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Patient Flow Simulation in an Orthopedic Emergency Surgery Department

An assessment of using a discrete event system based model to analyse the patient flow of an orthopedic emergency surgery department

Master's thesis in Master Programmes Complex Adaptive Systems, Systems Control and Mechatronics

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Abstract

This study presents a programmed discrete event simulation model of an emergency surgery department that utilizes patient data to predict schedule outcomes. Patient data, including parameters such as name, operation code, start time, ASA-class, BMI, and age, are used to generate process times and worker demands for each patient.
The study investigates and discusses the limitations of using patient data and regression algorithms for time prediction and by extension deterministic simulation outcomes, highlighting the low correlation between process times and patient parameters that according to worker experience has the largest impact. Despite this limitation, a simple neural network is constructed and found to perform comparably to the current method of using a moving average for time predictions. However, significant performance improvements are needed for reliable and useful predictions. To address the limitations of regression algorithms and deterministic simulation outcomes, the study suggests employing Monte Carlo simulations to generate outcome distributions to investigate the uncertainty of schedules. By analyzing variations in input and output distributions, valuable information about schedule uncertainty can potentially be obtained. The study emphasizes the importance of high-quality data, particularly regarding resource requirements in terms of worker hours and specific tasks performed on each patient, to improve the model's practical applicability.

Keywords: Patient Flow Simulation, Discrete Event Systems, Monte Carlo Simulation, Machine learning.

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Chat GPT was used to enhance the sentence structure (including this one) and overall quality of this report. It is important to note that all statements presented in this report are made solely by the report's original authors, and no factual information or content was generated by the AI tool.

David Johnsson & Petr Moldan, Gothenburg, May 2023

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1
Introduction

1.1 Background

In the aftermath of the COVID-19 pandemic, healthcare providers worldwide are facing a significant strain [32]. Increased demand for healthcare services has surpassed the available supply in many regions, leading to prolonged waiting times for patients [32]. This, in turn can exacerbate medical conditions and necessitate more complicated treatments. Moreover, the increased demand for healthcare services is also impacting the efficiency of hospitals, resulting in a unsustainable [32] workload on personnel and resources.

This trend is evident in the Swedish healthcare system as well. For example, the Orthopedic Surgery Department 1 at Sahlgrenska University Hospital – Mölndal[1] is experiencing a backlog of thousands of patients. The department is unable to expand its operations mainly due to a national shortage of qualified healthcare professionals.

The patient flow of this department is also highly susceptible to disruptions that can cause delays and in some cases even cancellations of surgeries. This often leads to discrepancies between the planned surgery schedule and the actual outcome. Disruptions in this context can be both unforeseen medical complications, as well as human errors. These unforeseeable events make scheduling difficult and inefficient. Partly due to the necessity of taking disruptions into consideration during scheduling, which can occasionally lead to inefficient resource utilization while other times result in delays and excessive demand on the available resources. Delays can result in workers having to work overtime which is detrimental for both worker health and morale, but it is also expensive in terms of cost.

Addressing these problems are highly complex tasks that require understanding the patient flow within the department to make correct decisions, such as staff allocation and surgery scheduling. The central aim of this project is to develop a simulation model of the patient flow specifically for the emergency surgery department. While modelling emergency department patient flow is not a new phenomenon [5, 25, 12], it is still not widely utilized within the healthcare industry [25]. Due to the sheer complexity of modern healthcare systems, modelling complex patient-flows is still arguably not a “solved” problem. Previous studies have mostly modeled entire hospitals on a strategic level [18, 2, 11], or less complex departments such as elder care [30] or emergency rooms [33, 17]. The studied surgery department at Sahlgren-

[1]Hereby referred to as simply “the department”

ska university hospital is an arguably more complex system with large amounts of shared resources and highly specialized personnel. It also faces a problem of having a skewed patient profile. This surgical department treats almost exclusively "difficult" cases, since simpler procedures are mostly performed by other actors such as private clinics. These "difficult" cases often involve underlying conditions and/or unrelated comorbidities combined with complicated injuries. According to the data, the majority of patients in the department are classified as ASA class 2 or 3[2]. The relatively difficult patient profile results in the department experiencing a relatively high variance in treatment time and resource demands, which results in a comparatively low patient throughput.

1.2 Purpose

The objective of this project is to assess the effectiveness of a modeling approach for analyzing patient flow in a hospital department. This includes investigating the possibility of using a simulation model to predict the outcome of an surgery schedule and gain valuable insights in its risk of disruptions in terms of uncertainty of a schedule. Furthermore, it seeks to explore to what extent patients with a less complicated treatment and with a less stochastic nature results in a more predictable schedule outcome according to a model.

1.3 Limitations

This thesis focuses primarily on the development of a model, making it impractical to acquire supplementary or complementary data in the case that the data provided is insufficient. In instances where data is absent, the principal approach employed will be to depend on the domain expertise of the healthcare-personnel engaged in the project if applicable.

The patient data is highly sensitive, which means that some information may need to be removed to prevent any possibility of identification of patients. This is necessary to safeguard the privacy of the patients and to prevent any sensitive data from being exploited, as some unique cases could be traced back to specific individuals.

Capturing the intricate parallelism of multiple healthcare professionals treating a patient poses challenges in modeling the treatment process. To overcome this, certain simplifications will be implemented. Additionally, our study will solely focus on studying personnel resources, particularly nurses, while omitting physicians and medical equipment. Surgeons, being highly specialized individuals, are not easily interchangeable, and the process of assigning the appropriate surgeon to a patient involves various parameters such as diagnostic images. Although the field of medical image analysis is rapidly advancing and the classification of injury severity is

[2]The ASA (American Society of Anesthesiologists) Physical Status Classification System is a 6-point scale used to assess a patient's physical health prior to surgery. The scale ranges from ASA 1 (a healthy patient) to ASA 6 (A declared brain-dead patient whose organs are being removed for donor purpose) [1]

potentially feasible, it is not viable within the scope of this project. Currently, surgeries are predominantly scheduled based on the availability of the correct physicians. Furthermore, limited resources such as department-owned imaging equipment have not been incorporated into the model. The decision to exclude medical equipment stems from two primary reasons. Firstly, it is uncommon for imaging equipment to be bottlenecks. Secondly, the data often lacks clarity regarding the timing or necessity of using imaging equipment. Including it in the model would introduce an additional unknown variable that is rarely a practical concern.

Simulation performance analysis and optimization in terms of memory allocation and computational complexity are beyond the scope of the project.

1.4 Research Questions

- How accurately does the proposed patient flow model that considers shared resources, predict the outcome of a planned schedule in terms of treatment times and the resulting schedule[3]?
- How does the uncertainty in process times impact surgical schedule delays according to the model? Does uncertainty in any of the processes have a disproportionate impact? How does this compare to the workers experience?
- How can the available data best be incorporated into a model to estimate the total treatment time of a patient in the patient flow? And what additional data that is currently not collected from the patient flow could further increase the validity. In other words, how well do the results that the model produces reflect reality?

[3]Currently treatment times are predicted with a moving average of the last ten surgeries of the same type performed by the same physician physician. Only predictions of the actual surgery time (anesthesia-time + surgery process times) are estimated, the pre-surgery time is not predicted.

2

Theory

This chapter presents the relevant theory on Neural Networks and Monte Carlo simulation in their respective sections. While the main approach in this thesis employs Monte Carlo simulation, an alternative approach involving the use of Neural Networks for predicting process times was tested and discussed.

2.1 Neural Network

A Neural Network is made up of layers that consist of neurons that hold a state belonging to the real values $\mathbb{R}$. A visual illustration of the Neural Network used in this thesis is presented in Figure 2.2. Each layer is associated with a set of weights and biases that will be applied to the input of the layer to calculate the state of the neurons. In a feed forward network, the state of each neuron can be calculated by applying the weights and biases to the state of the previous layers and feed the value through the activation function for the corresponding layers [20]:

$$n_j^l = G_l\left(\sum_k w_{jk}^l \, n_k^{l-1} + b_j^l \right). \tag{2.1}$$

In (2.1), the activation function is denoted by G_l and corresponds to the function of a specific layer, where l represents the layer number. Within a layer, j represents the neuron number, n represents the neuron's state, w represents the weights, and b represents the bias. Finally, k denotes the neuron of the previous layer. The activation function used in this scenario is the Rectified Linear Unit (ReLU) function:

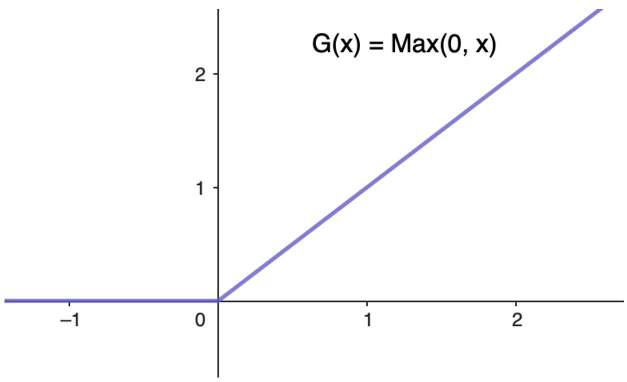

Figure 2.1: ReLU activation function

The parameters for each layer are optimized and updated during each epoch in training through back-propagation with an optimization algorithm to minimize the loss function that is used to calculate the error. A frequently used optimization algorithm is the “Adam” [16]. Adam is a version of gradient descent that use momentum to help escape local minima of the loss function. Unlike gradient descent, it stores a decaying exponential average of previous squared gradients and a decaying average of previous gradients [23].

Mean Squared Error (MSE) a commonly used loss function for regression purposes. Other popular choices of loss functions for regression are Mean Absolute Error and Cosine similarity. To mitigate the risk of over-fitting, which refers to the phenomenon when a Neural Network fails to generalize well, several techniques can be employed. One effective approach is the use of a dropout layer, which randomly deactivates a certain percentage of neuron connections by setting their weights to zero. This technique helps in preventing over-reliance on specific neurons and encourages the network to learn more robust and generalized representations [28].

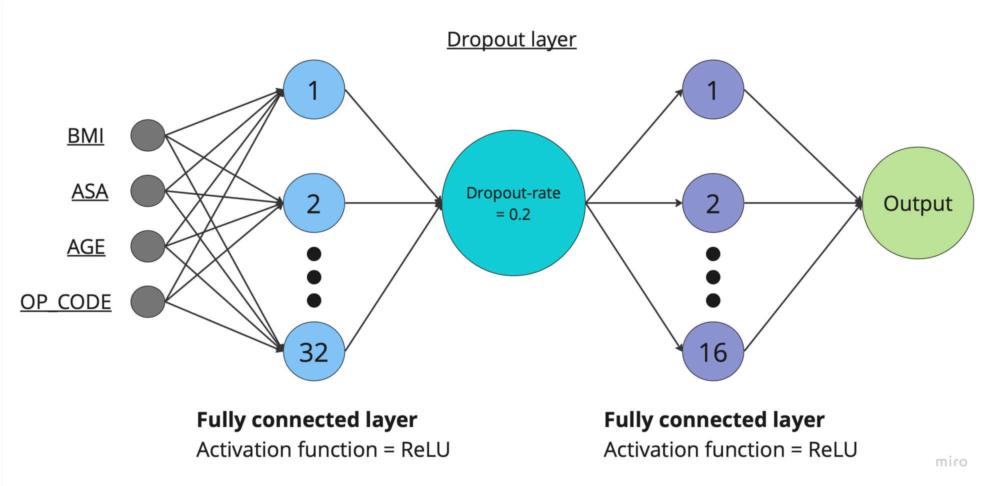

Figure 2.2: Structure of the Neural Network trained to predict pre-surgery ward time and surgery time

2.2 Monte Carlo Simulation

The purpose of a Monte Carlo simulation is to study the behavior of a system by repeated random sampling of input variables and statistical analysis of the outcome [22]. The structure of the Monte Carlo method is case-dependent but it generally follows the following structure [22]:

- Generate a realistic deterministic model.
- Identify underlying distributions of the input variables.
- Generate sets of random variables from the distributions and feed to the model.
- Collect the outputs for each set.

In the context of this thesis the deterministic model is a Discrete Event system presented in Chapter 4. A visual overview of how a Discrete Event system can be integrated into a Monte Carlo simulation is seen in Figure 2.3. The deterministic Discrete Event model has been augmented with timing for state transitions and a variable resource requirement for each transition, which are the sampled input variables. The process running the model on new samples is repeated until the output of the system converges to a desired level of accuracy [21]. During each iteration of the simulation, the model is run with new times and resource requirement, assigned as input variables to the Discrete Event system.

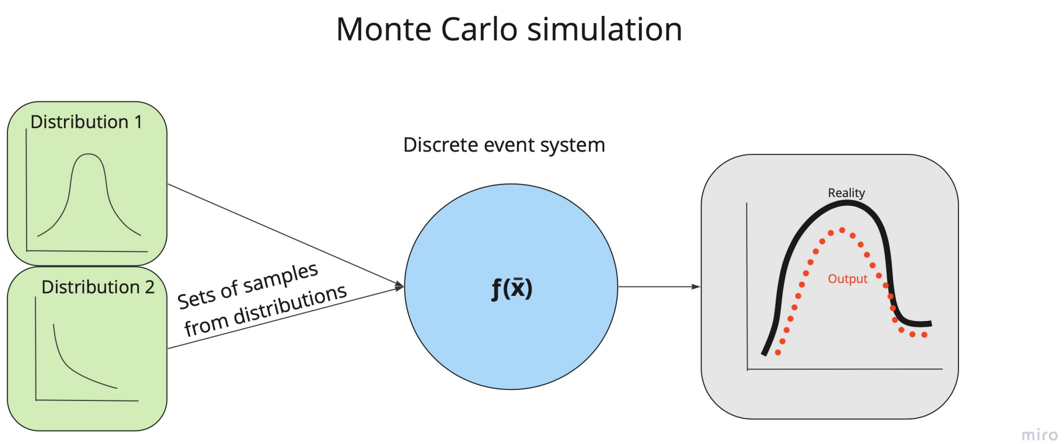

Figure 2.3: General structure of a Monte Carlo simulation

2.3 Patient Flow

The following two sections describe the patient flow in the surgery department that has been modeled. The description of the patient flow is based on observations made by the authors of this thesis and corroborated by the medical professionals involved in the project.

The patient flow in this thesis is focused solely on the patient flow within the surgery department itself and does not consider the clinical pathways of the patients before admission to the department.

A literature review regarding the state of the art of the patient-flow modelling field was conducted and is presented in the last section.

2.3.1 Description of the Patient Flow

In order to model a surgical department, it is first important to understand individual patient movements within the department. Individual patients can have significantly different clinical pathways and injuries before being admitted to the surgery department.

Regardless of injury and previous pathways within the hospital, once the patients are admitted to surgery, their stay at the department will be characterised by three processes in sequence: preop, anesthesia, surgery.

Preop is short for pre-operative care, which typically takes place in the pre-surgery ward. It is a combination of relatively uncomplicated medical interventions such as intravenous fluid administration and verifying relevant patient information.

The preop process is followed by the anesthetic process where the main objectives are to complete all the necessary preparations before surgery. The distinction between the preop process and the anesthetic process can be defined as the moment when the patient is given anesthetic medication by the anesthesiologist or anesthetic nurse. Administration of anesthesia can occur either in the actual surgery room or the pre-surgery ward. The anesthetic process is complex and will vary significantly depending on the type of surgery and health of the patient.

Besides anesthesia, the anesthetic process also includes all the other necessary preparations for surgery such as fixing the patient in an appropriate position and intubating the patient.

The third and final major process is the surgery itself. It can be distinguished from the previous process by the presence of a number of surgeons, which are not present during anesthesia. The surgical process is further distinguished from the anesthetic process by the fact that the surgery rooms are generally sealed during the surgical process. The reason for this is to maintain a sterile environment which is important in order to minimize the risk of infection.

In most cases the staff assigned to a surgery room is the same for the anesthetic process and the surgery process. The notable exception being complex surgeries requiring multiple shifts. While there are clear distinguishing characteristics between the two processes. They are also overlapping processes, both with regards to logistics as they occupy the same facilities and resources; but also from the medical perspective, since anesthesia needs to be maintained during surgery. Once surgery is finished, the patient is prepared for transportation and dispatched to another department. The same nurses and the surgery room are still allocated during this rather quick preparation. Therefore, this step is considered to be included in the surgery process. In theory the three processes can describe the vast majority of cases since only medically stabilised patients are admitted to the department. This means that even emergency patients are processed in a manner similar to planned surgeries.

