribute to zero.

Algorithm 10 Operating Room Component

```

Input: id_or
Initialize open = 0
Initialize patient_call = 0
Initialize estimated_end = 0
Initialize queue_or
Wait activation
while open = 1 do
    Set patient_to_activate = 10000
    if queue_or not empty then
        for all Patient  $p$  in queue_or do
            if  $p.duration + actual\ time \leq estimated\_end + 20minutes$  &
check  $\leftarrow$  Next Ward Availability check( $p.patient\_id$ ) then
                patient_to_activate =  $p.patient\_id$ 
                break
            end if
        end for
    end if
    if patient_to_activate = 10000 then
        Wait activation
    else if queue_or not empty & patient_call == 0 then
        Activate Patient[patient_to_activate]
        Wait for Patient[patient_to_activate].duration
    else if queue_or not empty & patient_call == 1 then
        patient_call = 0
        Activate Patient[patient_to_activate]
        Wait for Patient[patient_to_activate].duration
    else
        Wait activation
    end if
end while

```

Algorithm 11 Next Ward Availability check

```

Input: patient_id
Initialize check = True
if Patient[patient_id].transfer < Patient[patient_id].length_path
then
    next_id_bed  $\leftarrow$  ID of the WardBed component such that
    WardBed.specialty = Patient[patient_id].list[transfer+1]
    if WardBed[next_id_bed].capacity_res <= 0 then
        check = False
    end if
end if
return: check

```

7.5.3 Ward Bed Component

The WardBed component manages patient bed requests and utilization. Essentially, it is assigned a certain number of beds (**capacity**) associated with a specific **specialty**. Upon creation, each ward generates two associated queues: one for patients who are already hospitalized and require a transfer (**queue_pl**), and a second for new admissions (**queue_pl_ric**).

The component continuously checks for patient requests whenever beds are available, first checking the queue of already admitted patients, and only afterward the queue of new admissions. If both queues are empty, the component becomes passive and waits to be activated by the arrival of a new request.

The decision to use two separate queues reflects real world hospital operations: patients who are already admitted are given higher priority to facilitate discharges. By preventing unnecessary extensions of their hospital stay, this approach allows a greater number of patients to be treated overall.

Algorithm 12 Ward Bed Component

```

Input: capacity, specialty, id_bed
Initialize capacity_res = capacity
Initialize queue_pl
Initialize queue_pl_ric
while True do
    Wait activation
    if capacity_res > 0 & queue_pl not empty then
        Select first patient queue_pl
        Activate patient
    else if capacity_res > 0 & queue_pl_ric not empty then
        Select first patient from queue_pl_ric
        Activate patient
    end if
    Wait activation
end while

```

7.6 Simulation Framework Overview

Following the description of the components that make up the simulation, a schematic representation of the simulation itself is presented below:

At the beginning of the run, all components are created: the patients derived from the ILP model assignment, each with their own admission date;

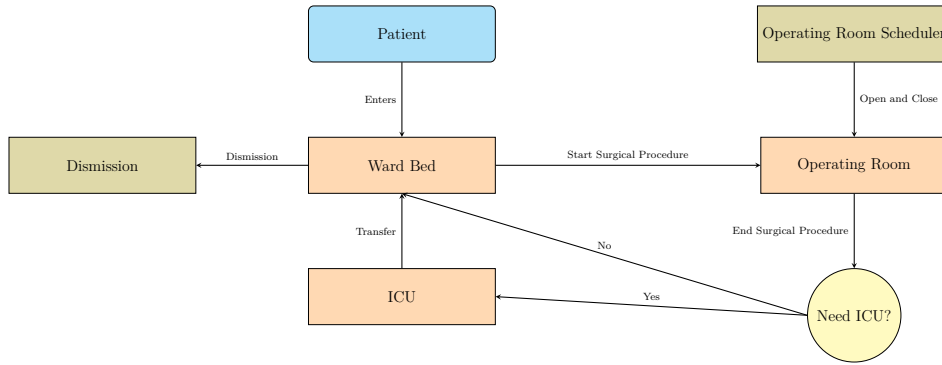


Figure 7.1: Conceptual simulation of surgical scheduling

the operating rooms, which are managed by the operating room scheduler; and the wards, which will host patients during their hospitalization.

The diagram also includes the ICU block, even though it conceptually belongs to the Ward Bed components. Its inclusion highlights that while single-transition patients are admitted to the wards and return there after surgery, some patients experience an intermediate stay in the ICU before returning to their assigned ward.

7.7 Simulation Scenarios

One of the objectives of developing this simulation is to test different approaches for ordering patients within operating room slots, in order to identify the strategy that minimizes scheduling disruptions and facilitates patient flow. The strategies tested for patient ordering were as follows:

- Patients ordered by decreasing surgery duration: **Decr_surg_time**
- Patients ordered by increasing surgery duration: **Incr_surg_time**
- Patients ordered by decreasing total length of stay: **Decr_los**
- Patients ordered by increasing total length of stay: **Incr_los**

The other objective is to evaluate the impact of inaccurate predictions of surgery and hospitalization durations on the system. To achieve this, deterministic durations were replaced with normal distributions, where the mean was set to the original value and the standard deviation varied from 0 to 1 in increments of 0.1. In the versions where probability distributions were used,

the Operating Room component, when selecting patients from its queue, performs the check to ensure that the procedure ends within the slot estimated end plus 20 minutes using the original duration. This is because the actual duration is considered unknown at that moment.

The four ordering criteria were tested in each of these scenarios, and the results are shown in the following graphs.

On the horizontal axis the applied standard deviation values for the durations are shown. On the vertical axis, the corresponding metric is reported, which, as mentioned, includes the number of patients not scheduled on, the total number of minutes of operating room overrun, and the number of hospital admissions that were postponed.

