Optimising the Operation of Hospitals through Process-related Data Analysis using the Example of Intra-Hospital Patient Transport

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Abstract

As secondary processes, organisational healthcare processes support the primary medical processes in hospitals. In principle, increasingly digitised processes enable data-driven process improvements. However, dealing with with real-world process data is an ongoing challenge in research due to complexity. In addition, approaches rarely use real-world data to analyse and support the decision-making to improve organisational processes in hospitals.

This thesis examines the benefits of data-based analysis and recommendations for improving the operation of hospitals, using the example of the intra-hospital patient transport, as this process plays a central role in the timely and efficient provision of medical care. Capacity planning is particularly important in the context of this logistics process and process data can show how the allocation of resources meets transport requirements. Currently, there exist only a few approaches that provide data-driven, automated solutions to support process redesign, and these limited approaches typically require significant effort in modelling complex processes and systems. To enable autonomous learning and process optimisation, this thesis explores the use of a combination of an artificial neural network and a metaheuristic algorithm to optimise capacity planning in intra-hospital patient transport based on knowledge from process mining analysis.

A real-world dataset of the German hospital "Klinikum Magdeburg gGmbH" (700 to 800 beds) including 3.5 years of process information over 256,266 accompanied, completed patient transports involving more than 69,000 patients, serves as a case study. Hospital experts are also involved in the investigations. Currently, almost 35% of patient transports in the case study hospital arrive delayed. A process mining analysis helps to unveil problems, understand the key factors affecting the process and to derive already potential qualitative improvement ideas. However, there are challenges in evaluating planning alternatives quantitatively prior to practical implementation. To solve this issue, a multilayer perceptron artificial neural network is developed from the real-world dataset to conduct predictions of delayed transports on a day of the week basis. Data preprocessing is carried out to aggregate transport-specific information into hourly information to be used as input and label data for the prediction model training, validation and testing. Subsequently, a genetic metaheuristic algorithm is used to adapt hourly input variables to reduce the number of delayed transports predicted by the model over the course of the day. The number of active transporters, the number of planned transports, and the automation rate of transport dispatching serve as example input variables that can be altered. Without adding additional resources to the process, the novel process redesign approach achieves a theoretical reduction in delayed transports on an example day of the week (average Monday) ranging from 27% to 42% just by reallocating resources. The performance of both the multilayer perceptron prediction model and the genetic algorithm, together optimising the capacity planning, are validated using various metrics.

Before practical implementation, certain performance metrics of the prediction model still need to be improved, mainly by increasing the volume of training data. Further inclusion of domain expertise to the specification of objective functions also has a positive impact on the practical implications of the optimisation approach. However, the approach developed is already feasible to improve capacity planning for individual days of the week, is transferable to other processes and organisations, and serves as a benchmark for further research into the data-based optimisation of organisational healthcare processes.

Kurzzusammenfassung

Organisatorische Gesundheitsprozesse unterstützen als Sekundärprozesse die primären, medizinischen Prozesse in Krankenhäusern. Grundsätzlich ermöglichen zunehmend digitalisierte Prozesse datengetriebene Prozessverbesserungen. Allerdings ist der Umgang mit realen Prozessdaten aufgrund der Komplexität eine fortwährende Herausforderung für die Forschung. Darüber hinaus werden bei den Ansätzen nur selten Realdaten zur Analyse und Unterstützung der Entscheidungsfindung für die Verbesserung der organisatorischen Prozesse in Krankenhäusern genutzt.

In dieser Thesis wird der Nutzen datengestützter Analysen und Empfehlungen zur Verbesserung des Krankenhausbetriebs am Beispiel des innerklinischen Patiententransports untersucht, da dieser Prozess eine zentrale Rolle bei der rechtzeitigen und effizienten Bereitstellung medizinischer Versorgung spielt. Die Kapazitätsplanung ist im Rahmen dieses logistischen Prozesses besonders wichtig, und Prozessdaten können zeigen, inwiefern die Zuweisung von Ressourcen den Transportanforderungen entspricht. Derzeit gibt es nur wenige Ansätze, die datengestützte, automatisierte Lösungen zur Unterstützung der Prozessverbesserung bieten. Zudem erfordern diese begrenzten Ansätze in der Regel einen erheblichen Aufwand bei der Modellierung komplexer Prozesse und Systeme. Um autonomes Lernen und Prozessoptimierung zu ermöglichen, wird in dieser Thesis der Einsatz einer Kombination aus einem künstlichen neuronalen Netz und einem metaheuristischen Algorithmus zur Optimierung der Kapazitätsplanung im innerklinischen Patiententransport auf der Grundlage von Erkenntnissen aus einer Process Mining-Analyse untersucht.

Als Fallstudie dient ein Realdatensatz des deutschen Krankenhauses "Klinikum Magdeburg gGmbH" (700 bis 800 Betten) mit 3,5 Jahren Prozessinformationen über 256.266 begleitete, abgeschlossene Patiententransporte mit mehr als 69.000 Patienten. In die Untersuchungen sind auch Krankenhausexperten eingebunden. Derzeit kommen im betrachteten Krankenhaus fast