2.3.2 Description of the Department

The department of surgery under examination operates a maximum of six surgery rooms daily to accommodate both emergency and elective patients. At a macro level, patient flow is centered around the surgery rooms, which are equipped with dedicated resources such as nurses and equipment, assigned to cover the anesthetic and surgery process. The macro level overview is illustrated in Figure 2.4

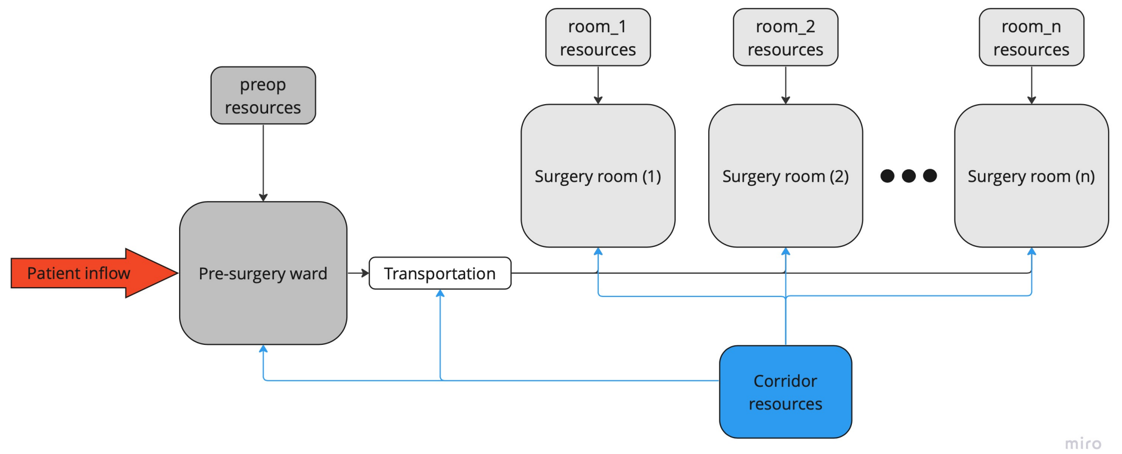

Figure 2.4: A macro level overview of the patient flow in the department with corresponding resources

While the surgery rooms are in principle self-contained units, the functions and resources that support them are shared. Once a patient is scheduled and admitted for surgery at the department, their pathway through the department typically becomes fixed.

Patients are admitted to the department through a pre-surgery ward which is where the preop process described in Section 2.3.1 takes place and where patients are kept until the assigned surgery room is ready to receive the patient.

These patients can arrive at the pre-surgery ward from various sources, including other departments within the same hospital, different hospitals, or even from their own homes. The pre-surgery ward acts both as a short-term buffer for scheduled patients and as an active part in the patient treatment.

The pre-surgery ward and the surgery rooms are supported by a group of nurses who are assigned to provide assistance to other stations as needed. This function is colloquially referred to as “the corridor” due to the fact that these nurses are usually stationed in the corridor between the surgery-rooms when idle.

Tasks carried out by the corridor nurses can broadly be categorized into three categories. The first are critical tasks. These are the tasks that the surgery-rooms or the ward cannot handle with the resources allocated to them. In the pre-surgery stage and anesthetic stage the tasks are typically tasks involving lifting or positioning of patients, which can require assistance from the whole corridor and surgery room depending on how frail or heavy the patients are. During surgery the main critical task of the corridor is to bring equipment and medication that cannot be stored inside the surgery rooms.

The second type of tasks the corridor performs is supplementing strained nurses. Effectively this usually means that a qualified nurse helps another with the purpose of speeding up a procedure. The third type of tasks are the auxiliary tasks. These are tasks that are not directly vital to patient care but are performed for administrative purposes. An example of these tasks are taking inventory of all drugs that are classified as narcotics.

2.3.3 Literature study

Research in the field of hospital patient flow modeling and optimization is a multidisciplinary and diverse field. Due to the complexity and large scale of modern healthcare systems, most research tends to focus on specific subfields of patient flow [12, 13].

Generally, the research can be categorized as either operational or strategic in nature, with some studies proposing a third tactical category [12]. While the definition of strategic is not necessarily well-defined it can generally be understood as models that focus on at least multi-department or hospital-system level modelling, usually with time-frames measured in weeks. Highly relevant issues includes predicting clinical pathways [18, 2, 11] and finding methods for forecasting demand for various treatments [12, 2], which are crucial problems to solve in order for higher utilisation of hospital resources. In contrast, operational models usually model a subsystem, such as a department or a couple of interdependent departments within a hospital [12] with objectives usually being to model hourly or daily operation. Within the operational domain, which is the domain this thesis should be categorized under, there exist multiple proposed modeling frameworks for modelling the operational-level patient flow [12, 15].

The most prevalent models are Discrete Event based models [12, 15]. Other less popular options include agent-based models [12, 10] and queuing theory [12, 2]. It should be noted that the majority of models are not strictly confined to a single category of model but rather a combination.

The prevalence of Discrete Event based models can most likely not be attributed to a single attribute but rather to a combination of desirable attributes. Arguably the most important attribute is the fact that hospitals are to a certain extent organized in a manner that in theory lends itself to Discrete Event based modelling. Virtually all medical personnel have well-defined responsibilities [15]. Strict rules exist to define what tasks each specialized medical professional is allowed to perform, and which patients fall under that worker's responsibility[1]. While the system shares some characteristics found in Discrete Event systems, such as assembly lines, telecommunication, and computer systems, it differs significantly from the technical systems typically studied. The main difference is the substantial presence of human elements that encompass both patients and resources within the system.

Patients with the same diagnosis and/or operation code can have significantly different requirements. Most of the Discrete Event models proposed for health-care simulation are therefore usually not strictly Discrete Event systems but rather hybrid systems, where transitions between states tend to have a probabilistic time [30, 33, 18] for the choice of transitions [18, 29]. Incorporating probabilistic process time in a Discrete Event simulation is a well established practice both for modelling patient flows [15, 29, 30, 33] and industrial applications [9].

Current proposed operational level models tend to model units with more linear patient flows such as elder-care [30, 31] with few if any shared resources. Or emergency departments [29, 33], which generally have fewer types of shared resources [33, 29] and generally have different challenges, such as the fact that the vast majority of patients are not diagnosed prior to arrival at the emergency department. Predicting length of stay in a surgery department is neither a novel or solved problem [8, 6].

To the authors' knowledge there are no published Discrete Event based models developed specifically for surgery departments that share resources during surgery.

[1]Responsibility in this context only refers to that a patient is allocated to a certain medical professional, not necessarily legal responsibility.

3

Simulation

3.1 Monte Carlo Simulation of the Department

The purpose of running a Monte Carlo simulation on the model is to simulate the impact of resource requirements on the process times. The expectation is that the generation of a distribution will enable observations of differences in uncertainty for both individual patients and the overall schedule. A simulation for that purpose has been developed.

Another possible approach is to feed the model with deterministic process times generated by a Neural Network. This approach was not used as the network built did not give accurate predictions with absolute errors in the order of hours, as presented in Figure 5.2 and Table 5.1. The predictions were however comparable to the current method for predicting process times.

The model is based on a Discrete Event system described in Chapter 4. On a macro level, the system models the surgery rooms and the surgery ward as processes. A visualization of the system can be seen in Figure 3.1.

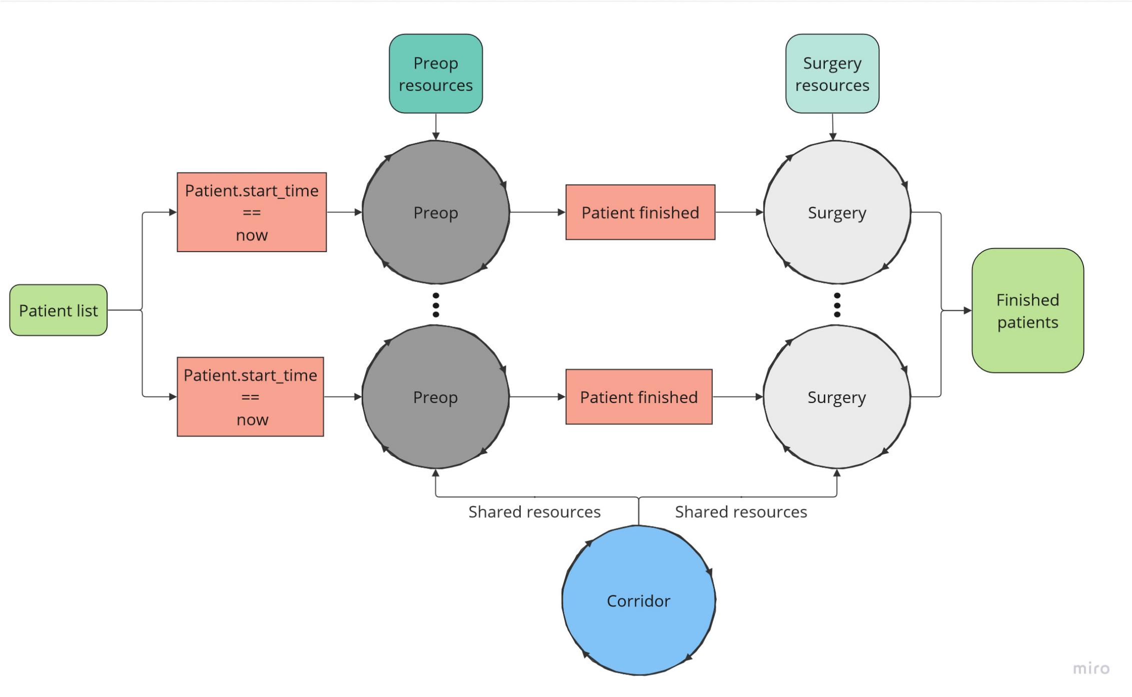

Figure 3.1: A high level overview of the Discrete Event model for multiple patients.

The preop process will start at the patient's designated start time and the surgery process will start as soon as the preop process is finished and the right resources are available as can be seen in 4.

In each iteration of the Monte Carlo simulation times for the corresponding processes are sampled, as described in Section 3.2. Furthermore patient information is used to determine what level of resource requirements a patient will need. Due to resources being shared, the processes will interact with each other, potentially causing delays if resources are not available. Due to sampling of new process times from the data, each iteration will result in a different outcome.

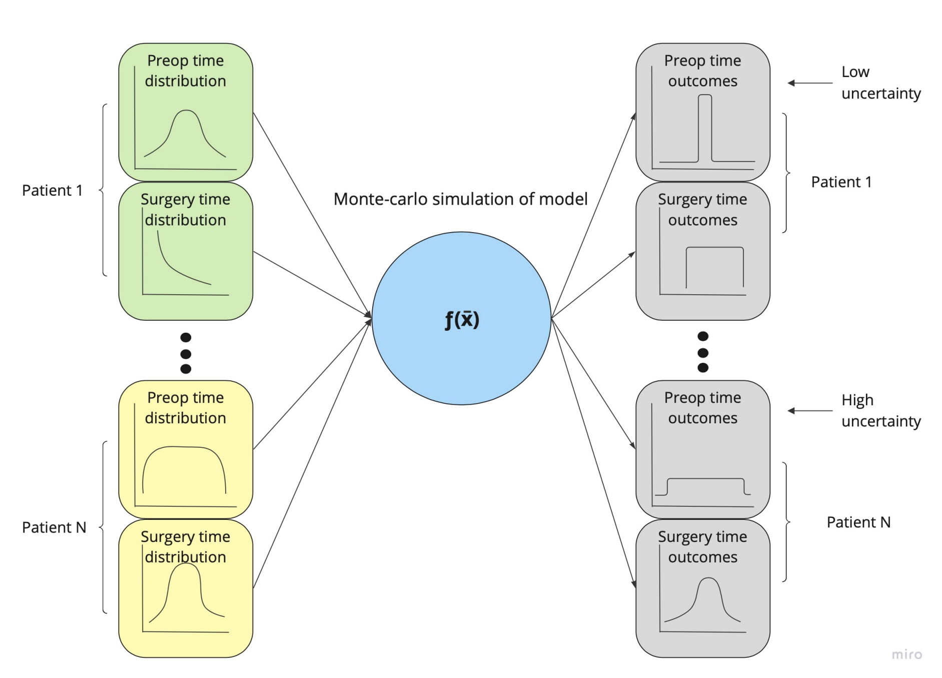

Figure 3.2: Illustration of generation of outcome distributions, $f(x)$ is the model presented in Figure 3.1.

By running the Monte Carlo simulation, the expectation is that the output distribution will also enable observations of differences in uncertainty for both individual patients and the overall schedule as well as the accuracy of the model in terms of an expected outcome.

3.2 Patient Data

In this thesis, the simulation uses patient data obtained from the surgery department, covering the period from January 2018 to December 2022. The data used in the simulation can be classified into three distinct categories.

1. Process data
2. Medical procedure data
3. Patient data

Process data refers to the time requirements associated with various processes outlined in Section 2.3 for individual patients, along with their scheduled admissions to the department.
The second type of data indicates what procedure was performed, represented in the form of standardized codes that correspond to specific procedures. In this thesis, these codes are referred to as "op-codes". In Sweden, this parameter is known as "Klassifikation av vårdåtgärder" (KVÅ), as stated by the KVÅ documentation [26]. The KVÅ system serves as a standardized framework for categorizing surgical procedures. The KVÅ system does not inherently imply the difficulty of a specific procedure, it is reported both by staff at the department and generally accepted

within the medical profession [1] that the patient's physical status affect both the outcome of the surgery and complexity of the surgery. In order to make the process times more comparable, process times are sampled based on the op-code but also patient data. The data that were initially considered by the model were:

1. ASA-class
2. BMI
3. Age

However, currently only ASA class is used because of poor correlation between patient parameters and process times, as seen in Chapter 5. Also, ASA class is specifically intended to give an assessment of the patients physical status [1] and incorporates the other parameters in that assessment. In summary, the process times are sorted based on the procedure and the patient's physical status, which in theory should result in the distributions sampled by the model being more representative of the patient simulated.

4

Model

The following chapter contains a high-level overview of the programmed simulation. Topics covered include both important technical design decisions, as well as information regarding how the simulated components relate to the examined surgery department.

4.1 Programmed components of the model

The subsequent section provides a description of the programmed components used to build up the simulation model. The model extensively relies on the SimPy [24] Discrete Event simulation library. The components outlined below are extensions and customizations of SimPy's original components designed to better suit the specific needs and objectives of this study. For each component, there is also a description of the design decisions that were made to enhance the realism of the simulation model, and in some cases limitations of SimPy that resulted in certain simplifications.

4.1.1 A brief introduction to SimPy

SimPy is a Discrete Event simulation library for python [24]. It simulates Discrete Event systems as a interaction between processes. A process is implemented as a python generator function, which is a function that unlike regular functions retains its state between function calls. The processes interact with each other by requesting or releasing various kinds of resources through events within a SimPy environment [4]. A SimPy environment acts as the central clock for the system and as a scheduler for events that occur. SimPy simulates parallelism by queuing all events that happen within a time-step in a queue and executing them sequentially [24]. Events therefore never occur truly simultaneously but rather sequentially in a deterministic order according to the first in first out principle [24].

4.1.2 Patient

Patient is an extension of the SimPy Process class [4]. Each Patient object is initialized with the following parameters.

- Name
- Operation code
- Start time
- ASA-class
- BMI
- Age

The initial parameters are used when sampling process times from previous data. The process times are then translated into tasks. Tasks essentially describe which processes the patient will undergo and what the resource demands of each process will be. The tasks are then added to a list that defines the patients complete pathway through the system. This object oriented and “patient-centered” approach to modelling has the distinct advantage of easily permitting a simulation to handle a diverse range of different patients. Modelling each patient as its own process has the advantage that the state of each patient is kept at the patient level rather than at the department, allowing for great flexibility when designing the simulation. The cost in this case is a somewhat cluttered model where the definition of a process becomes fluid.

Initially the intent was to use multiple factors when determining process times. As previously mentioned, patients can have significantly different requirements, an example given by the staff is that patients with immobilizing injuries such as a hip fracture, combined with a high BMI tend to be significantly more personnel-demanding when transferred from a transportation bed to a surgical bed. Due to the generally low correlation between process times and all of the parameters listed[1], incorporating this information when sampling process times would not add any clear value. Due to said limitations and the fact that incorporating domain expertise on a surgery-code level basis is not a feasible solution it was ultimately decided to only use the ASA-class as basis for sampling process times. The main reason being that ASA-class is a holistic indicator where the physicians take into account many of the complicating factors including age and BMI [1].

4.1.3 Task

The task class is the “middle-layer” between the processes and resources in the simulation. Tasks mainly exist to define process times and resource requirements of a patient. Each task is initialized with the following parameters.

- process : In which process the task can be done
- req_time : How long the task will take

[1] See chapters 5 and 6 for more information regarding the outcome of the regression parts of the model and the limitations of current available data.

- sub_tasks : A list of worker specialities that has to perform its part of the task. A list of specialities of the workers that have to perform parts of the task. For example, a task may require the involvement of both an anesthetic nurse and an operating nurse, each responsible for their designated sub-task within the overall task. The sub-tasks may however be done independently.
- is_blocking : If preceding tasks have to be finished
- use_shared_workers : If shared resources can be allocated to perform task

SimPy has some limitations for the purpose of this project that primarily relate to the interaction between SimPy resources and processes. This includes the inability of SimPy processes to pause without interrupting each other, which is necessary when a higher priority task requires resources from another process. The solution to this limitation was to "slice" each task into a series of smaller sub-tasks. Each "slice" corresponds to a predetermined number of time-steps, and the sum of sub-tasks or slices is equivalent to the duration and other parameters of the original task. By slicing the task, two minor issues are also addressed. Firstly, priority inversion is partially mitigated by choosing a low number of time-steps per slice[2]. Since resources are technically released between each sub-task, any higher-priority task will be scheduled as soon as the current slice is finished. Secondly, slicing a task allows for varying resource requirements over the course of a process, which is important for simulating how a surgery department operates.

Additionally, a parameter called "is_blocking" has been introduced. This parameter stipulates that all preceding tasks in the sequence must be completed by all required resources for the process to continue. This approach strikes a compromise where workers are not instantly halted by the absence of a single resource, while still setting boundaries for the time gaps between completed tasks and available resources.