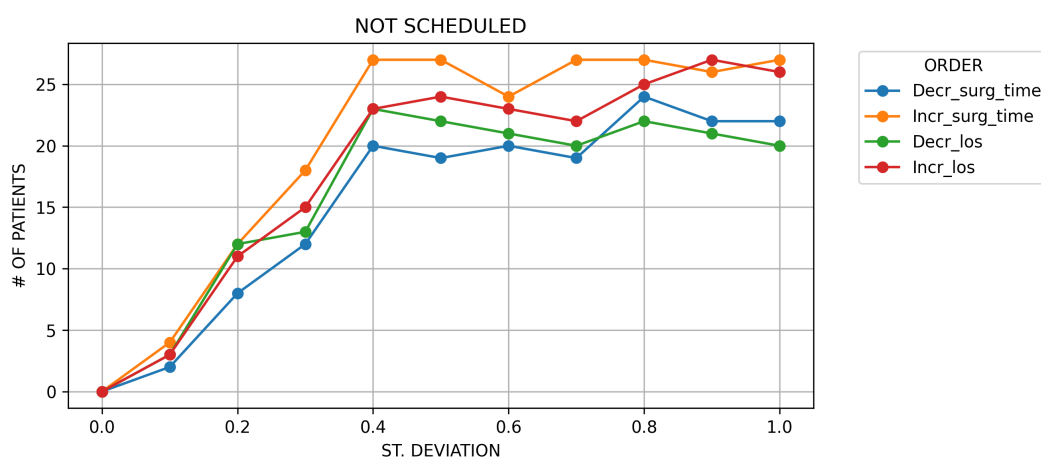


Figure 7.2: Not Scheduled Patients

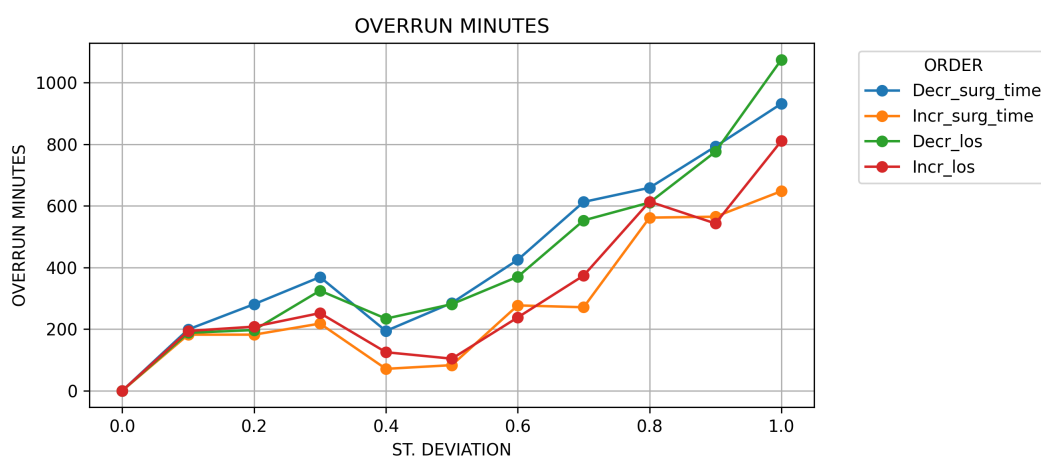


Figure 7.3: Overrun

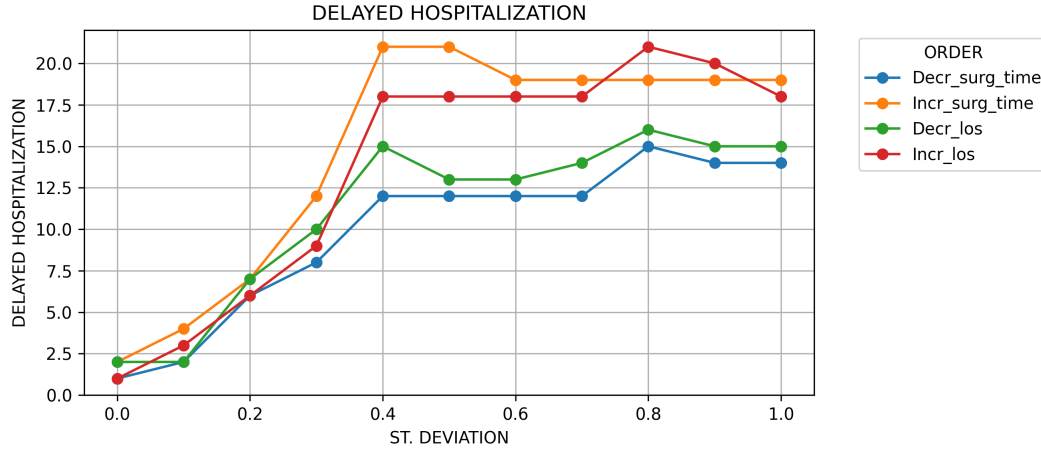


Figure 7.4: Delayed hospitalization

As can be seen in the graphs, both strategies that order patients in decreasing order, either by surgery duration or by total length of stay, perform better in terms of unscheduled patients and postponed admissions. This is because delaying a particularly long procedure has a greater cascading effect in subsequent days, as more demanding procedures in terms of resources will then have to be rescheduled. However, this approach also increases the likelihood of exceeding operating room time. On the other hand, the other two criteria help reduce the risk of overruns but can cause significant inefficiencies in keeping to the original schedule. Although overruns are certainly something to avoid, in real hospital settings, reorganizing surgeries on the following days is often extremely complicated. For this reason, it is generally more practical to schedule patients in decreasing order of surgery duration.

7.8 Discussion

The simulation model presented in this section provides an environment to simulate the performance of different surgical scheduling strategies. The presence of both operating room processes and the hospitalization pathway in the model mimics the dynamics of real hospital operations. This approach makes possible to study not only surgery delays but also their effects on patient flow.

Including both deterministic and stochastic representations of surgery and hospitalization durations, the simulation captures the uncertain nature of healthcare operations. This stochastic aspect is crucial when evaluating the

robustness of different scheduling strategies with respect to variability in the expected duration of surgery or patient recovery.

The experiments carried out showed how different ordering criteria, based on the duration of surgery or total LOS, affect system performance. The result shows that prioritizing longer procedures can reduce unscheduled procedures and delayed admissions, but it increases the likelihood of operating room overruns. Ordering patients by shorter durations helps to limit overruns but can lead to inefficiencies in maintaining the planned schedule.

In conclusion, other than comparing ordering strategies, the simulation was useful to measure how sensitive hospital operations are to inaccuracies in duration estimates. By adding normally distributed uncertainty around the expected values, the model made it possible to see how changes in prediction accuracy impact overall performance.

8 Conclusion

8.1 Summary and Findings

This thesis has presented an integrated and holistic framework for operating room (OR) scheduling that starts from data-driven patient information analysis, and then proposes an optimization model with a simulation based validation. The proposed framework has the objective of supporting hospitals in achieving efficient and resource based surgical planning, tackling probably the most complex and critical challenge in healthcare operations management.