35% der Patiententransporte verspätet an. Eine Process Mining-Analyse hilft, Probleme aufzudecken, die Schlüsselfaktoren, die den Prozess beeinflussen, zu verstehen und qualitative Verbesserungsideen abzuleiten. Allerdings gibt es Herausforderungen bei der quantitativen Bewertung von Planungsalternativen vor der praktischen Umsetzung. Um dieses Problem zu lösen, wird ein Multilayer-Perceptron (künstliches neuronales Netzwerk) auf Grundlage des Realdatensatzes entwickelt, um Vorhersagen über verspätete Transporte an Wochentagen treffen zu können. Dazu wird eine Datenvorverarbeitung durchgeführt, um transportspezifische Informationen zu stündlichen Informationen zu aggregieren, die als Eingabe- und Labeling-Daten für das Training, die Validierung und das Testen des Vorhersagemodells verwendet werden. Anschließend wird ein genetischer (metaheuristischer) Algorithmus verwendet, um stündliche Eingabevariablen anzupassen und die vom Modell vorhergesagte Anzahl verspäteter Transporte im Verlauf des Tages zu reduzieren. Die Anzahl der aktiven Transporteure, die Anzahl der geplanten Transporte oder die Automatisierungsrate der Transportdisposition dienen beispielhaft als Eingabevariablen, die angepasst werden können. Ohne zusätzliche Ressourcen in den Prozess einzubringen, erzielt der neuartige Planungsansatz eine Reduzierung der verspäteten Transporte an einem beispielhaften Wochentag (durchschnittlicher Montag) von theoretisch 27% bis 42%, indem lediglich die vorhandenen Ressourcen reallokiert werden. Die Leistung sowohl des Multilayer-Perceptron Vorhersagemodells als auch des genetischen Algorithmus, die zusammen die Optimierung der Kapazitätsplanung ermöglichen, wird mit verschiedenen Metriken validiert.

Vor der praktischen Umsetzung müssen jedoch bestimmte Leistungskennzahlen des entwickelten Vorhersagemodells noch weiter verbessert werden, hauptsächlich durch Erhöhung des Volumens an Trainingsdaten. Die weitere Einbeziehung von Expertenwissen in die Spezifikation der Zielfunktionen wirkt sich ebenfalls positiv auf die praktische Aussagekraft des Optimierungsansatzes aus. Der entwickelte Ansatz ist jedoch bereits für die verbesserte Kapazitätsplanung einzelner Wochentage umsetzbar, ist auf andere Prozesse und Organisationen übertragbar und dient als Benchmark für weitere Forschungen zur datenbasierten Optimierung organisatorischer Prozesse im Gesundheitswesen.

Declaration of Originality

The doctoral thesis covering the subject "Optimising the Operation of Hospitals through Process-related Data Analysis using the Example of Intra-Hospital Patient Transport" represents my own independent work. I only used the sources and aids indicated without any impermissible assistance by third persons. In particular, I have indicated any and all contents taken over from other works either literally or in substance. I credit the use of *DeepL* (https://www.deepl.com/de/translator), *DeepL Write* (https://www.deepl.com/de/write) and *ChatGPT* (versions 3.5 and 4; https://chat.openai.com/) in helping me to review and revise my writing (vocabulary, grammar, spelling and punctuation). The use of *ChatGPT* to support programming tasks is mentioned in the thesis where applicable.

Karlsruhe, 07th July 2025	Tobias Peter Kropp
Place, date	Full name

Preface

As a researcher at the Institute of Technology and Management in Construction (TMB) in the professorship of Facility Management (FM) at the Karlsruhe Institute of Technology (KIT) in Germany, the overall work consists of improving the operation of buildings. With a multitude of processes and interdependencies between departments, staff and patients, as well as various multi-functional areas, hospitals are one of the most complex areas of facility management that furthermore affect people's health and are therefore particularly worthy of research (*Lennerts* 2009; *Lennerts* et al. 2005). I am very happy to be able to contribute to the improvement of hospital operation by submitting this thesis. It has been an adventure for me full of new experiences, with plenty of ups and downs, but the ups definitely steal the show.

I would particularly like to thank my doctoral supervisor, Kunibert Lennerts, for encouraging me in my topic selection, as well as his invaluable support, guidance, and collaboration throughout my time at the TMB. In addition, I would like to acknowledge the consistent and valuable feedback provided by Shiva Faeghinezhad and Rainer Sibbel, who served as co-supervisors, contributing to the improvement of the quality of my work. I want to extend my appreciation to Sascha Gentes, member of the examination committee, for his contribution and the time he dedicated.

Furthermore, I would like to thank Knut Borrmann and Tobias Hunger from the German hospital "Klinikum Magdeburg gGmbH", which served as case study hospital for my thesis, for their valuable expertise and the constructive discussions during our numerous project meetings.

Finally, I would like to express my deepest gratitude to my family and friends, especially my parents Hannelore and Edgar, my brother Raphael and last but not least my partner Julia for their unconditional love and support throughout my journey. I dedicate this work to my grandparents Agatha, Artur, Maria and Alfred.

Contents

Glossary

AdaDelta Adaptive Delta (optimisation algorithm). 44

Adam Adaptive Moment Estimation (optimisation algorithm). 44, 127

AHP-ANN (hybrid) Analytical hierarchy process and artificial neural network. 64

AI Artificial intelligence. 34

ALNS Adaptive large neighborhood search (optimisation algorithm). 60

ANN Artificial neural network. 5, 30, 35, 40, 77

BI Business intelligence. 24

BPM Business Process Management. 22

BPMN Business Process Modeling and Notations. 29, 82, 88

BPS Business process simulation. 51

CAFM Computer Aided Facility Management. 21

CNN Convolutional neural network (feed-forward neural network sub-type). 44

CRISP-DM Cross Industry Standard Process for Data Mining. 23

DES Discrete-event simulation. 32, 59

DFGs Directly-Follows Graphs. 29, 87

ECG Electrocardiogram (German: Elektrokardiogramm - EKG). 105

ED LOS Length of stay in the emergency department. 60, 66

ER Emergency room (equivalent emergency department). 54, 86

FM Facility Management / Facilities Management. 13

FTE Full-time equivalent. 61, 140, 146, 148, 162, 178

FUDI Functional diagnostics (specialised hospital departments). 112, 113

FUDI EKG Functional diagnostics cardiology (electrocardiogram - ECG). 105, 106, 115