The intention behind blocking tasks is to provide a relatively good approximation of how surgery works in practice. The question that arises is how the tasks of different specialties depend on each other. During the field study, it was observed that while tasks generally occur simultaneously, they are usually not directly interdependent at all stages of the treatment, except during the actual surgery. Each specialist has well-defined tasks that are performed in parallel but may not necessarily depend on one another at every time-step. Instead, tasks are performed, with occasional tasks requiring other specialists to reach a corresponding stage in their list of tasks.

For example, in the anesthetic stage, the anesthetic nurse is initially tasked with activities such as administering pain medication and preparing the ventilator. Simultaneously, the anesthetic personnel administers an epidural catheter (which requires the patient to sit upright). Once all nurses complete their tasks, the anesthetic nurse sedates the patient, and the other specialists can proceed with procedures that require the patient to be sedated, such as intubation.

[2]Ultimately priority was not used during the simulations due to a combination of issues related both to data and the model. Currently the system uses the simple principle of first in first out.

4.1.4 Worker

The Worker class extends the SimPy PriorityResource class [24]. The key parameter of this class is:

- speciality: Specifies the worker's specialty and, by extension, the tasks it can perform.

During each of the patients' processes, workers are allocated to perform tasks for which they have the appropriate specialty. The PatientProcesses will only proceed with tasks if the required workers are available. Requests are sent to the workers and accepted when the worker is available. When a request is sent, it is automatically placed in a queue, and the request with the highest priority is accepted first.

Each PatientProcess (see Section 4.1.5) and the corridor have their own set of workers and the PatientProcesses run_patient_process() function, it is defined from which sets the workers can be allocated. If no workers with the right speciality are available, the task request is forwarded to the worker with the shortest queue that fulfills the requirement. An error will be presented if no suitable workers exist. Once all the requested workers have been allocated, they perform their assigned tasks on the patient. They continue working on that patient until they encounter a "blocking" task, or no task requiring their speciality is left, at which point they pause or stop their work on that patient and wait to be allocated either to the same patient or to another one. This approach simulates the behavior of workers performing a series of tasks on patients without switching between patients after every task, as well as simulating that some tasks require multiple workers at the same time.

4.1.5 PatientProcess

Important parameters:

- patient_list : Patients currently running the run_patient_process function.
- run_patient_process() : The function that runs the patients process.
- get_finished_patients() : Returns patients finished with the process.

PatientProcess is an interface that outlines the required properties and functions of a process that a patient will go through. In the developed model, the two classes Preop and Surgery implement this interface. The main components of the interface are a list of workers that can perform tasks in the process, the patients currently in the process, and a function that describes what the process should do for each patient at each time-step. Each patient will run its own instance of the process function and the processes will run in parallel.

The primary distinction between the Preop and Surgery processes are the condition for when workers are allowed to be allocated and how the tasks are performed. The Preop process waits for all workers to be available before allocating them, while the Surgery process will let all Workers work in parallel independent of whether the others are available or not. Figure 4.1 illustrates the different processes.

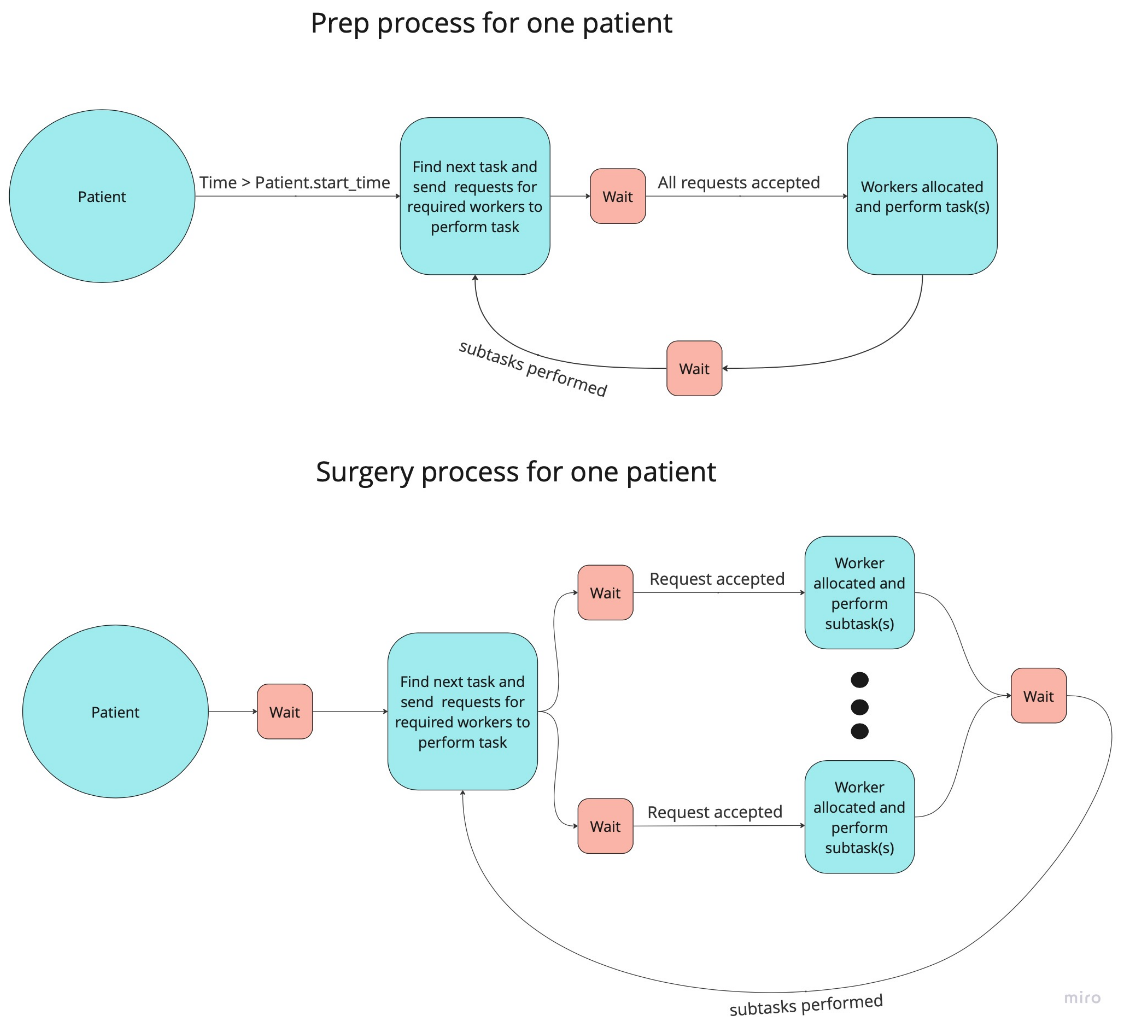

Figure 4.1: Illustration of the Preop and Surgery PatientProcesses in the model. Once all tasks in a process are done, the patient will be moved to the next process in accordance with a pre-defined order, in this case preop → surgery → finished.

This mainly aims to replicate the substantial parallelism between surgery and anesthesia, which in the simulation are both included in the surgery. The previously described concept of "blocking tasks" was introduced to restrict this parallelism.

4.1.6 Department

The department contains a list of processes that run in parallel with the patient processes and handles the logic of moving patients between the PatientProcesses. It is also responsible for running and creating tasks for the corridor process and holds the shared resources. Each timestep, the Department checks the patient lists of those processes and moves the finished patient to the next process in order. Even though it runs in parallel, it can be considered the process highest in the hierarchy because it keeps track of the "sub-processes".

4.1.7 Model validation

The model presented in this thesis consists of multiple components. In the context of verification there exists two components. Part of the model is the Discrete Event model, the rule-based system that simulates the processes. The other is the probabilistic component. While it is arguably less of a distinct component it is a combination of parameters that affect various aspects of the Discrete Event model. The deterministic component of the system was verified on a system-level. System level in this context means that the Discrete Event components were essentially tested as a system rather than individual sub-components. The main reason behind only verifying the component on a system level is mainly due to time-limitations but also due to the fact that testing individual components in SimPy on a component-level is a non-trivial task due to SimPy's different components (processes, resources and environment's) interdependence. Due to the environment acting as the global clock for the system, it is needed to test individual components.

In order to test the system, simplified schedules with deterministic parameters were created in order to cause a specific scenario. The output from the system was then compared to the hand-compiled result. Verifying the absence of deadlocks and livelocks on large scale has not been done. Nevertheless, the use of SimPy for simulating parallelism [24] combined with how tasks are implemented should make such occurrences impossible.

4.2 Setup for result collection

4.2.1 Data limitations

Due to the data limitations presented in this section the outputs from the model should more or less be considered examples of what information could technically be extracted from the model if the data presented in the discussion part is available.

At the hospital, data on the tasks performed on each patient, the duration of each task, and which worker performs each task is not currently being collected. Only timestamps that roughly correspond to the process times are known. Therefore tasks have been set up as series of generic tasks with probabilistic resource requirements. This effectively means that tasks have variable resource demands between each task-slice. Probabilities for the various requirements are generally speaking extremely rough estimates. The assumption made is that patients with a high ASA class have a higher resource requirement. This is generally consistent with the experience of workers. The data used for process times are from the surgery department only. Certain datpoints were omitted. Preop times longer than 90 minutes were omitted. According to the professionals consulted, there are no procedures performed during the preop phase that should reasonably take 90 minutes. Patients that have longer stays in preop are usually there due to the scheduled surgery room being delayed, since the procedures performed in preop should never require more than 1 hour. Incomplete datapoints were removed.

The relevant times logged by the department during treatment of a patient are:

- Arrival to pre-surgery ward
- Pre-surgery ward finished
- Anesthesia start
- Surgery start
- Surgery finished
- Anesthesia finished
- Patient-time finished

Because the anesthetic process and surgery process are overlapping and the anesthetic process usually is done in the surgery room with the same resources and because the patient will be woken up in the surgery room, the surgery time used in the model will be calculated as anesthesia start to patient-time finished. The reason for not separating the anesthetic process from the surgery process is due to the fact that the separate processes use the same resources. Separation of the processes would be motivated if better data existed for resource utilization.

The schedules used as a base for the simulation are from the spring of 2023. Only recent schedules can be used for testing, since only the outcome of schedules are recorded while planned schedules are discarded.

4.2.2 Setup

Simulation results were collected by running a planned schedule with real patients through the model as a Monte Carlo simulation and comparing the simulated outcome to the actual outcome[3]. The real schedule is prestented in Table 4.2. The simulation was ran on three different settings of tasks resource requirements based on the patients ASA-class. The different setups are made to see how the models' outcome reacts to changes in the stochastic nature of the patient flow with regards to resource demands, specifically when it requires extra resources from the corridor.

Tasks are therefore generated with a base resource requirement depending on the process and a percentage that defines the amount of time when all base resources are required. When all resources are required, there is also an additional stochastic element referred to as “Req extra resource from corridor” that will add requirement of $0-2$ extra resources from the corridor. The three levels base resource requirements are shown in Table 4.4 and the levels of “Req extra resource from corridor” are defined in Table 5.1. Due to the infinite setup space and limitations in data regarding actual resource demands, the collection of results only encompassed three different setups: low, medium, and high as defined in tables 4.4 and 4.6.

Additionally, the corridor resources will be allocated for some auxiliary tasks with different resource and time requirements with probabilities and requirements found in 4.5. To simulate morning rush, the preop process also had access to the resources from all surgery rooms for the first 120 timesteps. Process times were sampled from the corresponding distribution with the same op-code for each of the patients 4.3. Two schemes will be compared when sampling times. The first sampling will be

[3]The deterministic values presented are the expected values from the output distribution.

done from the partial distribution that takes into account the patients ASA-class, and the second when ASA class is ignored. Due to limitations of patient data, not all features of the simulation could be used as intended. Patient data does not contain information regarding the use of personnel other than those assigned to the surgery-room. Furthermore the documentation of the actual surgical procedure is limited to essentially just a start-time and stop-time.

Preop	1 NSSK, 1 USSK, 1 SSK
Surgery room (x6)	1 NSSK , 1 OSSK, 1 USSK
Corridor	2 NSSK, 2 OSSK, 2 USSK, 2 SSK

Table 4.1: Resource setup for Monte Carlo simulation

Name	op. room	op-code	age	bmi	ASA	planned start-time
sal2-pat1	sal2	QDB05	61	24.5	3	07:06
sal2-pat2	sal2	QCB05	63	16.1	3	13:33
sal2-pat3	sal2	NFJ59	74	25	3	18:07
sal3-pat1	sal3	NGB49	72	27.4	2	07:02
sal3-pat2	sal3	NGB49	77	25	2	09:45
sal3-pat3	sal3	NGB49	83	30.1	2	12:27
sal4-pat1	sal4	NFC41	87	24.6	3	07:14
sal4-pat2	sal4	NCE22	87	24	3	10:54
sal5-pat1	sal5	ABC36	78	30.1	3	07:15
sal5-pat2	sal5	ABC26	36	29.2	1	11:44
sal5-pat3	sal5	NFB19	80	20.7	2	15:51
sal6-pat1	sal6	NBJ69	56	20.7	2	07:01
sal6-pat2	sal6	NBJ69	74	28.2	3	15:08
sal7-pat1	sal7	NGJ49	45	32.4	2	07:07
sal7-pat2	sal7	QDB05	63	29.3	2	12:29
sal7-pat3	sal7	NFQ19	76	17.7	4	15:04

Table 4.2: Patients from real schedule

Operation code	Total	ASA 1	ASA 2	ASA 3	ASA 4
QDB05	164	21	50	88	5
NFJ59	798	31	266	452	49
NGB49	899	95	611	191	2
NFC41	33	0	15	16	2
NCE22	36	20	12	4	0
ABC36	68	17	36	15	0
ABC26	59	36	19	4	0
NFB19	549	4	141	362	42
NBJ69	475	232	181	58	4
NGJ49	6	4	2	0	0
QCB05	51	12	29	10	0
NFQ19	122	1	4	80	37

Table 4.3: Occurences of respective operation code in data in total and for each ASA class

	USSK	SSK	NSSK	OSSK
Preop	1	1	1	0
Surgery	1	0	1	1

Table 4.4: Baseline resource requirements for the tasks of respective processes

Corridor	-	0.5% per ts	USSK, NSSK, ANY	30 min
Corridor	-	7% per ts	ANY	5 min
Corridor	-	0.5% per ts	OSSK, NSSK, ANY	20 min

Table 4.5: Stochasticly occuring corridor tasks that will lockdown corridor resources

Low	Require all base resources		Require extra resource from corridor
	Preop	Surgery	Surgery
ASA 1	20%	100%	20%
ASA 2	30%	100%	30%
ASA 3	40%	100%	40%
ASA 4	50%	100%	50%

Medium	Require all base resources		Require extra resource from corridor
	Preop	Surgery	Surgery
ASA 1	20%	100%	20%
ASA 2	30%	100%	30%
ASA 3	80%	100%	80%
ASA 4	100%	100%	100%

High	Require all base resources		Require extra resource from corridor
	Preop	Surgery	Surgery
ASA 1	50%	100%	50%
ASA 2	60%	100%	60%
ASA 3	80%	100%	80%
ASA 4	100%	100%	100%

Table 4.6: Low, medium and high settings for stochastic resource altercations based on ASA class during surgery

5

Results

The results in this chapter are divided into three sections. The first section is a analysis of the patient data used as input into the model. The initial purpose of the data analysis was to explore the correlations between process times and various patient parameters that are considered important for estimating the process time for surgery [8].

The second section presents the result for estimating process times with the simple Neural Network based regression model presented in the Neural Network section of Chapter 2.

The estimated process times were found to be too inaccurate to be useful as input for the developed model. The model was instead configured to run as the Monte Carlo simulation that is described in Chapter 3. The results from this simulation are found in Section 5.3. The purpose of the Monte Carlo simulation was to instead explore how patient resource requirements affect the process times.

5.1 Correlation matrices

Correlation between the parameters frequently cited [8] as common complicating factors during surgery were shown to be too low to be useful. The only op-codes that show a significant correlation are those with too low sample-sizes to be considered reliable. The matrices shown in Figure 5.1 are the correlation matrices for the op-codes with the highest sample sizes that were scheduled on the particular day of testing. The matrices shown are considered to be representative of the typical scenario. The correlation matrices for all of the op-codes scheduled at the day of surgery are included in Appendix A.1.

op code NGB49: Primary total knee replacement with cement

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	0.153154	-0.214480	0.078305	0.030388
ASA	0.153154	1.000000	0.288165	0.086320	0.079692
age	-0.214480	0.288165	1.000000	-0.115152	-0.028271
op_time	0.078305	0.086320	-0.115152	1.000000	0.140527
preop_time	0.030388	0.079692	-0.028271	0.140527	1.000000

op code NFJ59: Osteosynthesis of femoral fracture with intramedullary nail

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	-0.099894	-0.187106	0.202549	0.045287
ASA	-0.099894	1.000000	0.371825	-0.073679	0.131551
age	-0.187106	0.371825	1.000000	-0.246926	0.004535
op_time	0.202549	-0.073679	-0.246926	1.000000	0.012727
preop_time	0.045287	0.131551	0.004535	0.012727	1.000000

op code NBJ69: Osteosynthesis of shoulder or upper arm fracture with plate and screws

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	0.124531	0.023131	0.239656	0.104650
ASA	0.124531	1.000000	0.547269	0.237930	-0.022609
age	0.023131	0.547269	1.000000	0.164691	-0.031676
op_time	0.239656	0.237930	0.164691	1.000000	0.114848
preop_time	0.104650	-0.022609	-0.031676	0.114848	1.000000

op code NFB19: Primary hemi- or partial hip replacement with cement

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	0.025283	-0.071152	0.039288	0.071780
ASA	0.025283	1.000000	-0.025723	0.016187	0.082202
age	-0.071152	-0.025723	1.000000	-0.039876	0.006506
op_time	0.039288	0.016187	-0.039876	1.000000	0.000530
preop_time	0.071780	0.082202	0.006506	0.000530	1.000000

Figure 5.1: Correlation matrices for the four most frequently occurring op-codes of the real schedule.