This research started with an analysis of the waiting list information, aiming to extract meaningful features using **Natural Language Processing** techniques. This part of the work was important to improve the quality of input data necessary for the following part of the work, both in the optimization and simulation phases. Using a larger amount of information from the waiting list, we achieved a more accurate representation of surgical resource requirement improving realism and adherence to reality.

The next step was the development of a mathematical optimization model, that unlike traditional scheduling approaches that used to focus solely on the operating room efficiency and sometimes a single ward scenario, attempts to incorporate the hospitalization pathway, including post operative intensive care unit (ICU) and bed occupancy. This integration was necessary, as the bed availability often represents the main bottleneck in surgical planning processes. By optimizing the assignment of patients to operating room and post operative patient flow, the model achieves a more balanced utilization of hospital resources, reducing procedure cancellations, delays and bed shortages. The objective of the model was not only to improve resources utilization but also to ensure greater equity of treatment, respecting patient's urgencies according to the Regional guidelines.

For large size instances, using the **ILP Model** becomes computationally difficult. The research therefore proposes **Metaheuristic Algorithms** designed to efficiently produce good quality solution in a reasonable computation time. Many experiments, conducted on different instance sizes, demonstrate that the proposed algorithms achieve near optimal solutions. They also offer the possibility of generating multiple scheduling proposals suitable for implementation in real hospital settings, facilitating their use by surgeons and nurses responsible for preparing the operative notes.

To validate and assess the performance of the proposed assignment solutions under realistic and uncertain conditions, a simulation model was proposed. This model has two main goals: to test the model solution across different scenarios of uncertainty and to find the best policy for ordering patients within the surgical procedure time slot. By evaluating different scenarios, we provided decision makers with useful metrics, highlighting the potential of the proposed framework to align surgical planning with institutional goals, such as patient safety, service quality, and resource efficiency.

Overall, this research contributes to the field of Healthcare Operations Management by proposing an end-to-end methodological framework that integrates data analytics, optimization, and simulation. The holistic approach, which begins with data preprocessing and extends all the way to operational validation, ensures that the methodology is both rigorous and practically applicable.

8.2 Future Work

The proposed work was primarily designed to support the weekly operational planning of scheduled patients. With minor adjustments, it can also be applied over a longer time horizon to support tactical-level decision-making. In this extended application, the model retains the ability to allocate operating room slots across different specialties, effectively integrating both scheduling and the development of a master surgical schedule.

Future research directions may also include the incorporation of urgent patient management, which can disrupt the planned schedule. To achieve this, it would be possible to introduce a dynamic rescheduling mechanism, allowing adaptation to new initial conditions in response to unexpected events.

An additional area for improvement is the predictive aspect, with the goal of more accurately forecasting the input parameters for the model and the simulation. As shown by both the simulation studies and the comparison between model outputs and real world data, the precision of these predictions greatly influences the overall performance of the hospital system. This could be accomplished by refining the selection of the most significant words or word pairs from the dictionaries. A more challenging and ambitious step would be to include medical test reports, which could offer deeper insights into patients' health conditions, often containing information even more valuable than that recorded in nursing notes.

Finally, the ultimate goal of this work is its application in real world settings, aiming to have an impact on the improvement of hospital systems. To achieve this goal, collaboration will be needed between the hospital IT infrastructure, Operations Management Engineers capable of adapting operations research and machine learning tools to the specific context, and healthcare professionals, thus engaging all stakeholders and fostering their cooperation.

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A Appendix A — Additional figures

A.1 Confusion Matrices

Confusion Matrices of the prevision Models:

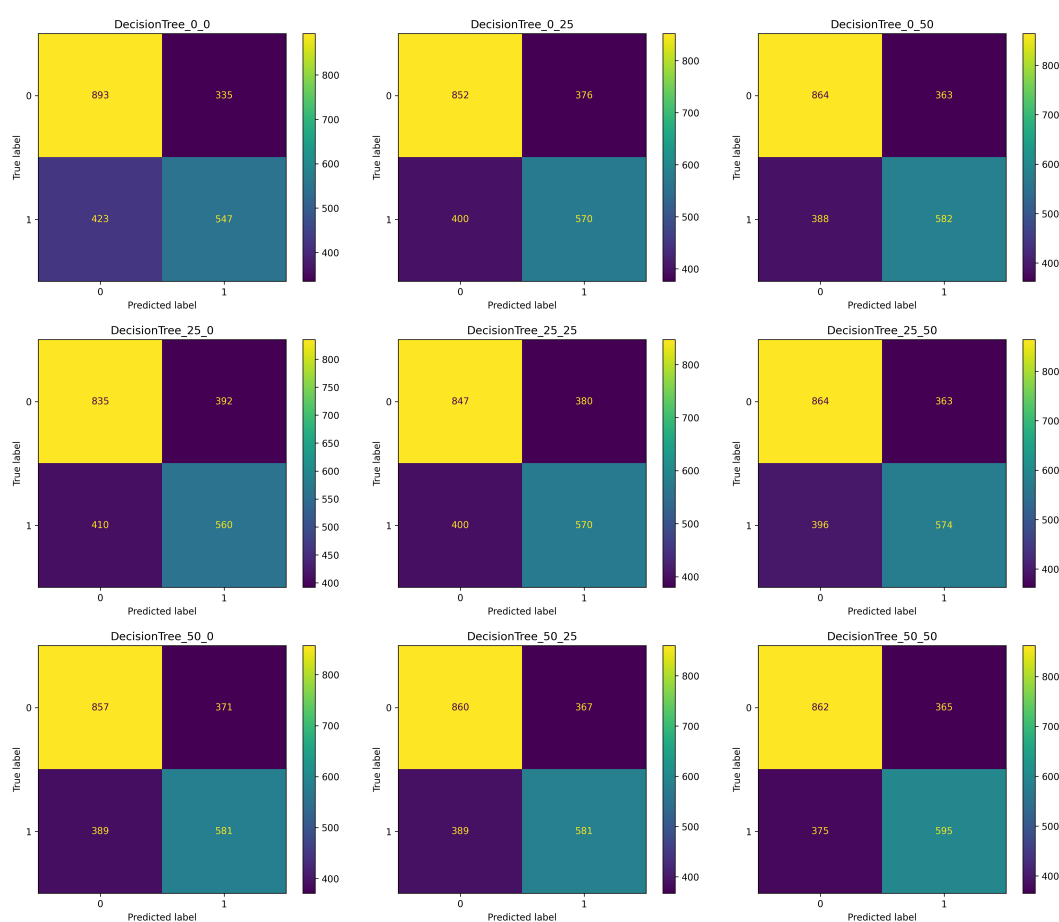


Figure A.1: Confusion Matrices Decision Tree

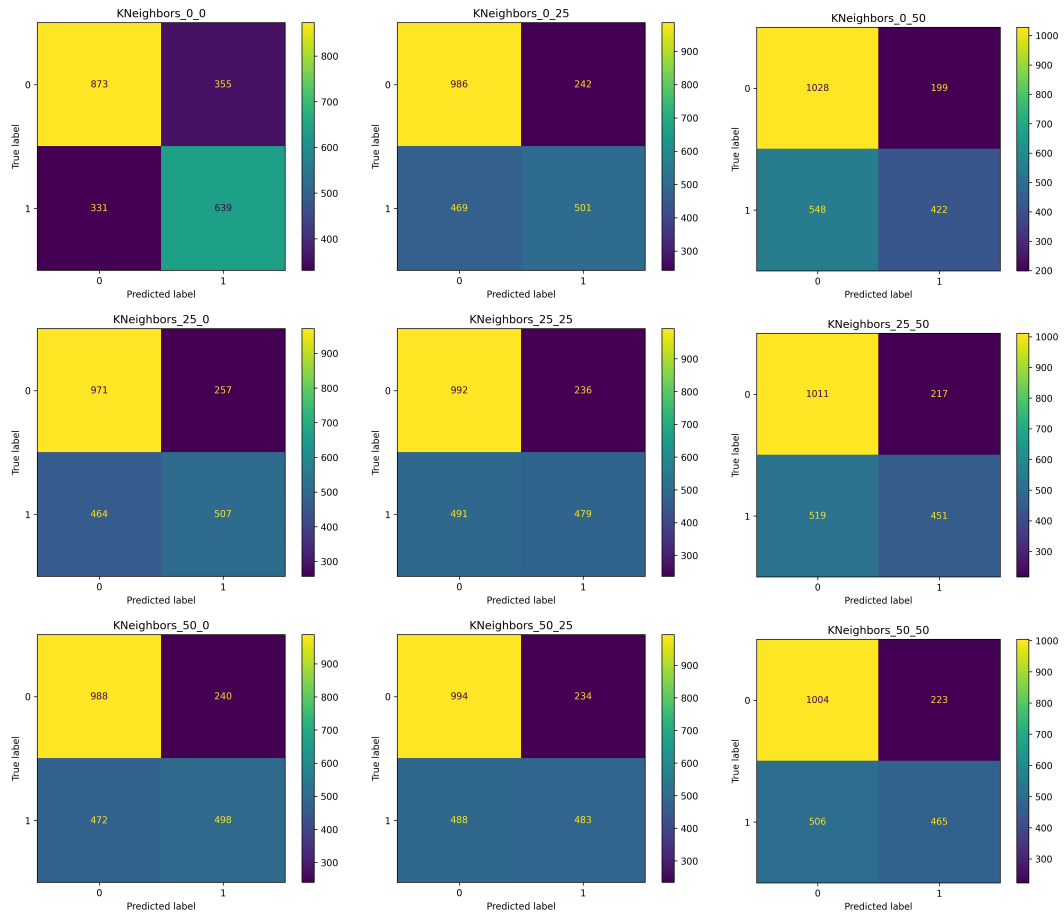


Figure A.2: Confusion Matrices K-Neighbors

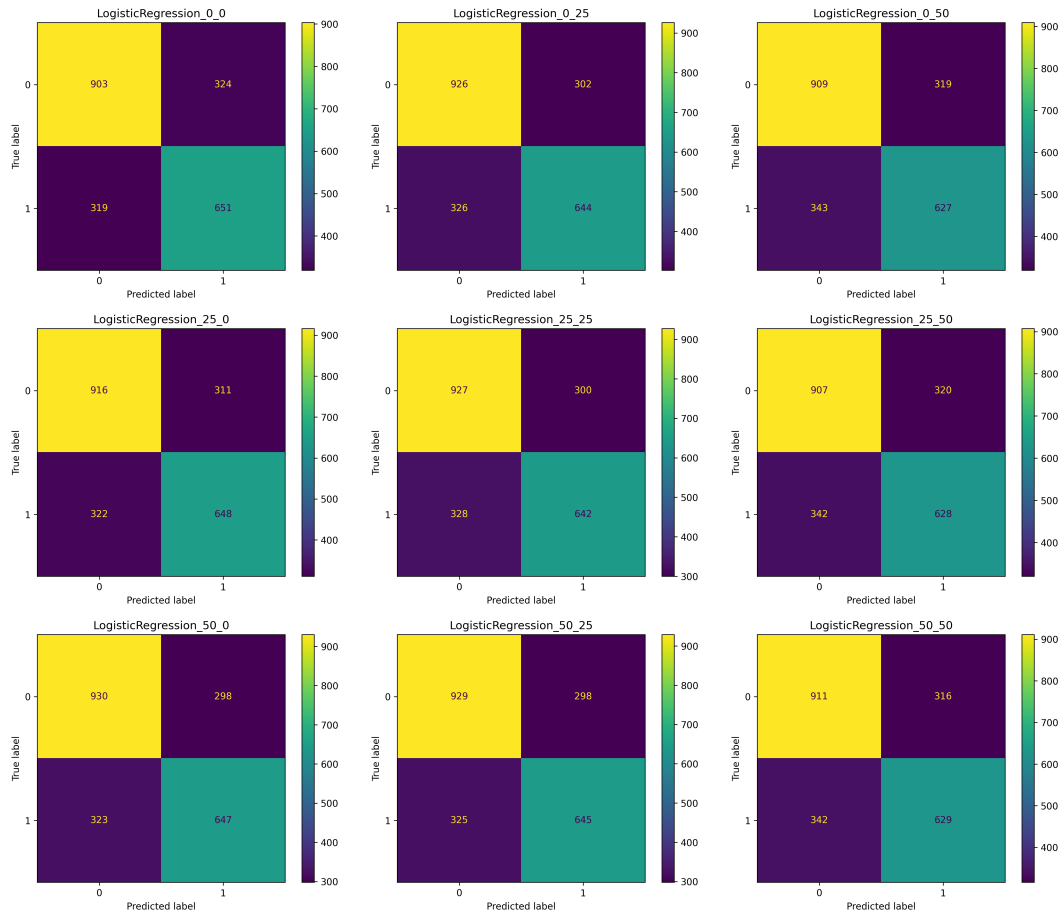


Figure A.3: Confusion Matrices Logistic Regression