GA Genetic algorithm (optimisation algorithm). 7, 49, 72, 90, 138

GEFMA German Facility Management Association. 21

GVNS Generalised variable neighborhood search (optimisation algorithm). 60

HIS Hospital information system. 3

IHPT Intra-hospital patient transport. 4, 16

ILP Integer linear programming. 63

IP Integer programming. 60

ISO International Organization for Standardization. 14

KHZG Hospital Future Act (German: Krankenhauszukunftsgesetz). 3

KPI Key Performance Indicator. 18, 46, 96

LNS Large neighbourhood search (optimisation algorithm). 63

LSTM Long-Short Term Memory (recurrent neural network sub-type). 45

MAE Mean absolute error. 130

MDLS Multi-directional local search (optimisation algorithm). 61

MEB Mean error bias. 132

MIP Mixed-integer programming. 59

ML Machine learning. 30, 34

MLP Multilayer perceptron (feed-forward neural network sub-type). 6, 40, 72, 90, 125

MSE Mean squared error. 126

OPIK Research Project at the Karlsruhe Institute of Technology (Germany): Optimisation and Analysis of Processes in hospitals (German: Optimierung und Analyse von Prozessen im Krankenhaus). 4, 15

OR Operating room. 17, 86, 112

PM Process Mining. 67

QR code Quick response code. 158

ReLU Rectified Linear Unit (activation function). 42, 126

RFID Radio frequency identification. 158

RMSProp Root Mean Square Propagation (optimisation algorithm). 44

RNN Recurrent neural network. 40

SD System dynamics. 32

SGD Stochastic Gradient Descent (optimisation algorithm). 44

Tanh Hyperbolic tangent (activation function). 42

UML Unified Modelling Language. 29

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Part I

Preliminaries

1 Introduction

The increasing emphasis on patient-centred care within healthcare organisations highlights the importance of providing efficient and timely healthcare services to patients. In addition, the increasing demand for healthcare services and the continuing cost pressures on hospitals and other healthcare organisations have led to a strong need to improve the quality and efficiency of healthcare processes. Two types of processes that occur in hospitals are distinguished by *de Roock & Martin* (2022) and *Lenz & Reichert* (2007): medical treatment processes, which are directly related to the patient's health, and organisational processes. Seamlessly functioning organisational processes are the foundation for the success of medical processes (*Lenz & Reichert* 2007). According to *Lennerts* et al. (2003), in hospitals, medical processes can also be seen as primary processes and all processes that support these primary processes can be seen as secondary processes (see subsection 2.2.1).

As opposed to other organisations, healthcare processes are complex, ad hoc, dynamic, and affect people's health and lives (*Munoz-Gama* et al. 2022; *Rebuge & Ferreira* 2012). In addition, processes can prove to be much more complex in practice than originally planned or assumed (*Munoz-Gama* et al. 2022). Supporting software systems, like hospital information systems (HIS), hold vast amounts of data from patients and monitoring systems that could be transformed into actionable information that enables value-based decision-making (*Munoz-Gama* et al. 2022).

1.1 Motivation

In Germany, the recent push by the federal government to digitise hospitals through the Hospital Future Act (Krankenhauszukunftsgesetz - KHZG) and the concurrent development of innovative digital and resource-saving solutions offers tremendous opportunities to optimise healthcare processes.

This development can help to considerably reduce healthcare costs and at the same time to improve patient safety and satisfaction. To assess the desired impact of digitisation, it is important to analyse the data collected from the digitised processes, use the findings to improve operational performance, and derive or monitor benchmarks. Nevertheless, for a risk-averse sector like healthcare, which interacts with human lives, the pace of application of analytical methods has been slow (*Scheinker & Brandeau* 2020).

Analysing process-related data using process mining techniques can provide valuable insights into how healthcare processes are actually performed, helping to improve the services provided (*Martin* et al. 2020; *van der Aalst* 2016). Process mining has been developed mainly over the last two decades (*van der Aalst* 2016). However, research on process redesign in healthcare (the last stage of process mining projects) is scarce, as literature focuses mainly on the analysis stage (*de Roock & Martin* 2022). Furthermore there are explicit shortages in research on organisational processes in healthcare (*de Roock & Martin* 2022). According to *Munoz-Gama* et al. (2022), dealing with real-world data is an ongoing challenge in research. This highlights the importance of this thesis, as an approach to real-world data-based process redesign using the example of a selected key organisational healthcare process, is provided.

This thesis examines the benefits of data-based analysis and data-based recommendations for improvement in hospital operation using the intra-hospital patient transport (IHPT) process as an example. This exceeds the current scope of the reviewed IHPT literature, as most research approaches do not use real-world data or only broader statistics of real-world data (see subsection 4.3). According to *Abel* (2009), *Beckmann* et al. (2004), *Hendrich & Nelson* (2005), and *Ulrich & Zhu* (2007), IHPT is an important organisational process in healthcare. In addition, the IHPT process impacts the costs in hospitals (*Storfjell* et al. 2008). Research at the Karlsruhe Institute of Technology (Germany) in relation to the project "OPIK", that aims to investigate on the analysis and optimisation of secondary (i.e. organisational) hospital processes (see also subsection 2.2.1), classifies the costs (i.e. staff and material costs) of IHPT in the middle of the spectrum of all organisational processes (*Abel* 2009; *Diez* 2009). However, delays in the transport process (regardless of the root cause) not only result in idle time for directly or indirectly related medical equipment and medical/technical staff, but also reduce patient satisfaction due to longer waiting times, leading to possible appointment cancellations and impacts on patient health (see also subsection 2.2.2).