The fact that the correlation between process times (op-time and preop-time) and the complicating factors (ASA, BMI and age) is negligible (less than 0.3) is a surprising result. The cause for the surprisingly low correlation is probably complex and dependant on many factors both within and beyond the scope of this thesis. An observation made both by the authors and medical personnel at the department is that complicated cases generally require more staff and resources. Which may result in the department having an equalising effect where simple patients are allocated less resources than the complicated patients. This equalising effect is not captured in any data.

5.2 Neural Network results

The following subsection presents the results obtained from predicting the preop ward time and surgery time. Predictions were made using a simple Neural Network. Network size and parameters as presented in 2.2. The optimizer used was Adam [16] and the loss function used was mean squared error.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2. \tag{5.1}$$

The simple Neural Network performed relatively poorly when estimating process times. The Neural Network consisted of two fully connected layers separated by a dropout layer with a dropout rate of 0.2. The first fully connected layer contained 32 neurons and the subsequent layer had 16 neurons, both employing the ReLU activation function. A visualization of the network structure is shown in Figure 2.2. The mean square error is about 2 hours both when estimating preop times and surgery times. This is not a useful estimate for any operational-level decision making. The network suffers from over-fitting when estimating surgery times (second figure in Figure 5.2).

While an argument can be made for that a different regression model or a Neural Network with different parameters may yield better accuracy, the fundamental problem is most likely that there are no significant correlations in the data. Compared to the method used by the department today[1] the Neural Network is slightly less accurate than the moving average as seen in table 5.1.

	Train loss	Validation loss	Current method MSE
Preop time	3724	3724	-
Surgery time	3119	3898	3502

Table 5.1: Training results Neural network compared to method used at department, note that the department does currently not estimate preop process time.

The department does not estimate the preop time, however it is assumed to take under a hour by the medical personnel, meaning that longer preop times may be attributed to delays in other parts of the system. Unfortunately, the patient data does not distinguish between patients staying in preop to receive treatment and patients which are simply waiting for surgery unattended.

[1]Currently, the department estimates surgery times with a moving average of the last 10 surgeries with the same op-code performed by the scheduled surgeon.

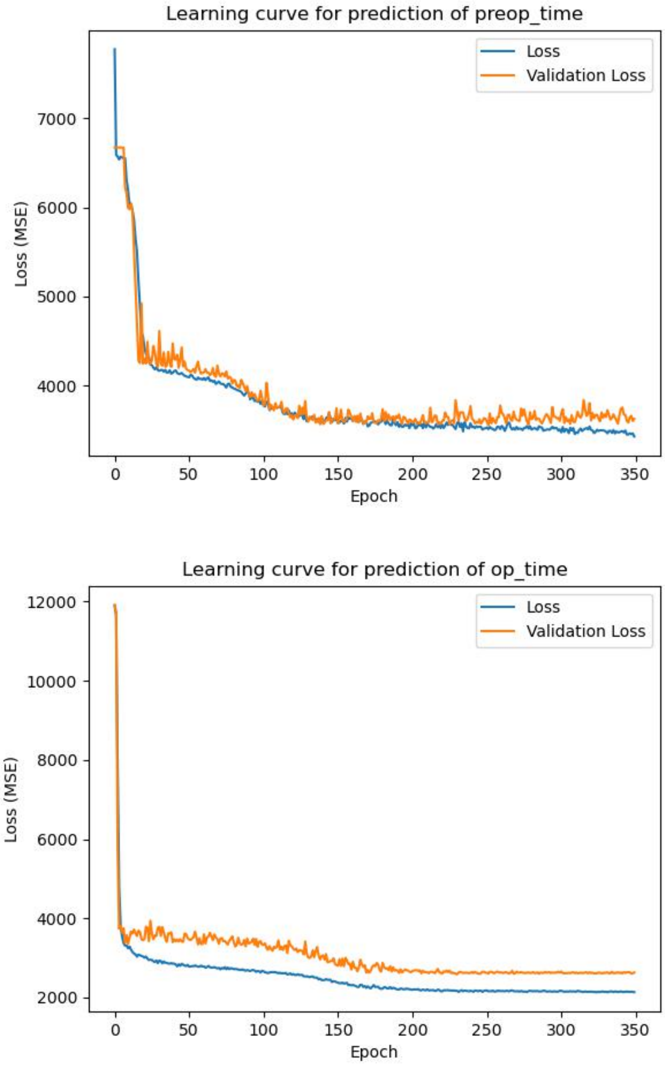

Figure 5.2: Learning curve for Neural Network to predict preop time and surgery time.

5.3 Monte Carlo Simulation

The following section presents the results of the Monte Carlo simulation run on the real schedule while sampling historical patient data in order to estimate the schedule outcome. Section 5.3.1 presents the simulation outcome process time distributions for individual patients in order to study how different resource demands alter the outcome distribution of individual patients. Section 5.3.2 studies how different resource requirement will affect the outcome of a the entire of the simulation on a department level and effectively serves as evaluation of the accuracy of the simulation.

5.3.1 Time and outcome distributions

This subsection presents a selection of distributions from the outcome of the three Monte Carlo simulation runs with 5000 iterations. The distributions shown in this chapter are only for a limited selection of patients[2].

The distributions are grouped by patient and found in Figures 5.3, 5.4, 5.5. Each figure consists of four rows. The first row shows the distributions of process times from which the simulation samples process times during each iteration of the simulation. The last three rows shows the outcome the three different simulation scenarios (low, medium and high), for which the simulation parameters were presented in Table 4.6. The first and second column of graphs show the simulated outcome distributions for the preop process and the surgical process respectively. The last column of graphs shows the distribution of the patients total treatment time[3] at the department, which is the time the patient's preop process was started to the point when the surgical process was finished.

[2]The results not presented in this section are found in Appendix B.1

[3]Some literature refers to total treatment time as ´´length of stay".

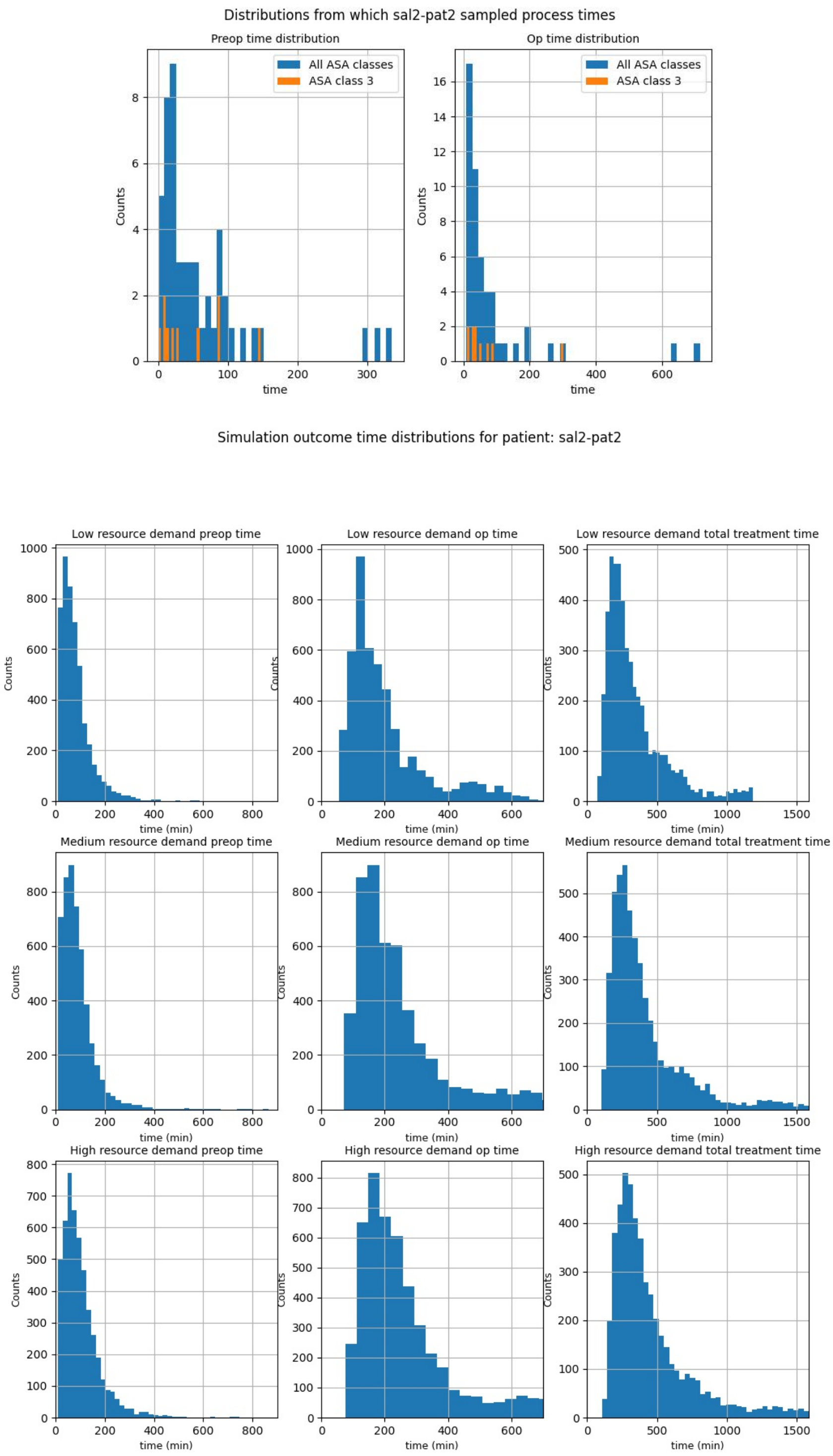

Figure 5.3: Process time distribution and corresponding outcome distributions

The outcome distribution for the patient in Figure 5.3 shifts with resource demand (both for the individual processes and total treatment time). Due to the wide range of outcomes, the x-axis can make comparisons between different outcomes challenging due to relatively significant differences appearing small in order to accommodate extreme edge cases in the graphs. The difference between the peak value for low and high resource scenario is 146 minutes for figure 5.3, which for practical purposes is significant. The trend is consistent for the other patients (presented in figure 5.4 and figure 5.5) where resource demands in general increase by similar amounts.

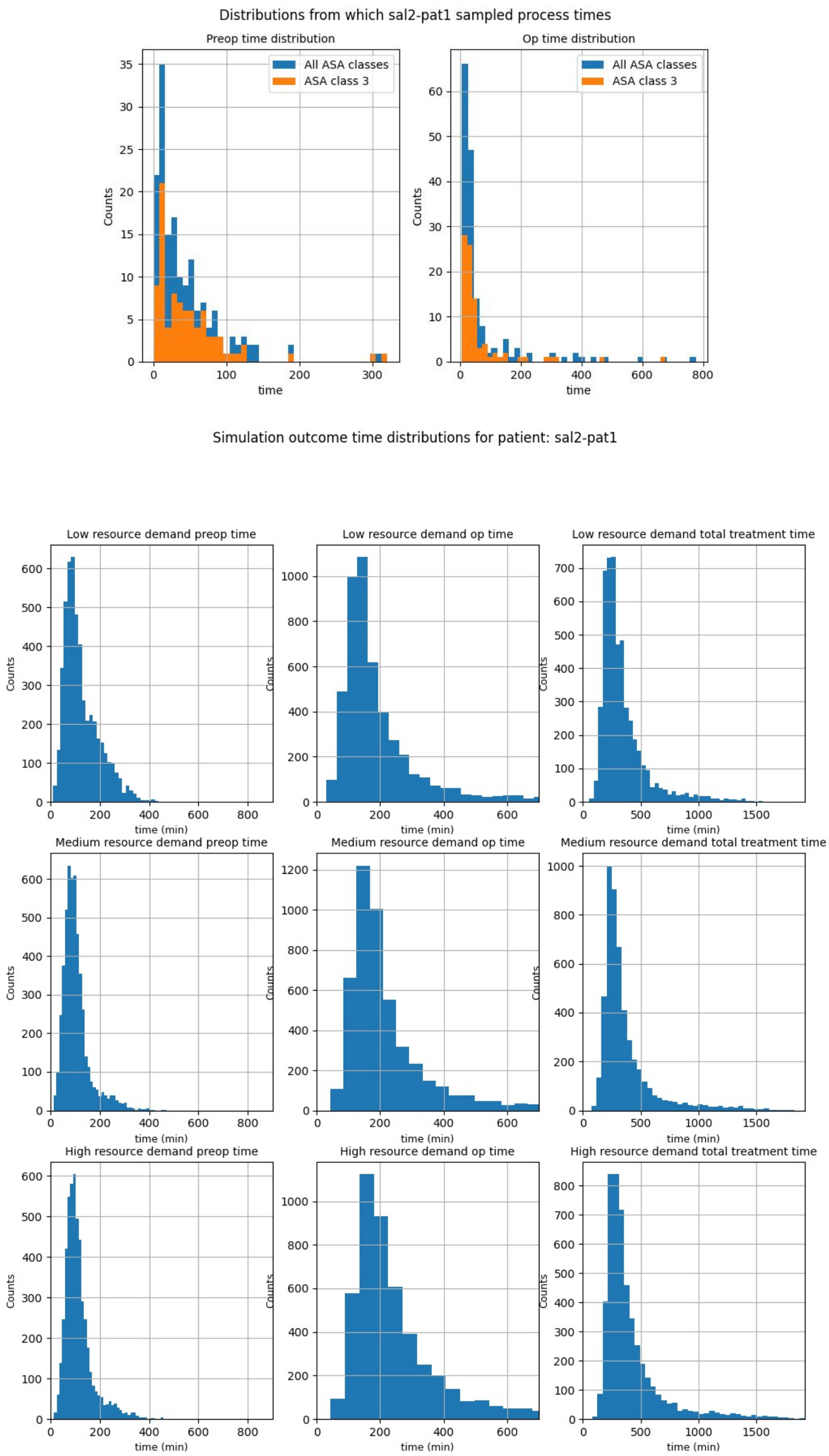

Figure 5.4: Process time distribution and corresponding outcome distributions.

It is worth noting is that the simulation can generate extreme edge-cases. These edge-cases, while rare, result in all of the distributions discussed to have tail-ends with values far beyond what is realistic[4] for the relatively common procedures which are presented in this chapter. The problem is less prevalent in the low-demand scenarios, but still occurs. Higher resource demand scenarios exacerbates the problem, with the longest length of stays being above 24 hours (1440 minutes in graph), which is extreme and possibly not even feasible for the patients with ASA-class 3 or 4 due to the physical strains of long surgery on the patient.

[4]None of the op-code presented is recorded by the department to have taken more than 16h.

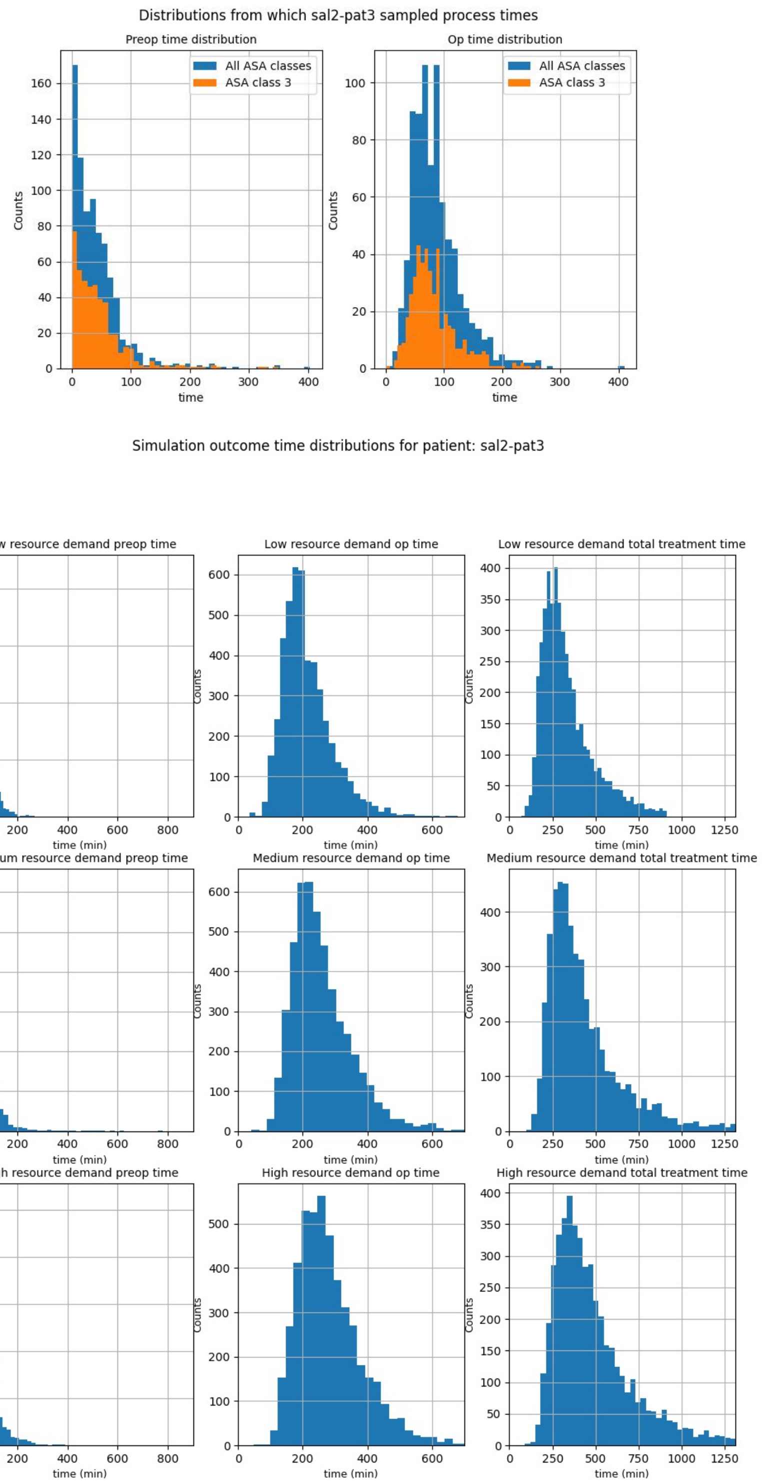

Figure 5.5: Process time distribution and corresponding outcome distributions

5.3.2 Simulation outcome schedule and corresponding actual outcome

By plotting the peak value for the three busiest surgery rooms, the difference between simulated outcome and the real outcome can be clearly seen not just in terms of process times but also patient length of stay at the department. Figure 5.6 show the high and low resource demand scenarios with resource demand parameters from table 4.4 and process times from table 4.6, only the low and high resource-demand scenario have been plotted. All of the simulation data plotted in figure 5.6 is found in table 5.2.