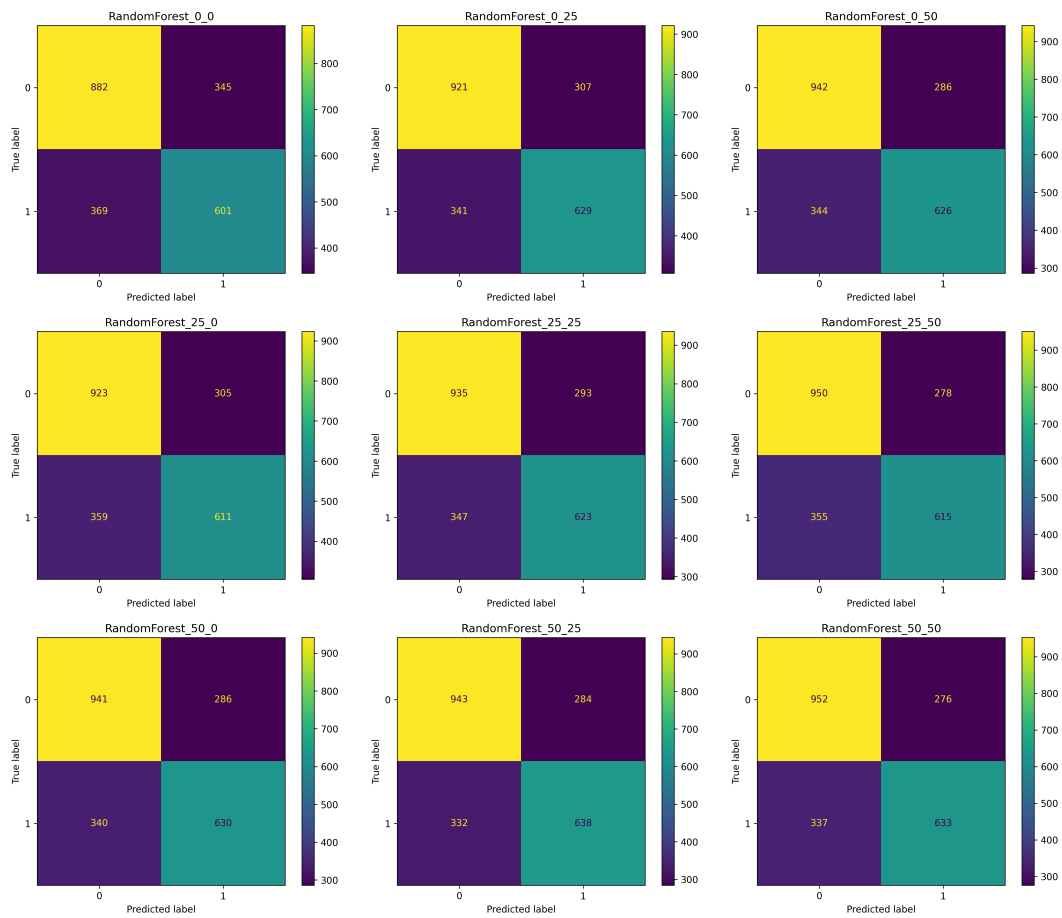


Figure A.4: Confusion Matrices Random Forest

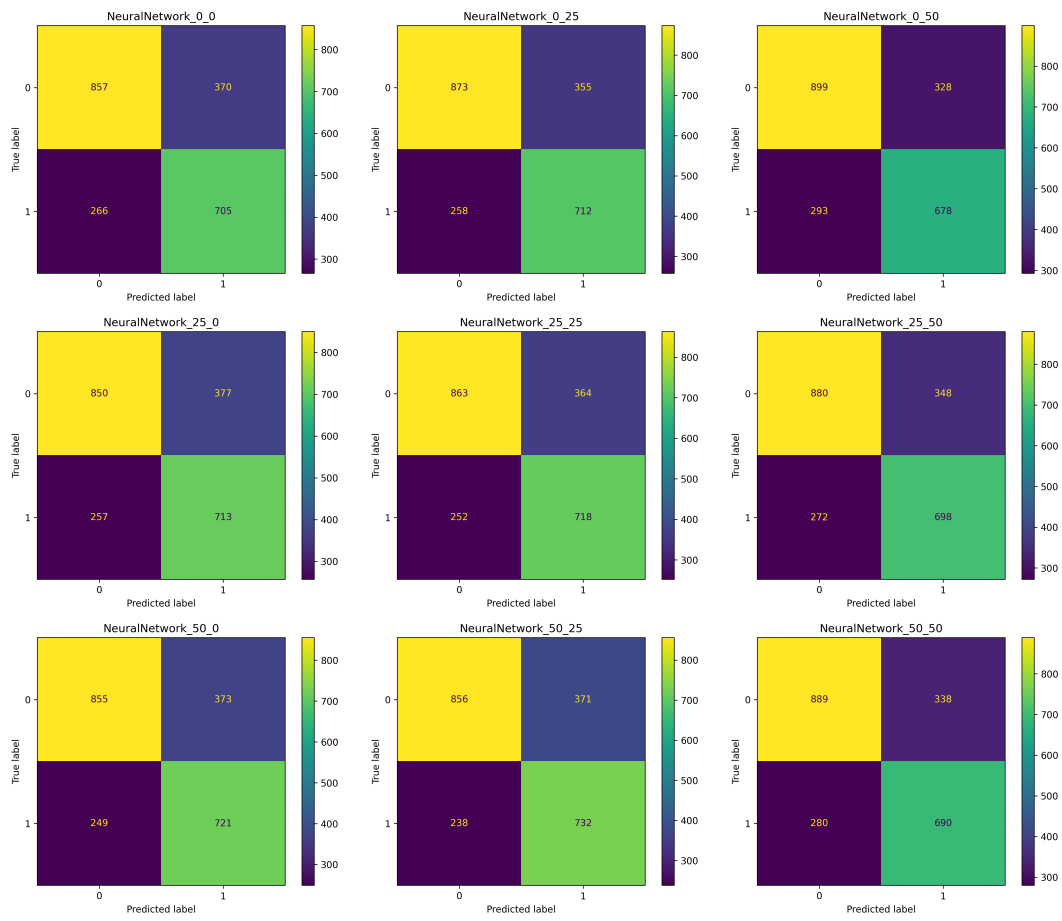


Figure A.5: Confusion Matrices Neural Network

A.2 ROC Curves

Roc Curves of the prevision Models:

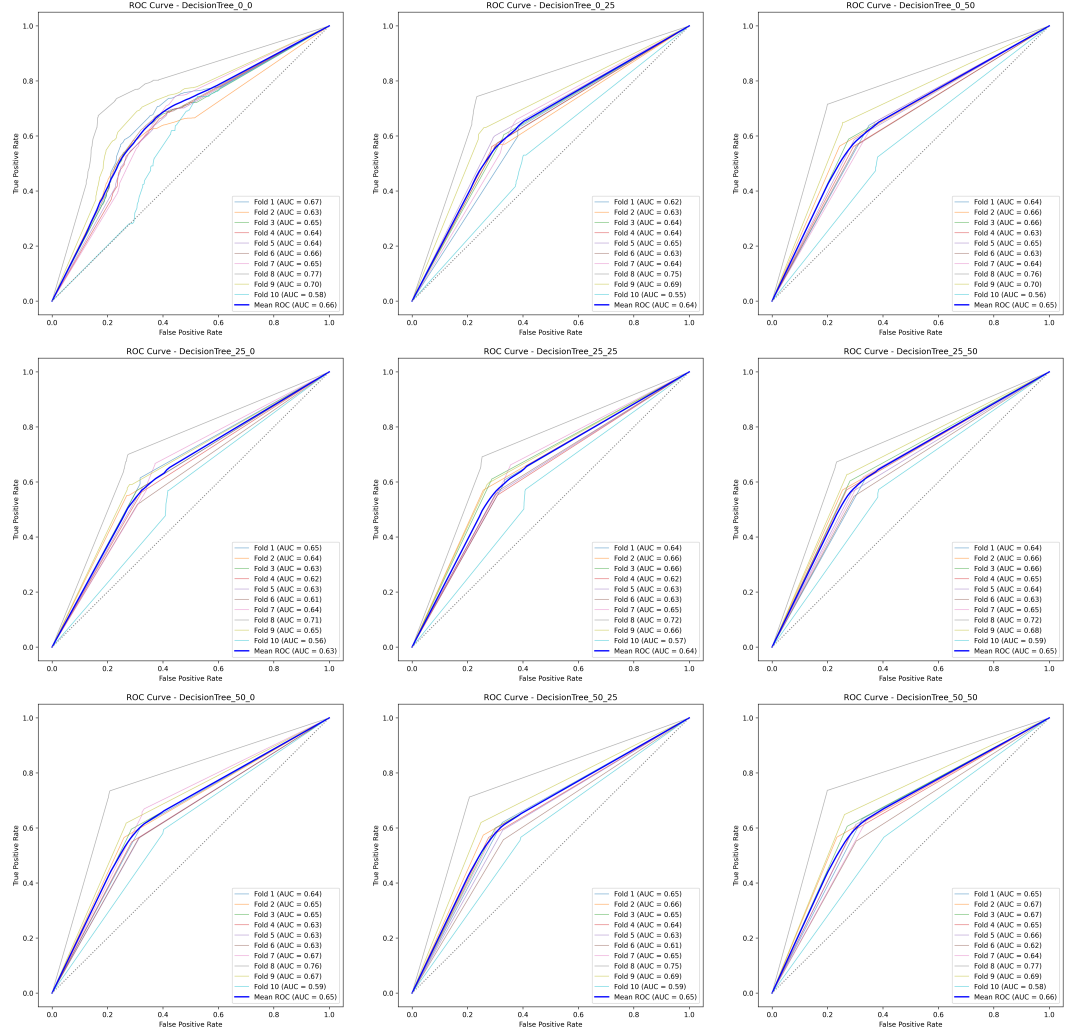


Figure A.6: ROC Curves Decision Tree

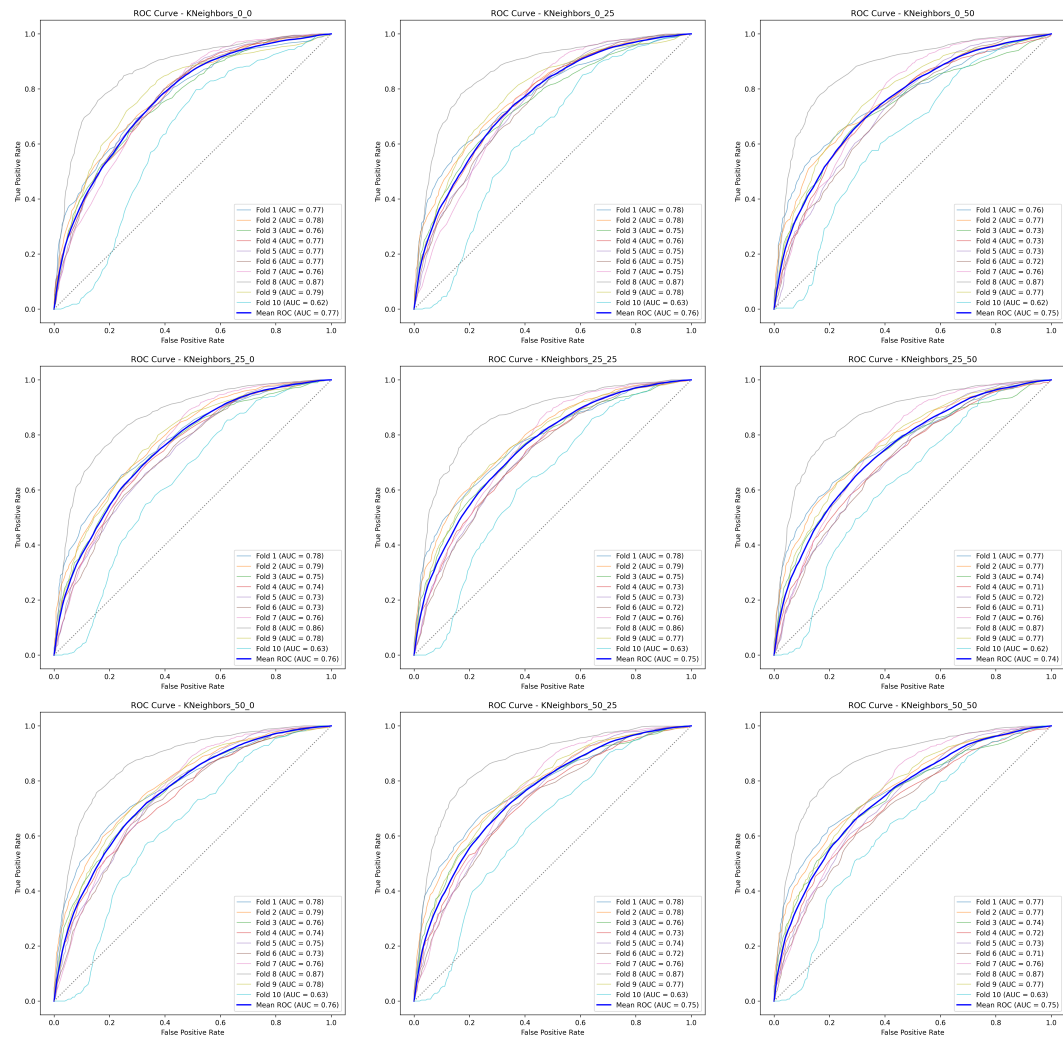


Figure A.7: ROC Curves K-Neighbors