To support the planning in the context of the IHPT process in a hospital, it is necessary to analyse how the capacity used in logistics activities meets the transport requirements. Process mining helps to identify bottlenecks and inefficiencies in processes (*van der Aalst* 2016), which can support the hospitals to improve their capacity allocation accordingly. Generally, analysis based on process mining are intended to create a basic understanding of the process to propose data-based process improvements (*van der Aalst* 2022). However, for the quantified evaluation of process alternatives, further prediction and optimisation methods are required (*van der Aalst* 2018).

1.2 Objectives and Outline of the Work

According to *van der Aalst* et al. (2016), improving or redesigning a process can be seen as a problem within certain constraints for which an optimised solution has to be found from a variety of possible solutions (see subsection 3.3). The goal is to establish and validate, through a case study, a practical approach that combines multiple methods to generate process knowledge and use this knowledge to improve the planning and execution in the context of the IHPT process.

This thesis aims to demonstrate and communicate the advantages of redesigning IHPT capacity planning by combining an artificial neural network (ANN) and a metaheuristic optimisation algorithm in IHPT with techniques recommended in literature using knowledge derived via process mining from real-world IHPT data. In addition, the results and limitations of the novel process redesign approach developed within this work also need to be transferable to other organisational processes and further organisations in healthcare. The underlying data for the case study is provided by the German hospital "Klinikum Magdeburg gGmbH", that has around 700 to 800 beds (see subsection 5.1).

The research questions that this thesis particularly aims to answer and which are derived from a comprehensive literature review in subsection 4.3 are defined as follows:

- Research questions towards process analysis of IHPT (*Kropp* et al. 2024a):

  RQ 1: How can process mining in real-world datasets with multiple case- and event-related attributes help to analyse capacity planning in IHPT beyond process discovery?

  RQ 2: What are the important factors and limitations to consider when proposing capacity improvement measures in IHPT based on real-world datasets with multiple attributes related to case and event?

- Research questions towards process redesign of IHPT (*Kropp* et al. 2024b):

  RQ 3: Is a combination of an ANN and a metaheuristic algorithm applicable to reliably improve capacity planning in the IHPT in terms of practical performance metrics through more efficient allocation of resources?

  RQ 4: What are the important factors and limitations to consider when applying the combination of an ANN and a metaheuristic algorithm to derive a reliable improvement of the IHPT process?

A main contribution of this work is to apply process mining methods to real-world data obtained from the IHPT-supporting software system in the case study hospital, as an example of an organisational process analysis. Additionally, the prerequisites for holistic data capturing to enable process mining methods from different perspectives (e.g. a more patient-oriented analysis) of the IHPT are highlighted. The analysis addresses process efficiency, delays, transport duration, throughput times between process steps, as well as the identification of problem points, their root causes and interrelationships of attributes. The findings can help to evaluate the appropriateness of the transport assignments and to assess patients' satisfaction. This work also provides important insights regarding limitations and challenges in using process mining from a managerial point of view.

To quantitatively evaluate process improvement alternatives, this work combines knowledge from the process mining-based process analysis with methods from the field of ANN. Quantitative process predictions are enabled through a self-developed ANN in the form of a multilayer perceptron (MLP).

In addition, optimisation methods, in the form of a metaheuristic genetic algorithm (GA), are applied to select the best alternative from a pool of different process improvement options. The data-driven approach developed in this thesis allows concrete suggestions for improving IHPT capacity management to be made to hospital stakeholders before practical measures are implemented.

Figure 1.1 visualises the structure of this thesis. Part I provides the introduction to this work within the current section 1.

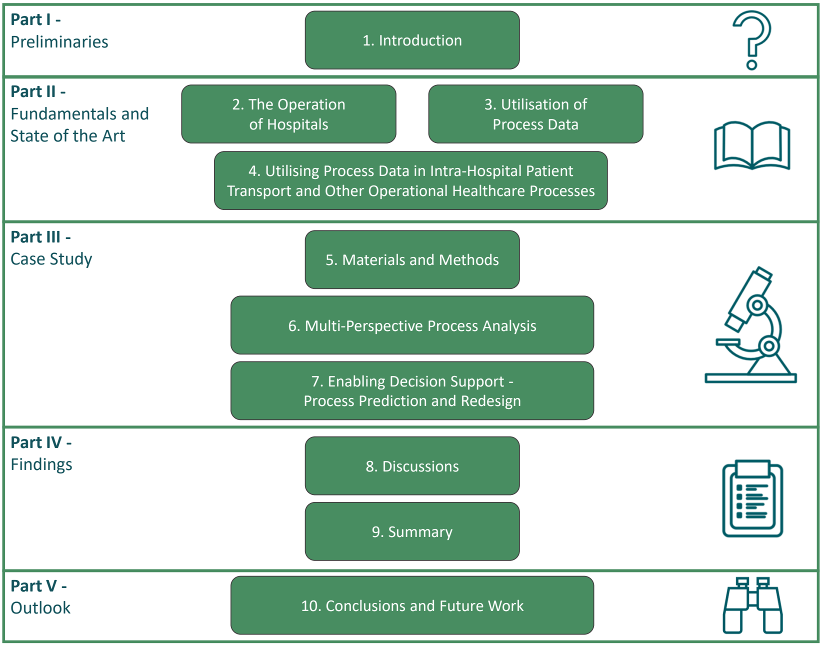

Figure 1.1: Structure of the work (own visualisation).

Part II presents the fundamentals of hospital operation in section 2 and of the utilisation of process data in section 3. As methods in process data utilisation such as process mining, ANN and metaheuristic optimisation algorithms are not necessarily familiar in the management field of hospital operation, the associated fundamentals are presented in more detail. Section 4 reviews the state of the art of using process data in IHPT and other organisational healthcare processes, then derives the research gaps and questions that will be addressed by this thesis.