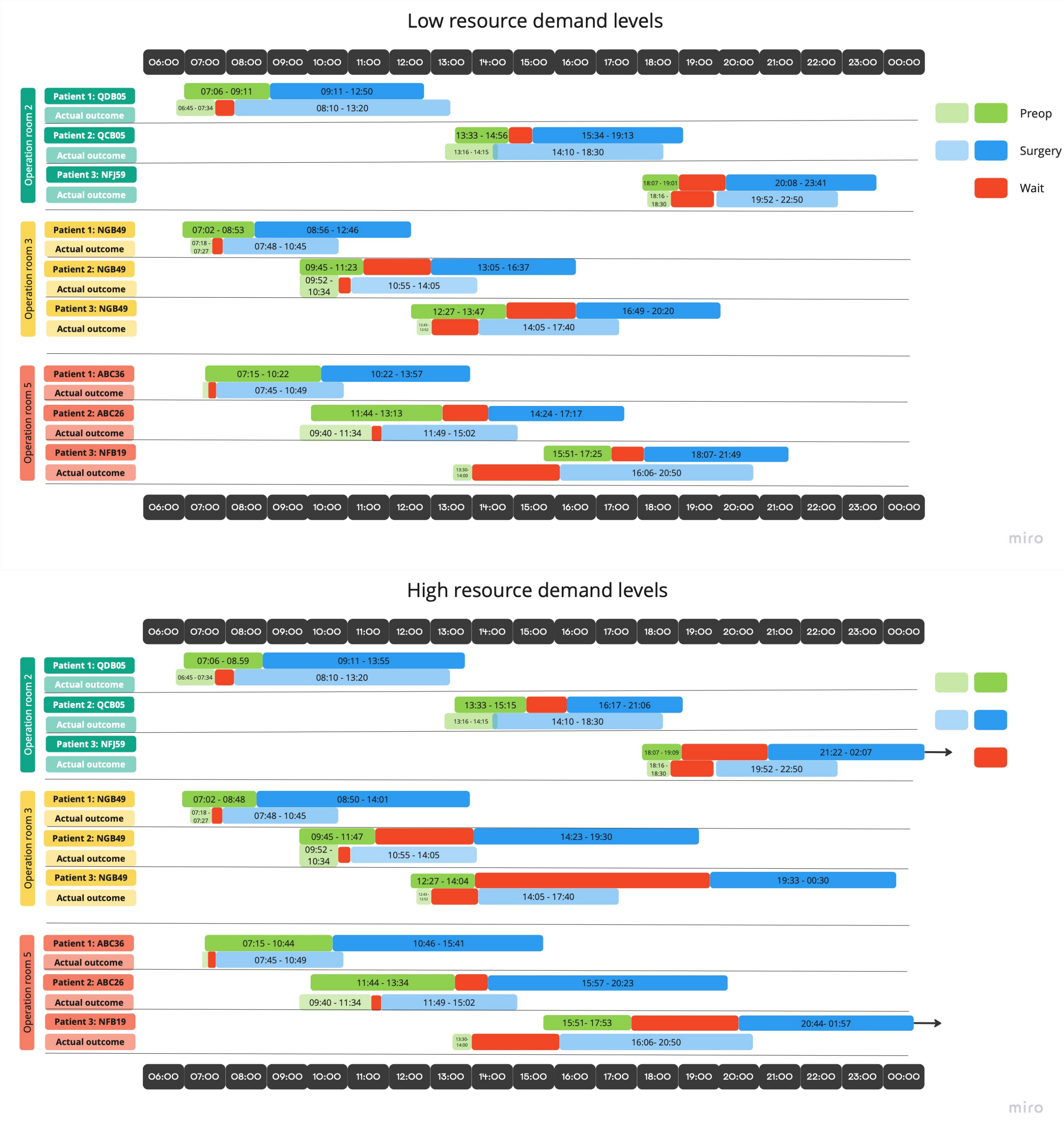

Figure 5.6: Visualization of the outcomes for the busiest operating rooms for two levels of resource requirement parameters previously presented in tables 4.4 and 4.6

Comparing the simulation outcome to the real outcome reveals that the simulation is not accurate. Both with regards to individual process times as well as the total treatment time for patients. The main cause for the low accuracy is most likely the combination of inadequate data regarding patient process times and resource requirements as mentioned in section 5.1.

As previously discussed in section 5.3.1, the outcome distributions vary significantly with resource requirements. By plotting them in a schedule next to the outcome this both the difference between different resource scenarios and the contrast to reality becomes clear. Essentially all estimates are inaccurate. In the extreme cases the simulation is inaccurate enough that a entire surgery could most likely be performed in the time difference between the actual outcome and simulated outcome. The simulation performs best in the low demand scenario. Operating Room 2 was simulated with the highest accuracy. The estimation error in operating room 2 is ca. ± 50 minutes, equivalent to ca. 25% per patient. A best case margin of error of 25% is simply not useful for operational level scheduling. Given that in many cases the error margin is large enough to fit a surgery in.

Another issue with the simulation is its inability to account for patients being admitted earlier or later than scheduled or that the patients may have received preop-treatment at a different department. A typical case of a patient being admitted early is patient 1 in operating room 2. The case of a patient receiving preop-treatment at a different department is patient 1 in operating room 5. Both of these situations are unfortunately cases that are not possible to estimate with the available data.

The estimates get significantly worse for all of the other operating rooms in both of the scenarios. Low resource scenario overestimates both wait-times (red) and process times. Due to the relatively high wait times between processes it is reasonable to assume that the main driver behind the overestimation of process times is in a large part due to a overestimation of patient resource demands.

Despite a patient skipping preop in operating room 5. The difference in estimation error between operating room 3 and 5 over the course of the entire day is comparable in both the high and low scenario, which may be a further indication that the main issue of the simulation are inaccurate assumptions about patient resource requirements. This creates unrealistic bottlenecks rather than the inaccurate admission times of individual patients.

Comparing the high and low resource demand simulations reveals that while the low resource demand simulation is overall closer to the real outcome, none of the simulations produce useful predictions.

Ultimately it is difficult to draw definitive conclusions both due to the inherently low accuracy of the simulation but also due to old schedules not being recorded, unlike the schedule outcome, leading to an extremely low sample-size.

Patient Name	Preop Start	Preop End	Surgery Start	Surgery End
sal2-pat1				
Low	07:06	09:10	09:10	12:49
Medium	07:06	08:49	08:49	13:12
High	07:06	08:59	08:59	13:55
Actual outcome	06:45	07:34	08:10	13:20
sal2-pat2				
Low	13:33	14:55	15:33	19:13
Medium	13:33	15:03	15:52	20:21
High	13:33	15:15	16:17	21:06
Actual outcome	13:16	14:15	14:10	18:30
sal2-pat3				
Low	18:07	19:01	20:08	23:41
Medium	18:07	19:05	20:52	01:15
High	18:07	19:09	21:22	02:07
Actual outcome	18:16	18:30	19:52	22:50
sal3-pat1				
Low	07:02	08:53	08:55	12:46
Medium	07:02	09:08	09:12	13:14
High	07:02	08:48	08:50	14:01
Actual outcome	07:18	07:27	07:48	10:45
sal3-pat2				
Low	09:45	11:23	13:04	16:37
Medium	09:45	11:46	13:34	17:19
High	09:45	11:47	14:23	19:30
Actual outcome	09:52	10:34	10:55	14:05
sal3-pat3				
Low	12:27	13:47	16:48	20:19
Medium	12:27	14:02	17:28	21:08
High	12:27	14:04	19:33	00:30
Actual outcome	12:43	12:52	14:05	17:40
sal5-pat1				
Low	07:15	10:21	10:22	13:57
Medium	07:15	10:26	10:26	14:49
High	07:15	10:44	10:46	15:41
Actual outcome	07:17	07:19	07:45	10:49
sal5-pat2				
Low	11:44	13:13	14:24	17:17
Medium	11:44	13:33	15:13	18:20
High	11:44	13:34	15:57	20:23
Actual outcome	09:40	11.34	11:49	15:02
sal5-pat3				
Low	15:51	17:24	18:06	21:49
Medium	15:51	17:49	18:57	22:48
High	15:51	17:53	20:44	01:57
Actual outcome	13:30	14:00	16:06	20:50

Table 5.2: Predicted outcome for low, medium and high resource requirements and the actual schedule outcomes for each patient in surgery rooms 2 and 3. See Appendix C.1 for results on surgery rooms 4,6,7

6
Discussion

6.1 The Importance of Data Quality for Predicting Schedule Outcomes

The model based approach proposed and developed in this study use patient data to predict schedule outcomes and its performance is highly dependent on the quality of its data. By using Monte Carlo simulations instead, the impact of unknown input parameters on the output distribution can potentially be estimated. It should be noted that testing "what if" scenarios with Monte Carlo simulations is inadvisable as there is no guarantee that the scenarios the simulation generates are realistic or accurate [22]. Ultimately, any results from the simulation should not be considered valid, as important data about what the actual resource demands of individual patients are in terms of man-hours for different resource categories is not known. By employing regression, the model could provide deterministic estimates that would enhance the model's practical applicability, for example as a basis for decision making when scheduling surgery.

However, the correlation matrices presented in Figure 5.1, demonstrate a generally low correlation between the process times and the patient parameters that, based on worker experience, are believed to have the most significant impact. With the exception of which surgeon is operating [3, 6], which was not included mainly due to privacy reasons. The observations suggest that the performance of algorithms relying solely on these patient parameters may be limited. It should also be noted that surgeons at the examined department are generally difficult to compare, since even surgeons with the same specialization can have different qualifications and sub-specializations, meaning that they might not even be able to perform the same surgery or be directly comparable. During the field visit, it was noted by surgeons that while op-codes represent a single type of surgery, they do not necessarily indicate the severity of the injury or the specific treatment provided by the surgeon. This variability in treatment options can impact correlations and further complicate time estimation.

Despite the initial indication of low correlation between process times and patient parameters, a simple Neural Network was constructed to explore the potential of using a regression algorithm for time prediction. As indicated by the training results in Figure 5.1, the Neural Network learns information about the underlying distribution but the performance converges quickly to a relatively high error. Although many different network sizes and parameters were tested, the learning curve for the network trained to predict op-time exhibits a recurring issue where the validation loss is moderately higher than the training loss, Figures 5.1 and 5.2. This observation suggests that during the training process, the network may be prone to over-fitting. This is not surprising due to the previously discussed data issues related to disruptions and op-codes encompassing multiple injuries. These factors introduce noise into the data, potentially complicating the learning process.

However, as seen in Figure 5.1, the performance of this network to predict surgery time was found to be comparable to the current method of using a moving average to predict operation times. This finding suggests that there is potential in using regression algorithms, such as Neural Networks, for improving time predictions. By testing other algorithms or further altering the network it may be possible to get better performance and thus slightly improve the current scheduling. However, considering that the mean squared error for the preoperative and surgery time is approximately 1 hour, and 80 minutes for the altered surgery time, to generate reliable and usable predictions about the outcome of a schedule, a significant performance improvement is required.

As stated earlier, the unavailability of data describing resource requirements in terms of worker hours for each patient and the specific tasks performed on each patient is a significant limitation. To increase the applicability of the discussed approaches, it is crucial to have access to this data. This is important in order to accurately capture potential peaks and ebbs in resource demand, which is essential for the system to effectively predict a schedule's outcome. The outcome of a schedule in reality is significantly influenced by the worker logic and the logistical considerations of the department. In reality, the worker logistics and logic involved in scheduling are often dynamic and situation-dependent. This could make collection of the necessary data a challenge for certain tasks and patients. One approach could be to include in the model both time and motion studies of tasks that are more or less standardized and performed on all patients. In addition to the time and motion study, data distributions and Monte Carlo simulation could be used for the tasks and logic that is of a more stochastic nature.

To fully harness the advantages of Monte Carlo simulations, it is essential to have larger distributions than available for some of the operation codes. This is evident when examining the distributions for preoperative time (Figure B.9) and surgery time (Figure B.6) and the size of the datasets in 4.3, particularly in the case of op-codes NGJ49 and NFB19 for ASA class 1. Due to the low correlations between ASA and process times, the sub-sample of a distribution of times for a specific ASA class does not significantly deviate from the characteristics of the parent distribution. Consequently, the model does not effectively differentiate between patients with more complex health profiles and those with easier ones in terms of process time, only through the probabilistic resource-requirements. It is unclear if this is a reflection of reality or if ASA class is simply an insufficient metric for a patient's difficulty in terms of process times. It is possible that in reality, patients with a complicated health-status requires more resources that will cancel out extra time requirements, which would explain the low correlation. Furthermore, certain distributions exhibit a significant imbalance in terms of ASA class. This imbalance can be attributed to the department's specialization in treating more challenging patients, as mentioned in the Background 1.1. In such cases, the distribution may not accurately reflect reality, rendering sampling a less reliable approach.

6.2 Possible metrics for determining difficulty of patients

One observation made during the field study was the substantial reliance of surgeons on diagnostic images when making medical decisions before surgery. This includes deciding the appropriate surgeon and determining the suitable surgical method.

Recent advancements in deep learning and image analysis have paved the way for developments in injury classification and detection tasks. Deep learning solutions, particularly those based on Convolutional Neural Networks (CNNs), have demonstrated promising results, comparable to those of trained radiologists [27, 14, 19]. However, using deep learning for assessing severity injuries still appears to be in a less mature stage of development [7], but the advancements may cause automated assessment of the severity of orthopedic injuries to become feasible and accurate enough for the purpose of estimating surgery times and resource requirements. Incorporating such severity ratings into the estimated preop and surgery time as a metric for patient and surgery difficulty is an option worth studying, mainly due to previously discussed lack of correlation between the current metric (ASA class) and said times. It should be noted that most of the systems that exist are usually trained on analysing a specific type of injury [27, 14, 19]. Creating a system that can handle a broader range of injuries is most likely a monumental task and may not be feasible with current models.

6.3 Leveraging Monte Carlo Simulations to Estimate Robustness of Schedule

Designing the model to run a Monte Carlo simulation with sampling of times from distributions offers several benefits, including the use of uncertainty in the operation flow to generate distributions that represent the possible outcomes of a schedule. As previously discussed, with implementation of a poor performing regression algorithm to generate surgery times, the model's output would have no applicability. By instead sampling and analyzing how the output distribution of a Monte Carlo simulation changes in response to variations in the input distributions (process times), valuable information about the uncertainty of a schedule can be obtained.

With the developed model integrated into a Monte Carlo simulation, it can be viewed as a nonlinear function that takes multiple sets of distributions as inputs and produces new distributions as outputs, as illustrated in Figure 3.2. In theory, with the availability of high-quality data with a sufficient amount of data-points, the model can be used with a learning algorithm to give recommendations on which input distribution will generate a narrower output distribution, resulting in a more predictable outcome. Also, with other types of data, the model can easily be altered to generate distributions of other metrics as well. For example, resource use including workers and surgery rooms, and also test how the distributions change when altering the amount and/or types of resources. The results from a Monte Carlo simulation model would essentially work as a tool to get insight into the uncertainty of different metrics of a planned schedule and use the information to help making a more robust schedule. This is however with the premise that data describing resource requirements is available.