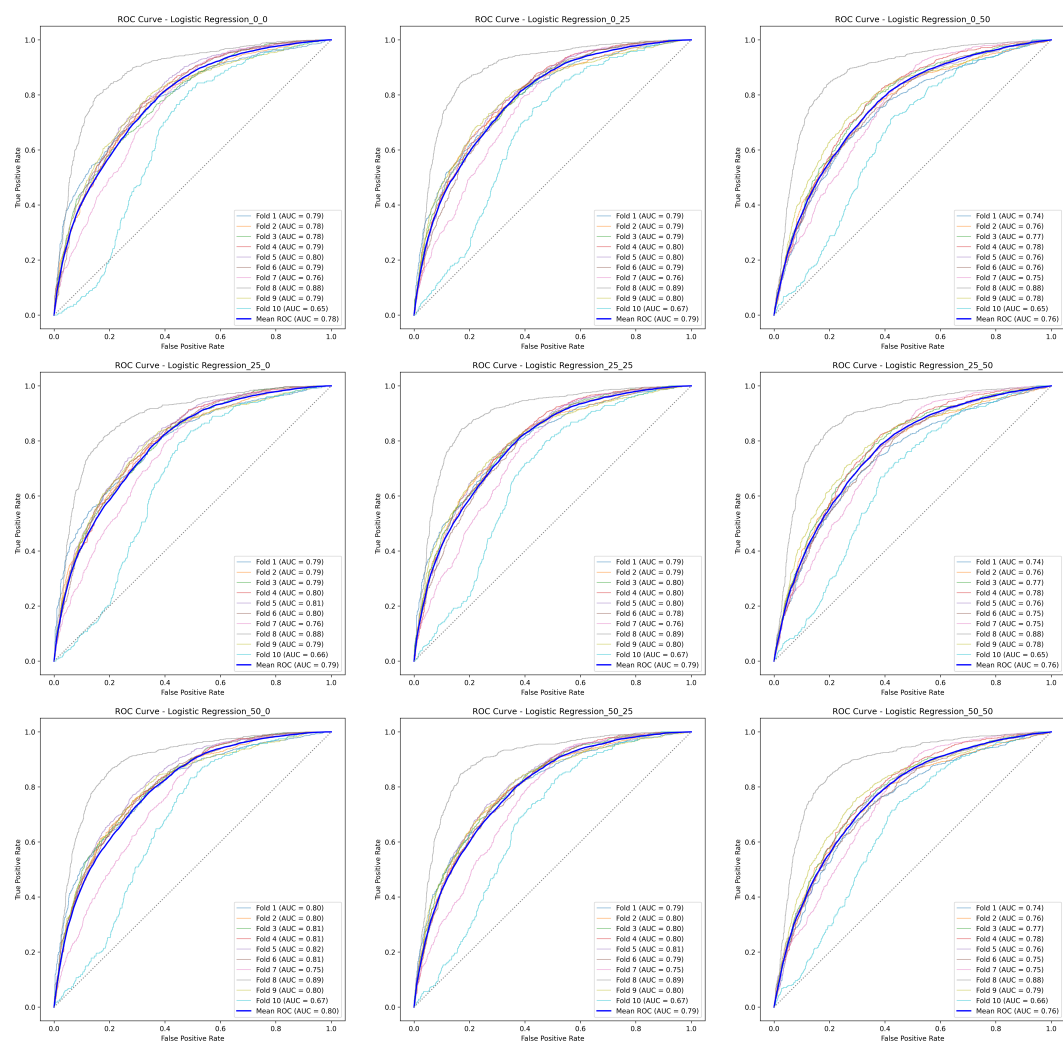


Figure A.8: ROC Curves Logistic Regression

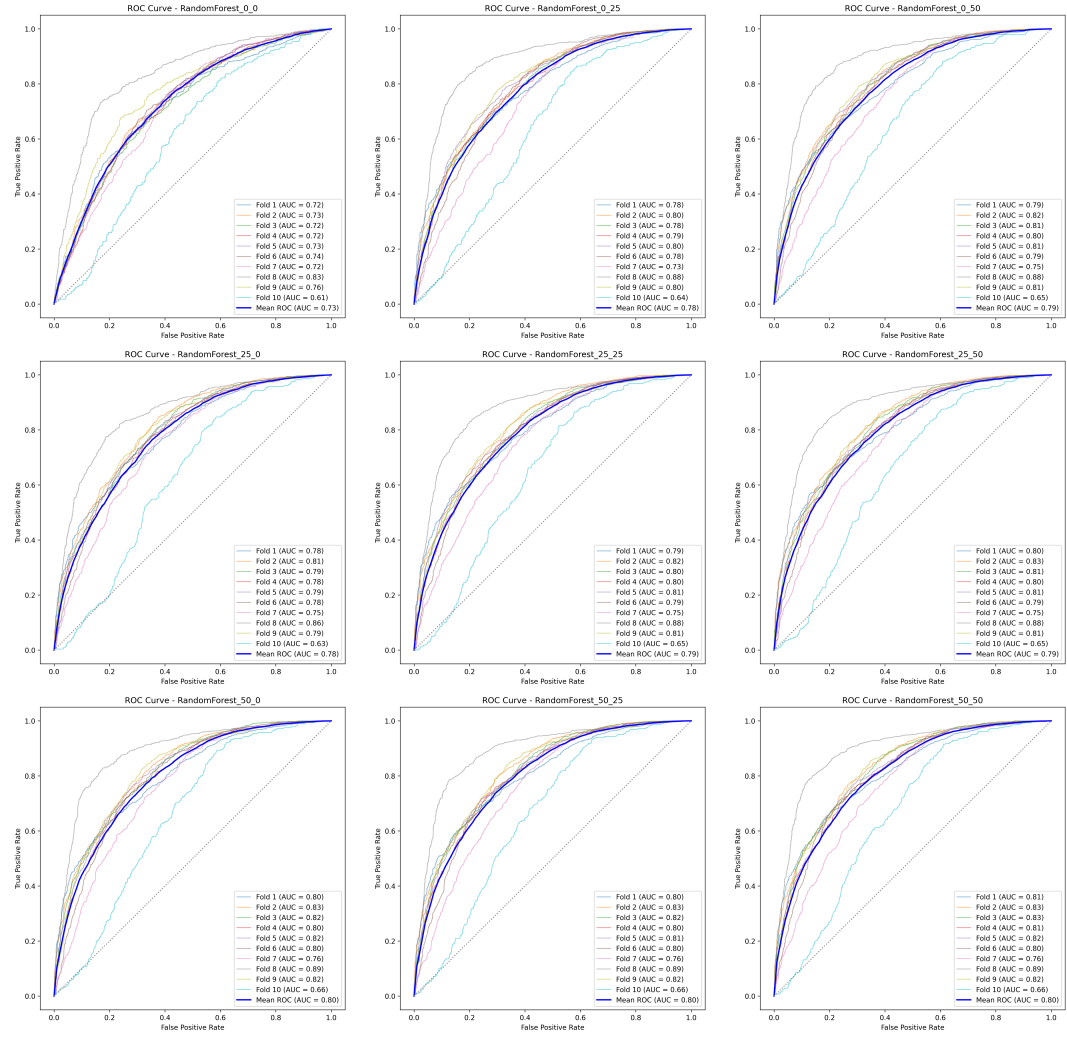


Figure A.9: ROC Curves Random Forest