Part III presents in section 5 the materials and methods used for the real-world data-based case study conducted within this work. Section 6 deals with a detailed multi-perspective IHPT process analysis using process mining. Section 7 presents a novel approach to process redesign that enables data-based decision support in IHPT capacity planning.

Part IV discusses in section 8 the results, as well as the transferability and limitations of the research conducted. Section 9 summarises the thesis.

Part V draws in section 10 a conclusion to this thesis and provides an outlook to future work.

Part II

Fundamentals and State of the Art

2 The Operation of Hospitals

This section presents general information on the relevance of German hospitals in subsection 2.1 to set the rough frame. The fundamentals of hospital operation processes and important IHPT process will be introduced in subsection 2.2. In subsection 2.3 the general challenges of optimising the operation of hospitals are described.

2.1 German Hospitals and their Impact

In 2022, there were about 1900 hospitals in Germany with about 480,000 beds. Of these, about 26,000 are intensive care beds and about 7,500 are intermediate care beds (*Federal Statistical Office - Germany* 2023b). In 2022, nearly 17 million cases were treated in these hospitals (each patient is counted for each hospital stay), with an average length of stay of about 7.2 days (*Federal Statistical Office - Germany* 2023b). The bed occupancy rate in Germany in 2022 was just under 70% (*Federal Statistical Office - Germany* 2023b). At the same time, there were nearly one million full-time equivalent employees on an annual average, of which approximately 18% were medical and 82% were non-medical (*Federal Statistical Office - Germany* 2023a). This means that, on average, more than 500 full-time equivalent employees per hospital are exposed to a wide variety of hospital processes, patients, staff, and other resources. Hospitals are also important energy consumer in the German building sector. German hospitals consume an average of around 6,000-10,000 kilowatt-hours of electricity and 25,000-29,000 kilowatt-hours of heat per bed per year, which is equivalent to the annual heat consumption of two modern single-family homes (*Energy Agency NRW* 2009; *Research Services of the German Bundestag* 2023; *Stiftung viamedica* 2009). The gross costs for the German hospitals, were at around 127 billion euro in 2021 (*Federal Statistical Office - Germany* 2022a), which means that if German hospitals reduce their costs by just 1%, the savings will be in the billions. This shows the great leverage that can be achieved in hospitals when it comes to the efficient use of resources or the execution of processes. Around 62% of the gross costs in German hospitals can be attributed to staff costs and 38% to material costs (*Federal Statistical Office - Germany* 2022a). More detailed percentage allocations of staff costs can be seen in Figure 2.1 and of material costs in Figure 2.2.

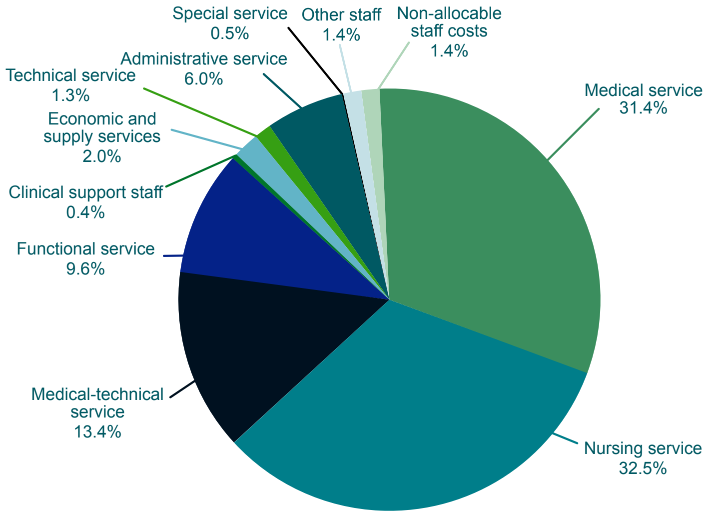

Figure 2.1: Percentage allocations of staff costs in German hospitals. Adapted from *Federal Statistical Office - Germany* (2022b).

Hospitals have unique operating conditions and a set of complex goals because, first, they are open 24 hours a day, 7 days a week; second, they provide particularly complex and human-centred services; and third, a mistake in a hospital can cost a life (*Lennerts* 2009). The large number of processes in hospitals (both primary and secondary processes) as well as the interdependence of the related objectives differentiates hospitals from many other business ventures or buildings in general (*Lennerts* 2009). Overall, a hospital is a complex and adaptive system in which clinical practice, information organisation and management, research, education, and professional development are interdependent and coexist in an evolving environment of multiple interacting systems (*Alberto* et al. 2017; *Sturmberg* et al. 2012).

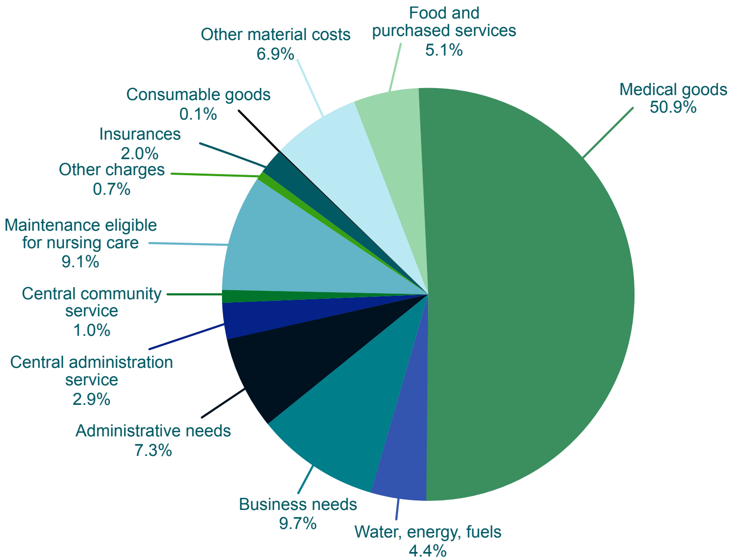

Figure 2.2: Percentage allocations of material costs in German hospitals. Adapted from *Federal Statistical Office - Germany* (2022b).