6.4 How distributions interact and what the result is

Illustrations of the expected schedule outcome in Figure 5.6 indicate that different resource demand levels do significantly change the expected outcome schedule. The model run with low resource demand levels appears to perform slightly better than the one with high resource demand levels. Also, the illustrations indicate that the surgery time appears reasonably accurate in the simulation with low resource demand levels, but the preop time is not. This results in overall poor accuracy of the output schedule for both settings. As described in Section 4.2.1, preop samples with unreasonable values could be removed with reference to worker experience. However, the same cleaning was not possible to perform for the surgery times due to many different op-codes as well as a very wide span of difficulties that may result in alternating values and as a result incorrect sampling leading to further inaccuracy. It is also important to note that with different schedules, variations in the characteristics of the output-distribution are to be expected. Because the same calculations may not be suitable for all types of distributions, an alternative method in order to effectively utilize and convert the outcome into an expected outcome schedule is needed.

The noticeable difference in waiting times between the simulation outcome and the actual outcome, see Figure 5.6, may be due to the available resources in the model being insufficient to meet the resource demand levels. It is very difficult to approximate the resource demand, which makes the creation of a good simulation model without the correct data a challenge.

When examining the output distributions generated by the system, it is evident that the level of uncertainty and other inherent characteristics remain relatively consistent across different resource demand levels. This implies that the system's predictions exhibit similar patterns and tendencies regardless of the resource requirements. The exception is that a few of the largest times are absent in the total treatment times distributions for low resource demands. While the overall uncertainty and characteristics of the output distributions remain consistent across different resource demand levels, some of the longest treatment times are noticeably missing from some of the distributions. The distributions for the higher resource demand levels are generally slightly displaced to larger values which is to be expected as resources will be more strained. As previously discussed in 6.1, the model cannot to a sufficient degree distinguish the difficulty between patients. To get a more applicable result, it is necessary to gain further insights into the uncertainty associated with different patients. One possible approach to achieve this is by introducing a metric for patient uncertainty, which can be used during sampling. An example of such a metric could be obtained through image analysis, as discussed in 6.2.

6.5 Recommendations for data-collection

The system developed as part of this project uses task and resource data that is based on a study visit and worker experience. However, a more data-inclusive approach that allows for data verification and comparison with worker experience would provide a more comprehensive and accurate result. Such an approach would require the collection of comprehensive worker data and a detailed mapping of tasks performed on patients so that each patient could be given more accurate expected process times that are sums of the expected time of the standardized tasks and the noise that exists due to the stochastic nature of the operation flow.

An alternative method to gather data on resource requirements for each patient is to implement a system that tracks the number of man-hours spent on a patient by workers of different categories. This can be achieved by sensors and tracking devices to log the presence of workers in surgery rooms or specific areas, thereby collecting data on their involvement. While this approach presents potential benefits that motivates investigation in its feasibility, it is essential to acknowledge that it raises several ethical and legal concerns, which are beyond the scope of this report.

To maximize the use of the available data, it is important to develop additional methods and gain deeper insights into disruptions to further clean the data by removing invalid samples, similar to what was done with preop times, as mentioned in 4.2.1. One possible approach is to involve experienced workers who can manually assess and exclude invalid samples. Alternatively, collecting additional information about disruptions and encouraging workers to further flagging data points during patients treatment processes, can facilitate the development of an automated method to effectively remove flawed samples.

6.6 Ethical considerations

The goal of improving the healthcare system's efficiency should not come at the expense of reducing the quantity or quality of care provided to patients. It is also important to take into account the working conditions of staff to ensure that healthcare providers are not subjected to unreasonable workloads.

When building models based on data, the risk of biases that may exist in the data should be considered. Demographic differences are likely to be reflected in the data and have therefore to be considered. This is already apparent in the current data because of the typical patient profile of the department studied, as presented in the Background 1.1. Biases in the data can be extended to the output of algorithms. Therefore, the explainability of any algorithms using data should also be considered. A model that is used to optimize a schedule in order to maximize the amount of patients treated could lead to unfair selection and unintentional prioritizing of patients thus potentially compromising patient safety. Limiting usage of such a model to finding optimal patients when an spot for surgery would otherwise be unfilled could be considered. This restriction would not eliminate the issue but reduce the scale of the bias. With a changing demography in society, continuous development and testing needs to be done to ensure the model is up to date and to reduce the risk of including biases from older data.

Handling patient data properly to prevent unauthorized access or sharing is crucial, as patient data can contain sensitive information. Even data that appears to be anonymous can potentially be linked to specific individuals. Transparency between the hospital and patient with regards to patient data collection should be standard to secure the integrity of the patients.

The privacy and trust of individuals, patients and workers should be respected when gathering information through conversations. Information shared in confidence should not be exploited or shared without permission. Negative views or opinions should only be shared if it can be guaranteed that the individual cannot be identified or if the individual has given permission for the information to be shared.

Academic integrity is especially important when working with healthcare. Being transparent about flaws in either results or methods is crucial as misrepresentation of either could in the worst case result both in unnecessary suffering and sow distrust between institutions that are mutually dependant.

7
Conclusion

Adressing the problems of correct staff allocation, surgery scheduling to make the patient flow as efficient and effective as possible is a complex task that requires profound understanding of the flow and the factors causing disruptions that lead to surgery cancellations and delays.

The significant variability in treatment duration's among patients, including tprehose undergoing similar treatments, is contributing to large deviations from the initially intended surgery schedules.

Previous studies on patient flows at an operational level such as this one, has utilized Discrete Event based models for research on flows that are less complicated. The flows has generaly been more or less linear with low or no amount of shared resources and less stochastic disruptions.

The model created within this project is built upon the patient flow dynamics of Orthopedic Surgery Department 1 at Sahlgrenska University Hospital in Mölndal and includes logic of shared resources. Utilizing real patient data, which consists of shared resources, treatment durations, and resource demands as inputs to the model and conduct a Monte Carlo simulation, was anticipated to yield valuable observations of the differences in uncertainty for both individual patients treatment times and the overall schedule outcome.

However, given the existing constraints on the available data, it is currently impossible to set parameters such as resource requirements, treatment times, and stochastic disruptions to reflect reality. Consequently, the model's predicted outcome suffers from low accuracy. Even with the availability of appropriate data, it remains uncertain whether the model would be capable of providing sufficiently accurate predictions for practical use. To comprehensively assess this approach and determine its potential or the need for further development, it is advisable to gather the required data.

The data distributions indicate that there is typically no discernible distinction in uncertainty levels among the various ASA classes. This lack of differentiation poses a challenge for the model in accurately distinguishing between these patient types. As a result, the examination of how uncertainty impacts the output was primarily confined to evaluating the randomness of resource allocation. Furthermore, even when attempting to modify this randomness, the resulting outputs still do not exhibit sufficient differences to allow for drawing conclusions regarding the impact. This finding contrasts with the opinions of workers who believe that more challenging patients would result in greater uncertainty. However, considering the extensive range of different operation codes, it is possible that certain codes align more closely with the workers experiential knowledge. Therefore, manually finding and exploring distributions for specific operation codes that better reflect the workers' experiences may give better insight into the models response to uncertainty.

To enhance the model's validity, it would be valuable to have additional information regarding the identification of invalid samples for data cleaning purposes. This information would provide guidelines or criteria for determining which samples should be deemed invalid and subsequently removed from the dataset. By incorporating such guidance, the data can undergo a more thorough cleaning process, ensuring that unreliable or inappropriate samples are excluded. Conducting a more in-depth analysis of the relationship between process times and patient parameters within the cleaned data can potentially enhance utilization of these parameters. This approach would possibly align the models process times with the experiences and insights of the workers, making it an ideal direction to explore. By thoroughly studying how patient parameters influence process time uncertainty, we can gain valuable insights that could improve the accuracy and applicability of the models.

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A

A.1 Correlation matricies

op code QDB05: Wound debridement, lower extremity

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	-0.028405	0.063894	0.025046	-0.056858
ASA	-0.028405	1.000000	0.522480	-0.109811	0.033307
age	0.063894	0.522480	1.000000	-0.251456	-0.036486
op_time	0.025046	-0.109811	-0.251456	1.000000	-0.121514
preop_time	-0.056858	0.033307	-0.036486	-0.121514	1.000000

op code NFC41: Secondary total hip replacement with cement, cup-revision

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	0.014404	-0.154872	0.066252	-0.052902
ASA	0.014404	1.000000	0.356471	0.007336	0.197258
age	-0.154872	0.356471	1.000000	0.033113	0.199109
op_time	0.066252	0.007336	0.033113	1.000000	-0.412976
preop_time	-0.052902	0.197258	0.199109	-0.412976	1.000000

op code NCE22: Suturing or replantation of ligament in the elbow joint

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	0.461533	0.483232	0.350593	-0.016164
ASA	0.461533	1.000000	0.692196	0.135700	-0.247120
age	0.483232	0.692196	1.000000	0.009358	-0.051113
op_time	0.350593	0.135700	0.009358	1.000000	0.093437
preop_time	-0.016164	-0.247120	-0.051113	0.093437	1.000000

op code ABC36: Decompression of nerve roots in the lumbar spine

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	0.258952	-0.015116	0.107704	0.104300
ASA	0.258952	1.000000	0.560580	0.185937	-0.119355
age	-0.015116	0.560580	1.000000	0.130208	-0.172652
op_time	0.107704	0.185937	0.130208	1.000000	-0.174062
preop_time	0.104300	-0.119355	-0.172652	-0.174062	1.000000

Figure A.1: Correlation matrices for specific op-codes

op code ABC26: Open discectomy in the lumbar spine

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	0.171345	0.105070	-0.042875	0.239641
ASA	0.171345	1.000000	0.489824	0.227830	0.123194
age	0.105070	0.489824	1.000000	0.189652	0.026049
op_time	-0.042875	0.227830	0.189652	1.000000	-0.262848
preop_time	0.239641	0.123194	0.026049	-0.262848	1.000000

op code NGJ49: Osteosynthesis of knee or lower leg fracture with cerclage, pins, or similar

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	0.000000	0.731214	-0.930896	0.532556
ASA	0.000000	1.000000	0.672690	-0.056857	-0.212012
age	0.731214	0.672690	1.000000	-0.759438	0.250307
op_time	-0.930896	-0.056857	-0.759438	1.000000	-0.473388
preop_time	0.532556	-0.212012	0.250307	-0.473388	1.000000

op code QCB05: Wound debridement, upper extremity

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	-0.095556	-0.096740	0.005615	-0.006151
ASA	-0.095556	1.000000	0.421614	-0.047048	-0.211590
age	-0.096740	0.421614	1.000000	-0.150713	-0.018168
op_time	0.005615	-0.047048	-0.150713	1.000000	0.116392
preop_time	-0.006151	-0.211590	-0.018168	0.116392	1.000000

op code NFQ19: Transfemoral amputation

	BMI	ASA	age	op_time	preop_time
BMI	1.000000	0.050783	0.057066	0.252545	0.054871
ASA	0.050783	1.000000	0.265448	-0.181041	0.066543
age	0.057066	0.265448	1.000000	-0.374149	-0.087586
op_time	0.252545	-0.181041	-0.374149	1.000000	0.087704
preop_time	0.054871	0.066543	-0.087586	0.087704	1.000000

Figure A.2: Correlation matrices for specific op-codes

B

B.1 Outcome distributions

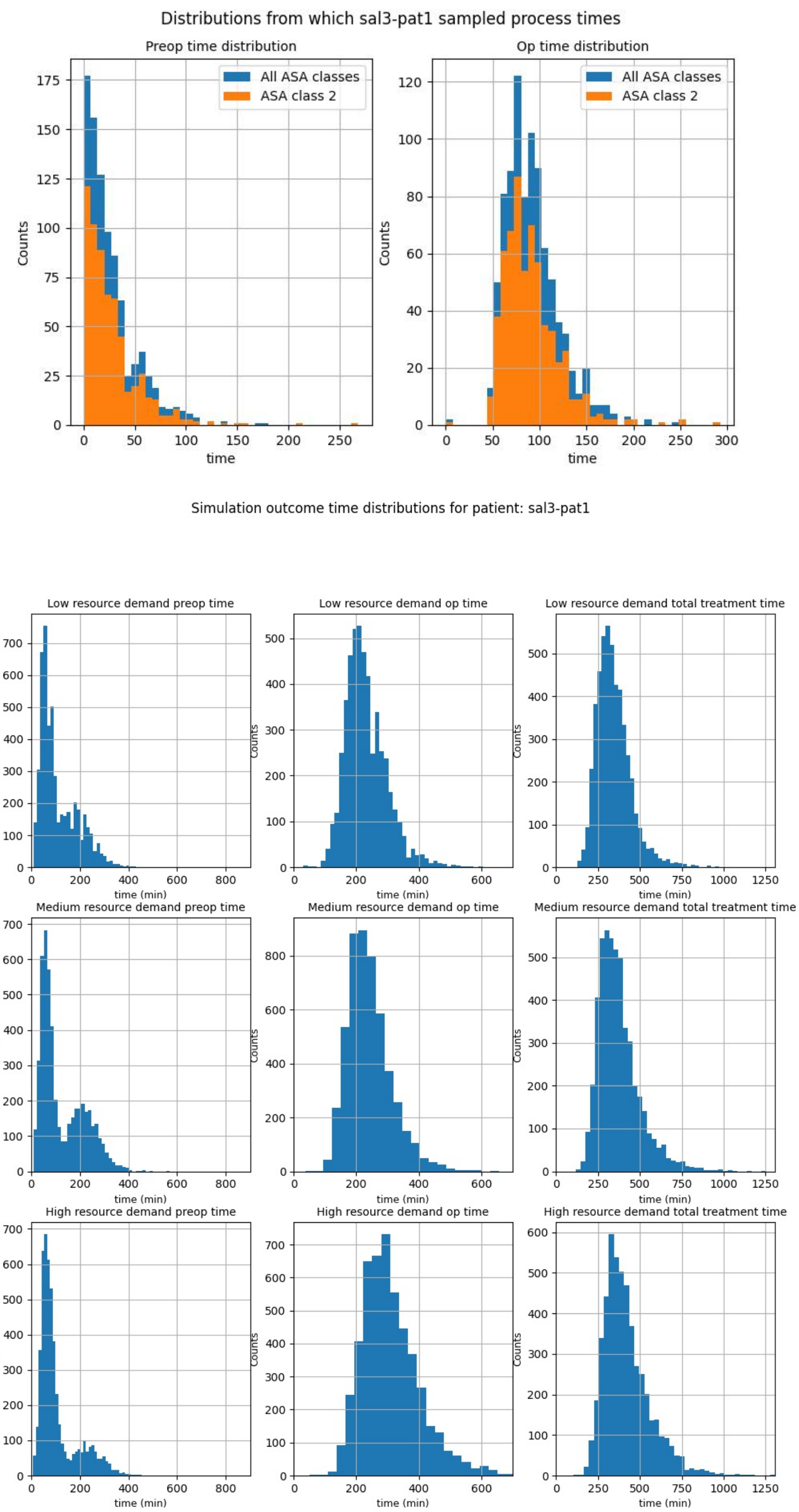
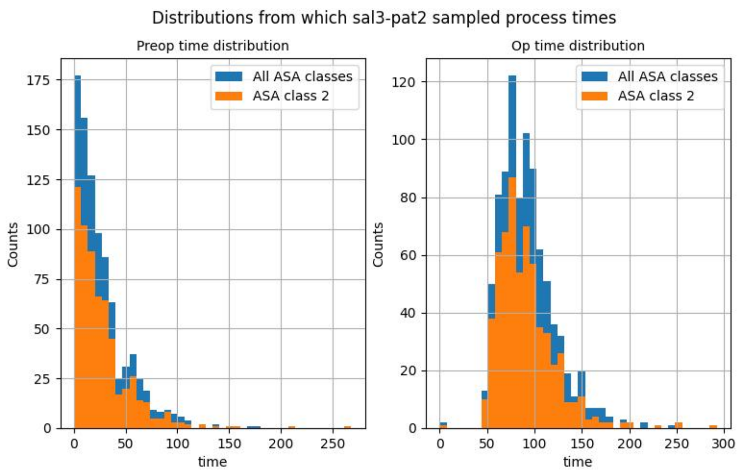