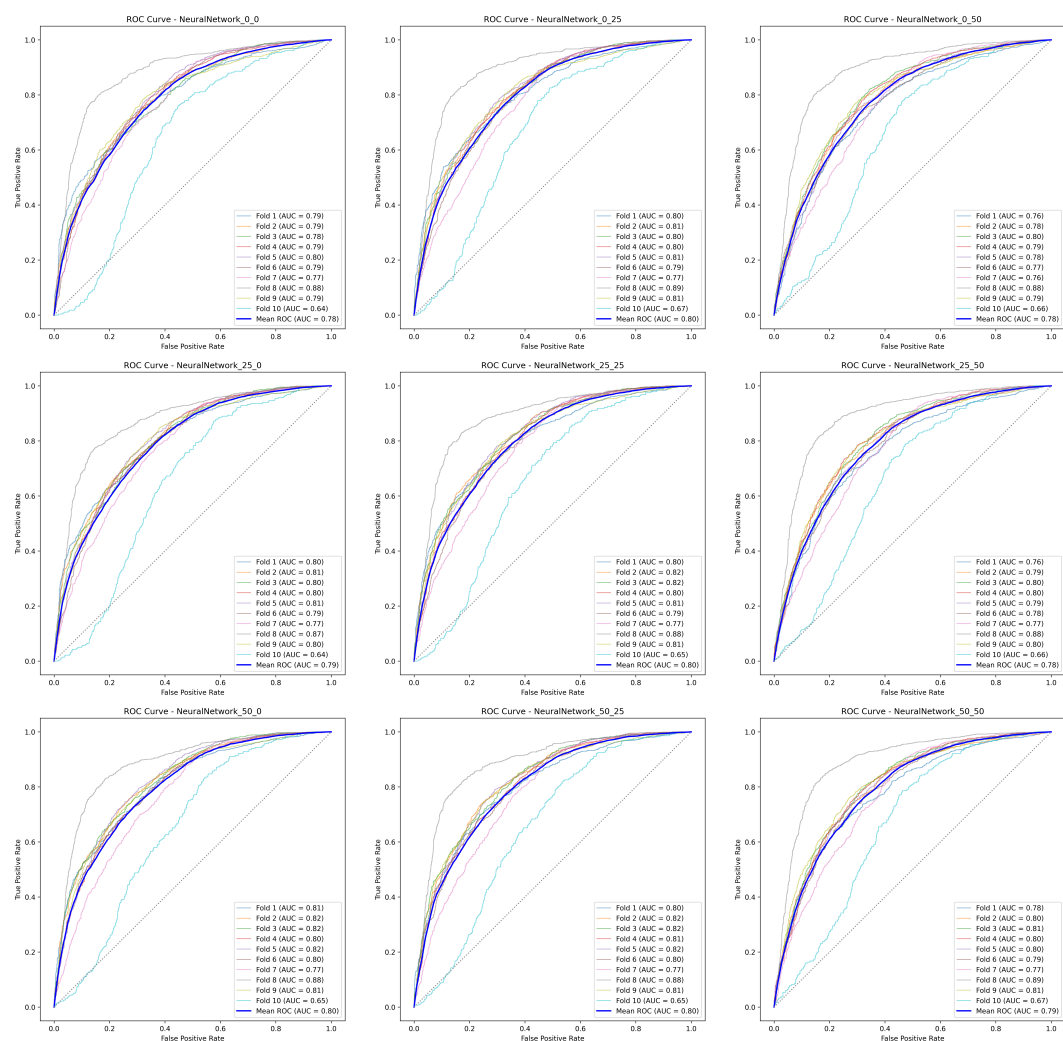


Figure A.10: ROC Curves Neural Network

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