2.2 Hospital Operation Processes

First, a general view and summary of hospital operation processes is presented in subsection 2.2.1. Then the fundamentals of IHPT with associated challenges and impacts are described in subsection 2.2.2, as this process will be of particular interest for the main body of this thesis.

2.2.1 General View

It can be assumed that one third of hospital costs are not related to core/primary (i.e. medical) processes, but to non-core/secondary (i.e. supporting) processes (*Lennerts* et al. 2003). The literature often refers to supporting processes in hospitals as organisational processes (*de Roock & Martin* 2022; *Lenz & Reichert* 2007). However, they can also be defined as Facility Management (FM) processes that reflect all the remaining services in a hospital that are not direct healthcare services performed to cure patients (*Lennerts* 2009; *Lennerts* et al. 2003; *Lennerts* et al. 2005).

The *International Organization for Standardization (ISO)* defines "Facility Management" or "Facilities Management" in the ISO 41011:2017-04 (*ISO 41011:2017-04* 2017)[1] as the "organizational function which integrates people, place and process within the built environment with the purpose of improving the quality of life of people and the productivity of the core business.".

In Hospitals, where the primary processes are patient-centric, FM aims to meet the patients' needs by providing healthcare FM service support without interrupting the medical emergency, surgical, specialized chronic care, and rehabilitation services (*Xie* et al. 2022). This is also called patient-centric FM and according to *Xie* et al. (2022), who enhance the general FM definition of the *ISO*, defined as "the integration of processes within a healthcare organization to deliver and maintain required services which support efficient and timely medical care activities to meet patients' needs".

Figure 2.3 from *Lennerts* (2009) shows 29 hospital specific FM products in Germany (the displayed products can vary per country) that reflect the whole range of supporting services provided for the benefit of costumers in hospitals, where patients are considered as ultimate customers. Clinical units can be considered as intermediate customers to which the FM can allocate process-oriented costs (*Lennerts* 2009). The FM products from Figure 2.3 are sub-grouped into three categories according to the cost allocation type (*Lennerts* 2009):

- products that can be reasonably allocated using floor space as the basis for allocation.
- products that can be quantified numerically, although data and system limitations mean that some products that can theoretically be quantified have to be allocated on a space basis,
- products that are used or performed only at the request of the customer or are not used on a regular basis.

[1] The ISO 41011:2017-04 has been adopted by the *European Committee for Standardization (CEN)* as EN ISO 41011:2018-05, which in turn has been adopted by the *German Institute for Standardization (DIN)* as DIN EN ISO 41011:2019-04, replacing the former DIN EN 15221-1:2007-01 in Germany (*DIN EN ISO 41011:2019-04* 2019).

The extensive range of services (see Figure 2.3) shows how broad the spectrum of FM processes in hospitals is. In their investigations related to the research project "OPIK" (see also subsection 1.1), *Abel* (2009) and *Diez* (2009) categorise the supporting services in hospitals into similar 29 FM products, too. *Diez* (2009) further subdivides into a thirtieth product that is named "administration, controlling, other", which characterises services specifically related to the organisation, documentation and control of the primary (i.e. medical) process, but also includes social services, patient support and certain infrastructure services. In general, the requirements of FM, and thus the range of supporting services (i.e. FM products/processes), can vary because they are defined by the primary processes they support (*Lennerts* 2009).

Allocation basis: floor space in m²
outside facilities
operation
building maintenance
technical maintenance
basic rent
cleaning
pest control
security

Order-related allocation
office supplies
caretaker services
reprographics services
mail services
removal services

Allocated on quantity basis	
waste disposal	ton of waste
bed conditioning	bed
information technology services	personal computer
fleet management	vehicle
hygiene advice	analysis
maintenance of medical equipment	value
cooling service	kilowatt-hour
broadcasting service	television
catering	meal
sterilisation services	sterile unit
power supply	kWh
telephone services	extension
patient transport	transport
heating supply	kWh
laundry services	ton linen
water supply	m³

Figure 2.3: Classification of the 29 FM products in Germany according to their cost allocation type and their cost proportions. Adopted from *Lennerts* (2009).

Professional FM methods in hospitals can help to achieve efficiency increases and cost reductions and have good leverage effects due to the high absolute FM costs in hospitals (*Lennerts* et al. 2003). In the course of this thesis a commonly used term for secondary/operational/non-core/FM processes in healthcare is "organisational processes", but this term also refers to the FM products/processes and definitions presented in this subsection. The mainly used term in healthcare literature is "organisational processes", so this term will be used interchangeably in this thesis.

2.2.2 Intra-Hospital Patient Transport

Intra-hospital patient transport (IHPT) is a hospital logistics process (*Beaudry* et al. 2010), see also Figure 2.3 in subsection 2.2.1. It is a challenging task because it involves medical aspects and requires coordination between different functional areas to avoid long waiting times and medical complications for patients (*Beaudry* et al. 2010). In general, it is estimated that hospital logistics-related costs (all logistics, not only IHPT) account for up to 46% of a hospital's total operating budget (*Bourgeon* et al. 2001; *Landry & Philippe* 2004).