Figure B.1: Process time distribution and corresponding outcome distributions



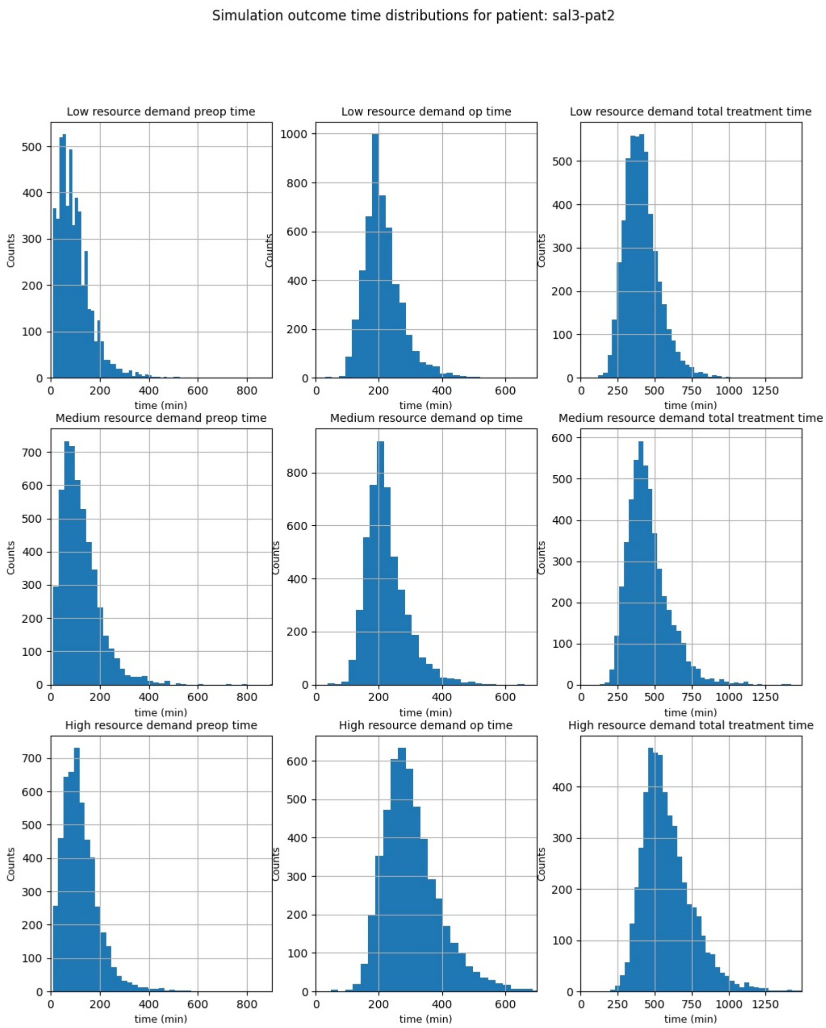
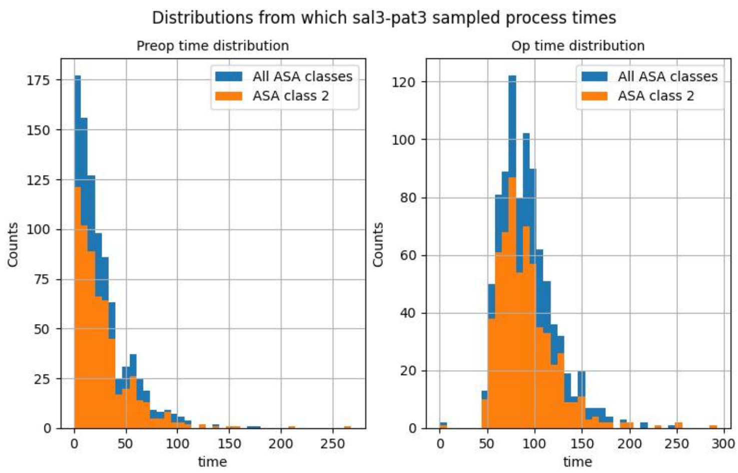


Figure B.2: Process time distribution and corresponding outcome distributions



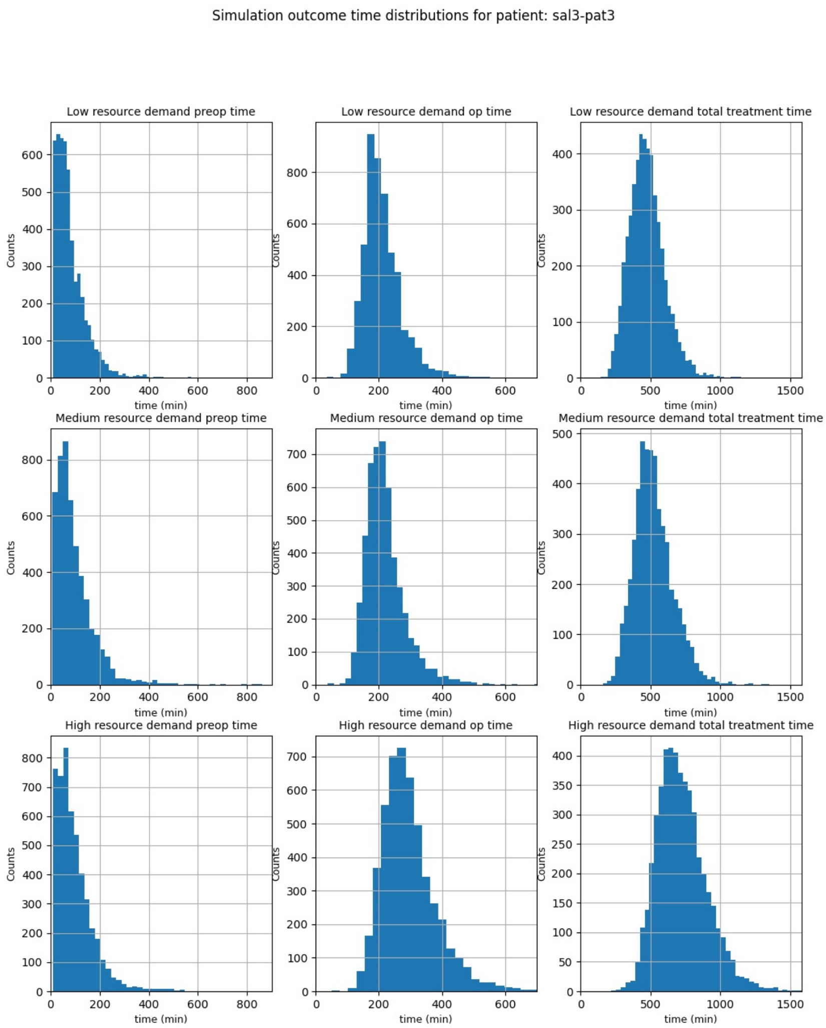
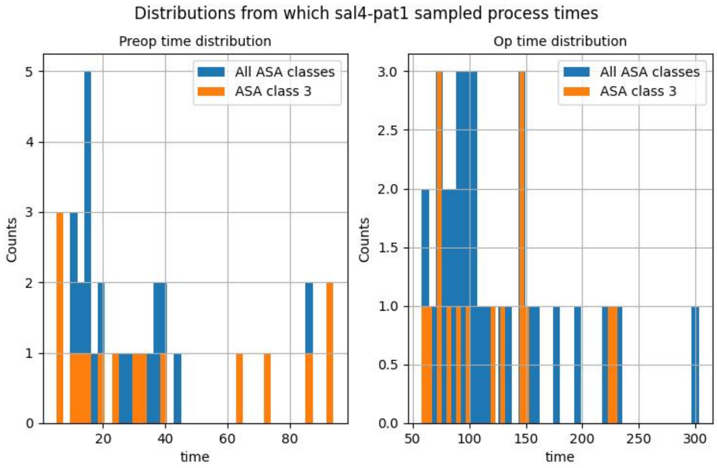