Due to its widespread use, IHPT plays a central role in providing timely and efficient medical treatments (*Beckmann* et al. 2004; *Hendrich & Nelson* 2005; *Ulrich & Zhu* 2007). IHPT refers to the internal transfer of patients within a hospital, for example between different wards and functional departments (*Nakayama* et al. 2012). The quality of this service and its associated processes have a major impact on clinical outcomes and patient satisfaction (*Beckmann* et al. 2004; *Ulrich & Zhu* 2007). Efficient patient transport also ensures patient safety and efficient treatment (*Kuchera & Rohleder* 2011). According to *Alizadeh Sharafi* et al. (2021) and *Parmentier-Decrucq* et al. (2013), inefficient transport processes can cause a significant number of adverse incidents in the transport of critically ill patients. Findings from a cross-sectional analysis of 176 reports with 191 IHPT incidents showed that 31% of these reports highlighted adverse outcomes, including major physiological derangement, patient/relative dissatisfaction, prolonged hospital stay, physical/psychological injury and death (*Beckmann* et al. 2004). Around 61% of the 191 incidents rooted in patient/staff management issues and 39% in equipment problems. According to a study by *Picetti* et al. (2013), of 288 investigated transport cases involving brain-injured patients, 36% had at least one significant (mainly hemodynamic) complication during transportation. There can be many reasons behind complications and they are not always related to organisational issues in IHPT. However, as problems frequently occur during the IHPT, special attention must be paid to the process. *Meephu* et al. (2023) highlighted that patient complications may occur due to increased waiting time as a result of insufficient service capacity in IHPT.

The duration of transport and associated waiting times are identified as important determinants of patients' satisfaction by *Hanne* et al. (2009). Next to the duration of transport processes, *Chang* et al. (2010) highlight respiratory, circulatory, and equipment as four safety indicators in IHPT related to emergency departments.

Sibbel (2004) derived from literature that, in general, the capacity (i.e. performance capability or performance potential) of human-related services is mainly determined by personnel (i.e. employees) and material/infrastructural (i.e. property, buildings, facilities, equipment, medical and technical devices, beds, etc.) resources. Nevertheless, the organisation of a hospital and the organisation of its processes also affect the service capacity, as summarised by *Sibbel* (2004).

Regarding IHPT (and also other processes), relevant process information can be captured in the supporting software systems during the planning and execution of the process. Information collected and stored in so-called "event logs" (see subsection 3.1.4) can be very detailed, i.e. specific to individual events that took place within a transport ("event attributes"), or somewhat higher-level, i.e. transport case-specific ("case attributes") (*van der Aalst* 2016). There may also be other general information about the process, such as general responsibilities or guidelines in the process, that are not directly related to, e.g. a transport case or the specific events during the transport process of that case.

In *Kropp* et al. (2023), *Kropp* et al. (2024b), and *Kropp* et al. (2024a), which is work integrated in this thesis, the necessity of continuous data-based monitoring of workflows to improve the IHPT is pointed out and it is highlighted that inappropriate resource allocation in a German hospital (i.e. the case study hospital of this thesis) causes waiting times in IHPT. *Jaroon* (2018) has already shown in a case study of a hospital in southern Thailand that the use of a computer-based online patient transfer system could help to improve work efficiency and lead to an increase in the overall on-time service delivery rate from over 56% to around 66% (equals a relative increase of around 18%).

Haldar et al. (2019) examined the reasons for delayed IHPT cases and the implications for operation rooms' (OR) efficiency. Data was collected by an independent observer and transport cases were labeled delayed if the delay was greater than 35 minutes (*Haldar* et al. 2019). The most common reasons for delays were unavailable elevators, transporter-associated delays during shift changeovers, or involvement of the pediatric ward (*Haldar* et al. 2019). The two main effects of IHPT delays observed in operation rooms were routine cases being extended beyond the scheduled time (i.e. overrunning of the theatres) and the cancellation of scheduled later cases for the day (*Haldar* et al. 2019). The efficiency in OR functioning could be improved (i.e. more than 6% reduction in delayed arrivals to the OR and a similar reduction in overrunning OR) with feasible measures such as increasing the summon times (i.e. summoning the patient by telephone from the pick-up location to the OR) or raising awareness among transporters and nurses (*Haldar* et al. 2019). The Hawthorne effect (the phenomenon that observing and documenting a process can lead to marked differences in the performance of the people involved) is not eliminated in the study of *Haldar* et al. (2019). Delays in operating theatres can also result in large financial losses. According to a literature review on the OR costs conducted by *Smith* et al. (2022), the costs of an OR in the year of 2022 are on average around 46 US dollar per minute with a standard deviation of around 32 US dollar. However, the types of costs taken into account varied from study to study (*Smith* et al. 2022). Cost types considered frequently in literature were staff, maintenance and equipment costs (*Smith* et al. 2022).

According to *Klein & Thielen* (2024), no general IHPT problem can be defined due to the heterogeneous nature of hospital organisations and the different approaches and goals considered in literature (see also subsection 4.2.1). For IHPT problems, which are typically characterised by complex models, excessively long computation times for optimisation need to be overcome to increase practical applicability (*Klein & Thielen* 2024).

2.3 Hospital Operation Optimisation Challenges

Optimisation of FM (i.e. organisational) processes can take many forms and in addition to saving costs by optimising individual FM processes, savings can also be achieved by improving the coordination of primary and secondary processes (*Lennerts* 2009). Furthermore, benchmarking with other healthcare facilities provides a way to identify processes that can be improved (*Lennerts* 2009). The performance of facilities determines the condition of the services provided to the end users of the facilities and can be expressed through key performance indicators (KPIs) (*Lai & Man* 2017). FM performance data can be collected through the measurement of physical parameters (e.g. indoor air temperature, no. of completed work orders per staff), the gathering of end-user perceptions (e.g. perceived thermal comfort, perceived waiting times), or a combined approach (*Lai & Man* 2017; *Lai & Yuen* 2019). The data can be analysed to evaluate facility performance, and the resulting insights can provide valuable feedback to FM stakeholders at various levels - strategic (e.g., department head), tactical (e.g., manager), and operational (e.g., technician) (*Lai & Yuen* 2019). Figure 2.4 visualises the feedback procedure carried out to improve the FM.