Figure B.3: Process time distribution and corresponding outcome distributions



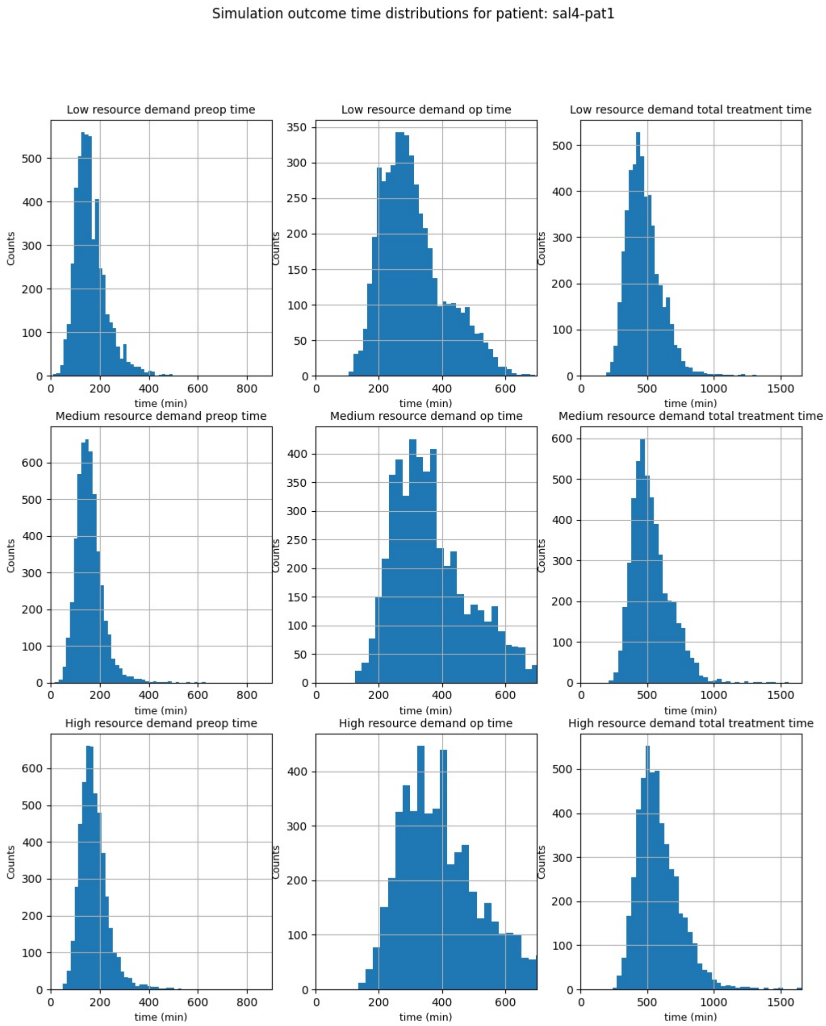


Figure B.4: Process time distribution and corresponding outcome distributions

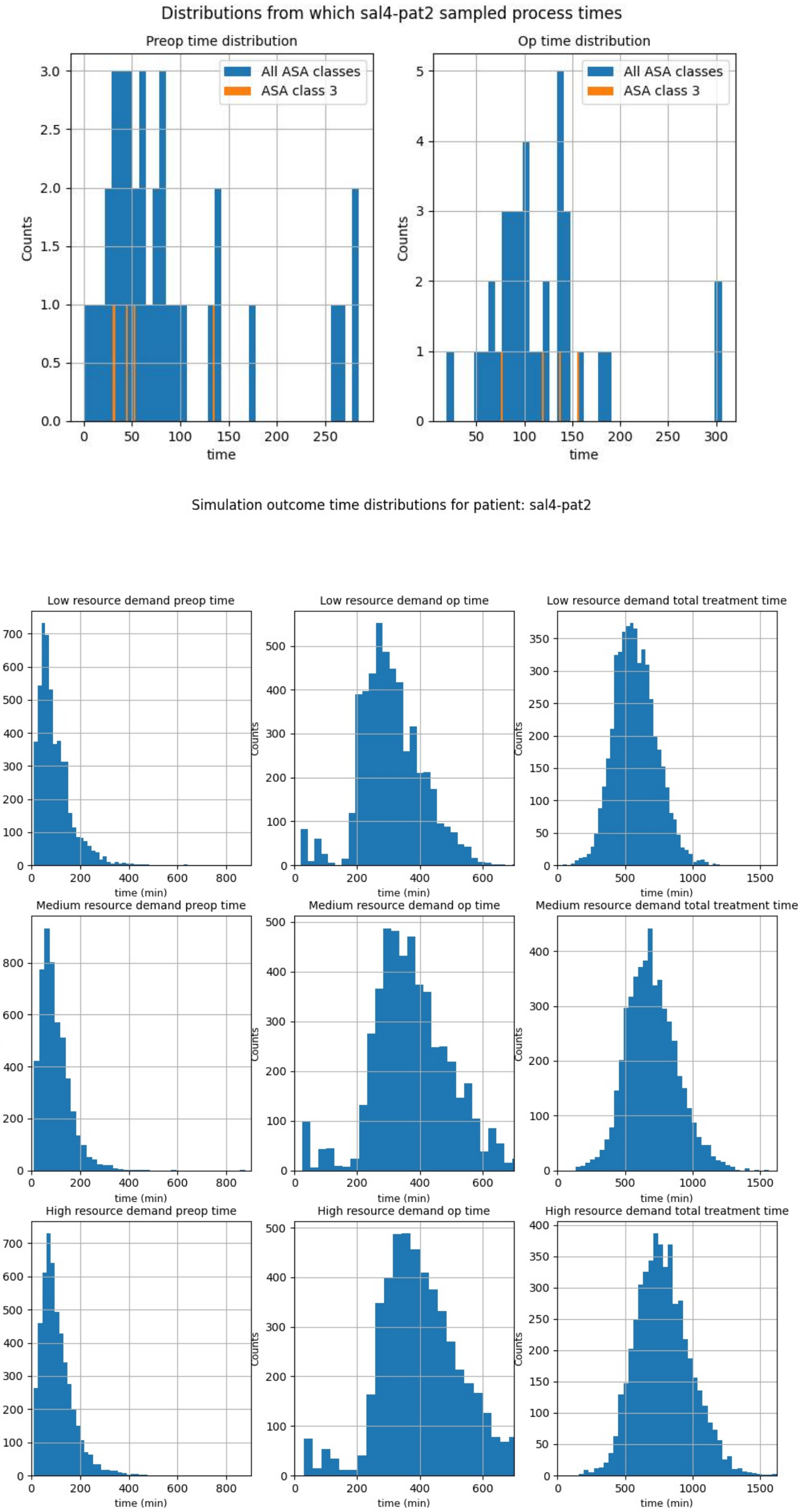


Figure B.5: Process time distribution and corresponding outcome distributions

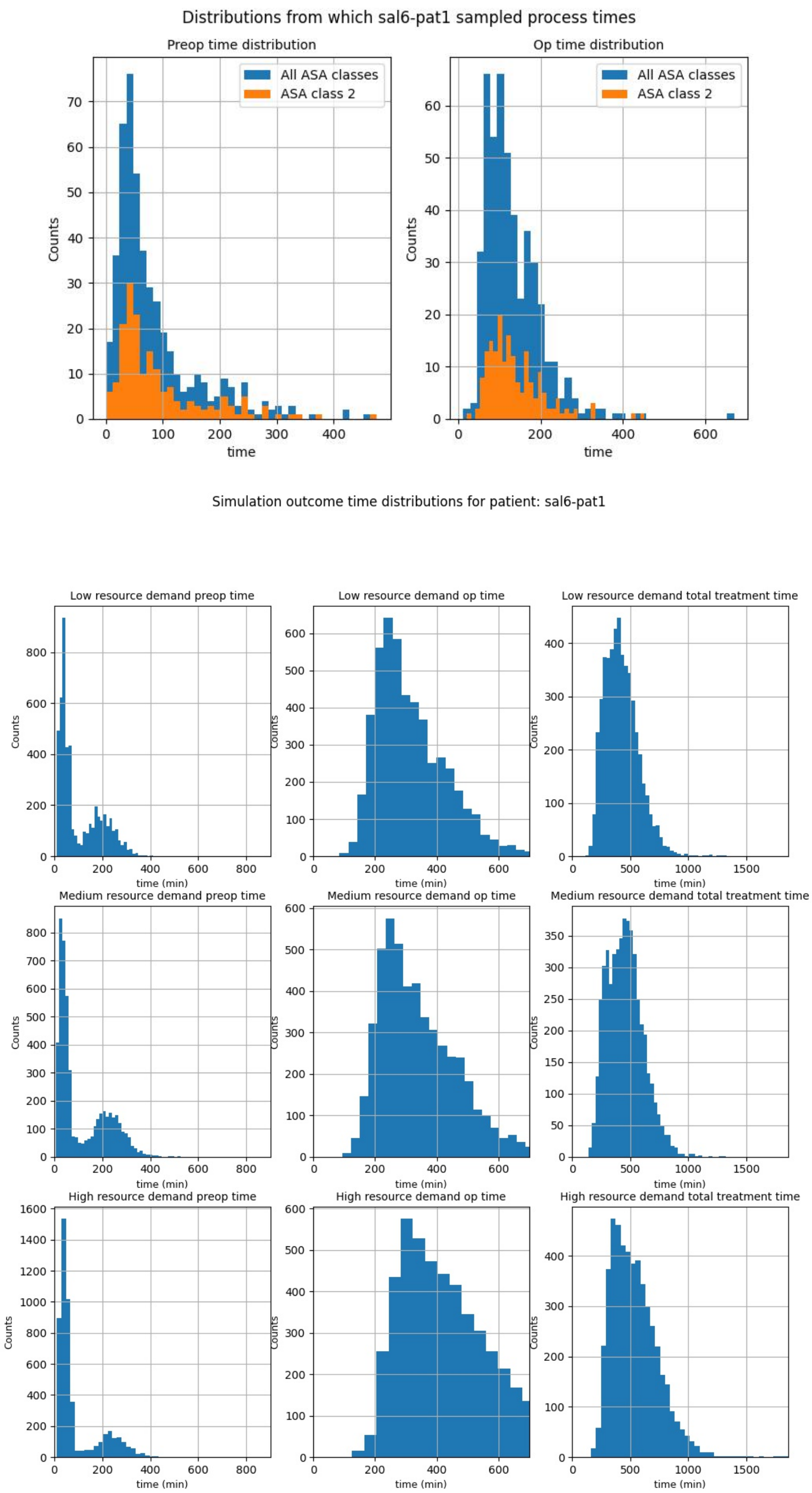


Figure B.6: Process time distribution and corresponding outcome distributions

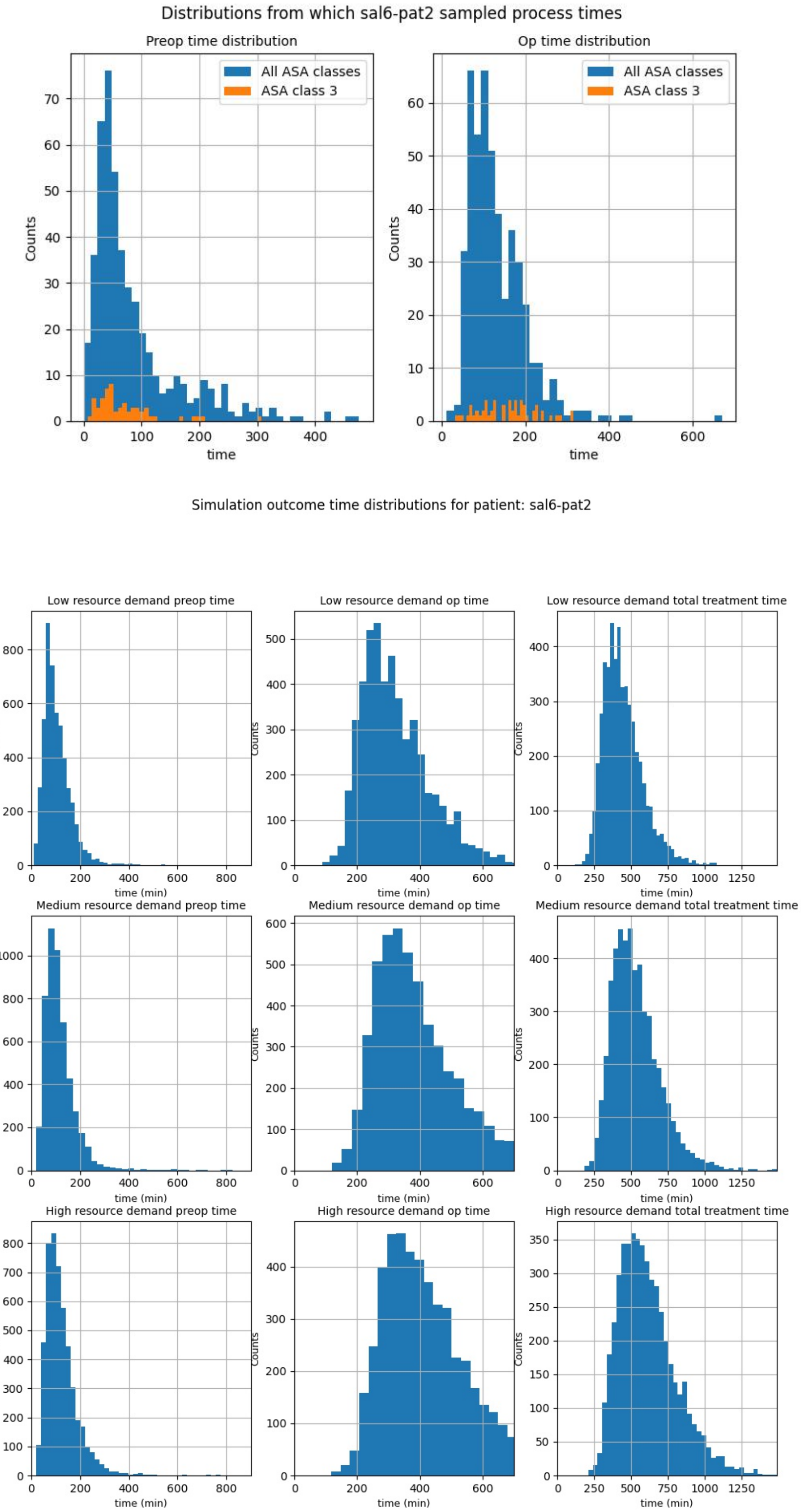


Figure B.7: Process time distribution and corresponding outcome distributions

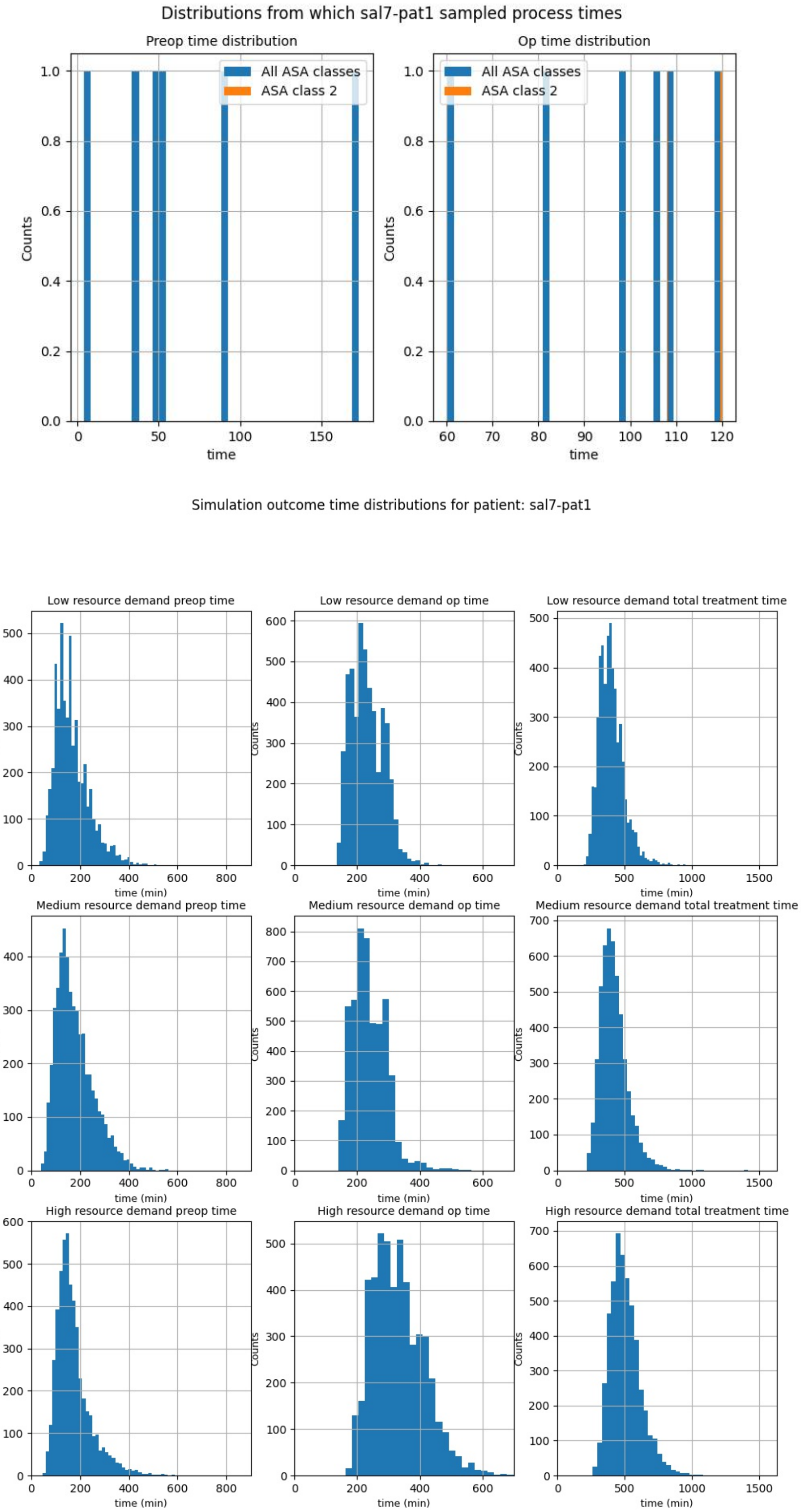


Figure B.8: Process time distribution and corresponding outcome distributions

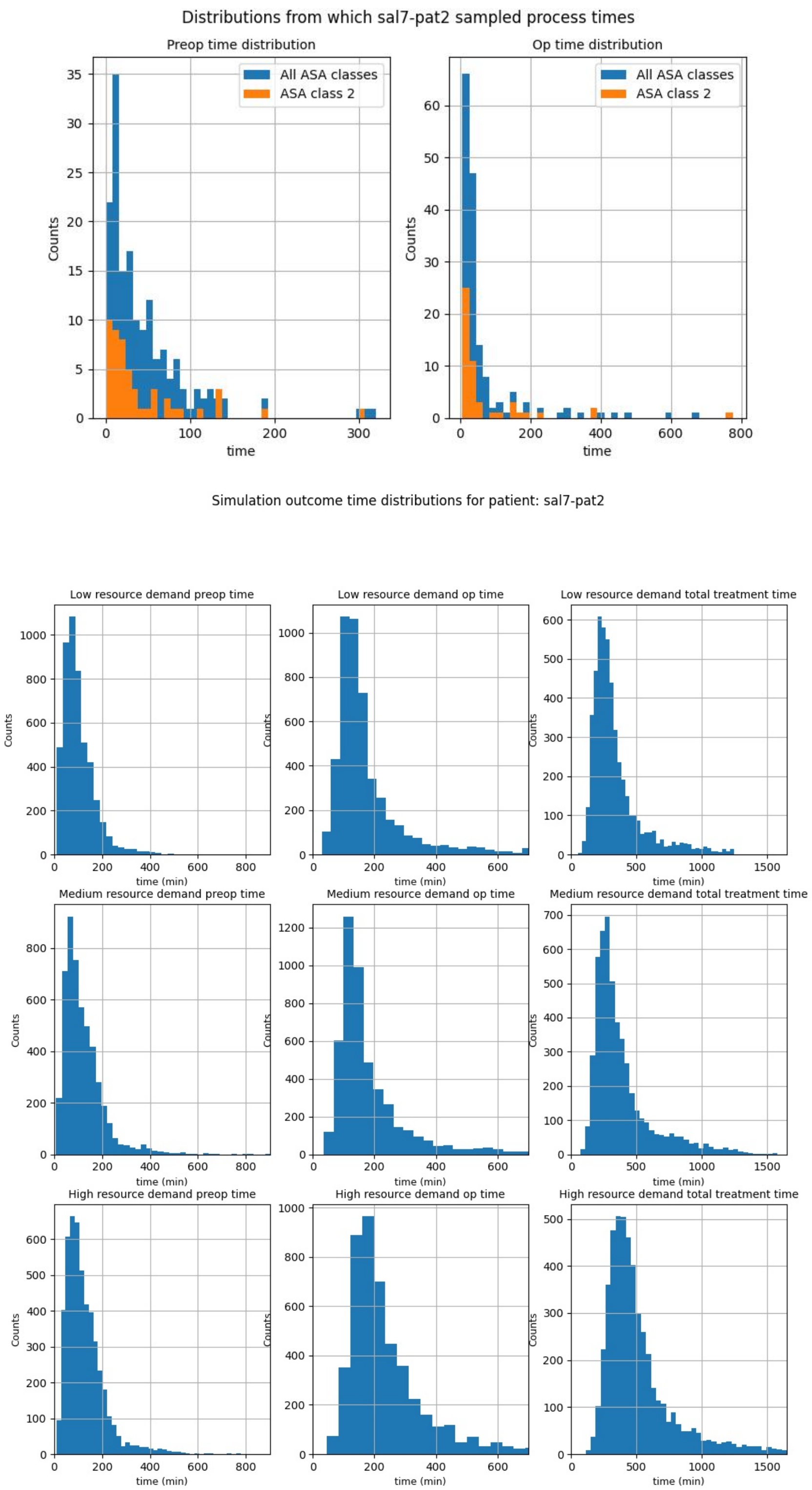


Figure B.9: Process time distribution and corresponding outcome distributions

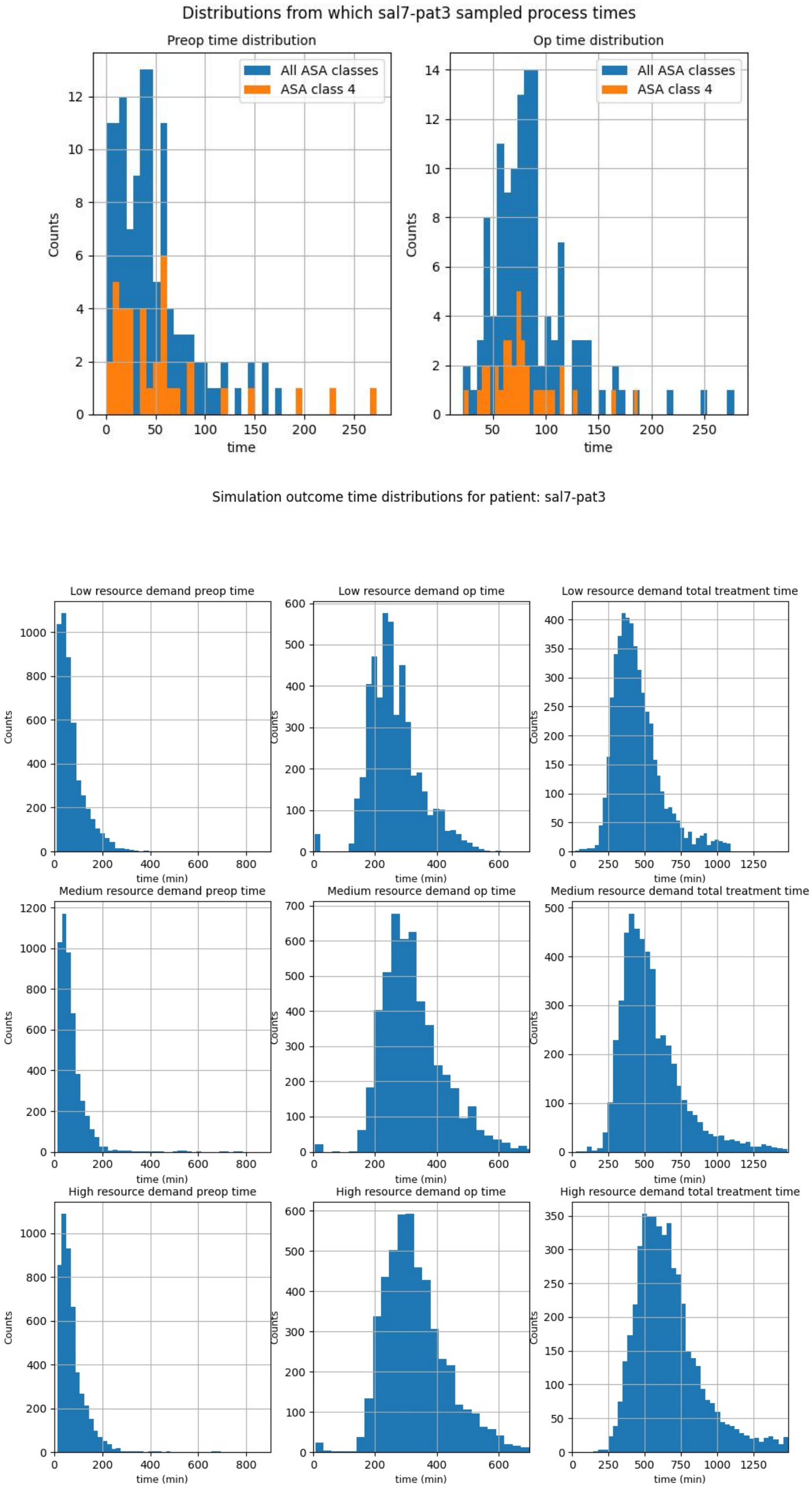


Figure B.10: Process time distribution and corresponding outcome distributions

C

Patient Name	Preop Start	Preop End	Surgery Start	Surgery End
sal4-pat1				
Low	07:14	9:57	9:59	15:08
Medium	07:14	9:52	09:53	16:02
High	07:14	10:09	10:13	17:00
Actual outcome	07:40	07:42	08:20	10:57
sal4-pat2				
Low	10:54	12:30	15:19	20:29
Medium	10:54	12:32	16:13	22:30
High	10:54	12:39	17:05	23:56
Actual outcome	09:03	11:08	11:15	17:20
sal5-pat1				
Low	07:15	10:21	10:22	13:57
Medium	07:15	10:26	10:26	14:49
High	07:15	10:44	10:46	15:41
Actual outcome	07:17	07:19	07:45	10:49
sal5-pat2				
Low	11:44	13:13	14:24	17:17
Medium	11:44	13:33	15:13	18:20
High	11:44	13:34	15:57	20:23
Actual outcome	09:40	11.34	11:49	15:02
sal5-pat3				
Low	15:51	17:24	18:06	21:49
Medium	15:51	17:49	18:57	22:48
High	15:51	17:53	20:44	01:57
Actual outcome	13:30	14:00	16:06	20:50
sal6-pat1				
Low	07:01	8:44	8:44	14:04
Medium	07:01	8:54	08:54	14:37
High	07:01	08:29	08:29	15:58
Actual outcome	07:03	07:30	07:53	12:20
sal6-pat2				
Low	15:08	16:52	17:08	22:31
Medium	15:08	17:04	17:25	23:57
High	15:08	17:11	18:08	01:18
Actual outcome	07:48	12:30	13:18	17:30
sal7-pat1				
Low	07:07	09:52	09:52	13:44
Medium	07:07	10:07	10:07	14:06
High	07:07	09:59	09:59	15:31
Actual outcome	07:29	07:32	08:32	12:36
sal7-pat2				
Low	12:29	14:10	14:48	18:07
Medium	12:29	14:29	15:20	18:51
High	12:29	14:36	16:19	20:59
Actual outcome	10:36	13:00	13:25	14:45
sal7-pat3				
	15:04	16:18	18:10	22:33
Medium	15:04	16:11	18:42	00:08
High	15:04	16:18	20:33	02:06
Actual outcome	11:31	14:18	15:20	18:25

Table C.1: Predicted outcome for low, medium and high resource requirements and the actual schedule outcomes for each patient in surgery rooms 4,6,7