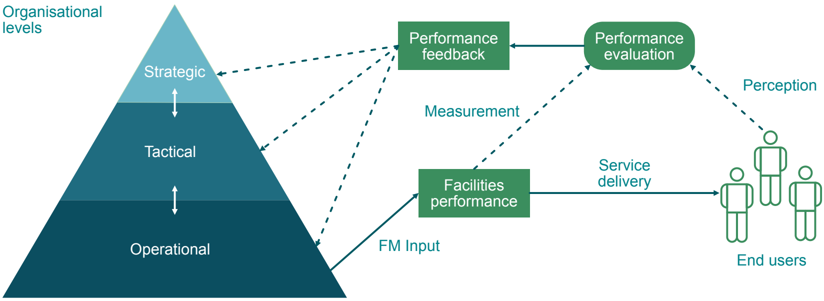

Figure 2.4: Information and resources flows in FM. Adopted from *Lai & Yuen* (2019), adapted from *Lai & Man* (2017).

Sibbel (2004) derived different aspects on organisational levels regarding the capacity planning of services in hospitals from literature. Stategic decisions generally set the framework and thereby limit the decision-making for the tactical and operational level (*Sibbel* 2004). To comply with or adapt to process and functional requirements in hospitals, it is imperative to consider the interdependencies that exist between the building structure, medical and technical equipment, as well as personnel or other involved resources (*Sibbel* 2004). Spatial and other infrastructural conditions, as well as the available equipment, generally make hospitals rather rigid and influence the processes that take place (*Sibbel* 2004). Effective service performance and necessary flexibility to adapt to changing requirements in hospital environments are mainly possible through the efficient organisation of processes and related personnel resources if the broad strategic (and tactical) framework is defined (*Sibbel* 2004).

Detailed process analysis can reduce friction between primary and secondary processes and maximise the efficiency of hospitals (*Lennerts* 2009). Healthcare processes, including the FM processes, are generally considered highly dynamic, highly complex, increasingly multi-disciplinary and ad hoc (*Rebuge & Ferreira* 2012). This is exactly where traditional business process management (see subsection 3.1.1) approaches involving interviews with stakeholders and process modeling efforts are time-consuming and may not provide an accurate picture of the actual business processes (*Mans* et al. 2008; *Rebuge & Ferreira* 2012; *Stefanini* et al. 2017; *van der Aalst* 2011). The extraction of process knowledge from the IT systems that support processes in hospitals can reduce the analysis effort and allow for accurate insights into the actual processes (*Mans* et al. 2008; *Rebuge & Ferreira* 2012; *Stefanini* et al. 2017).

According to *Lehner* (2022), FM in hospitals allows for savings potential of secondary services up to around 25%, with savings potential divided into the following areas:

- Optimisation of purchasing and logistics processes: 10 - 20%,
- Maintenance optimisation: 10 - 30%,
- Energy optimisation: 5 - 15%,
- Outsourcing of infrastructural services: 15 - 30%.

The potentials above from *Lehner* (2022) refer to optimisation potentials in a southern German hospital. However, no further background information on the from *Lehner* (2022) referenced underlying study that supposedly contains estimations for these potentials can be found. *Lehner* (2022) is also a software provider that may publish optimistic potentials to promote their tools. Therefore, further optimisation potential needs to be found in literature.

According to *Abel* (2009), optimised FM processes can save process-related costs between 3% and 70% within each of the processes. Depending on the inner proportion of total FM costs in the hospital, this can in total save up to approximately 25% of the FM related costs in a hospital (*Abel* 2009; *Lennerts* 2009).

3 Utilisation of Process Data

Generally a process can be defined as a "coherent series of changes that unfold over time and occur at multiple levels" (*vom Brocke* et al. 2021) and any operational processes (organisations and systems) can be investigated using different techniques on available information (*van der Aalst* 2016).

The *German Facility Management Association (GEFMA)* distinguishes three different types of data in IT systems that support FM which are also called Computer Aided Facility Management (CAFM) systems (*German Facility Management Association* 2021):

- master/stock data (graphical and alphanumerical basic data),
- process data (order/assignment, status, usage data),
- other data.

Static and dynamic data together form a representation of the managed facilities and the processes that take place within and around them (*German Facility Management Association* 2021). In hospitals, additional information can also be retrieved from other systems, such as HIS, which provide access to data available in hospitals in the form of electronic health records (EHR), radiology information systems (RIS), laboratory information systems (LIS) or supporting logistics software systems (*Fernández-Llatas* 2021b; *Rojas* et al. 2016).

There are multiple methods to use process-related data and improve processes. In this section the basics of different methods are presented. As methods of process data utilisation are not necessarily known in the management field of hospital operation, this fundamentals section is more detailed. Subsection 3.1 introduces various methods in the field of process analysis, in particular process mining. Subsection 3.2 presents techniques for the prediction of processes, including ANN, that allow for quantitative evaluation of different process scenarios. Finally, subsection 3.3 explains optimisation methods, including metaheuristic algorithms and thereby GA, that support the identification of tangible process improvements for process redesign.

3.1 Process Analysis

Within this subsection, fundamental methods for the analysis of processes are described. As process mining will be more relevant to the main body of this thesis, the corresponding subsection 3.1.4 will be more thorough.

3.1.1 Business Process Management

"Business Process Management (BPM) is the discipline that combines approaches for the design, execution, control, measurement and optimisation of business processes" (*van der Aalst* 2016). Firstly, BPM strives to enhance existing business processes without necessarily relying on new technologies (*van der Aalst* 2013). For instance, through process modeling and simulations, managers can explore ways to cut expenses and enhance service quality (*van der Aalst* 2013). Secondly, BPM frequently involves software systems to manage, control, and support operational processes (*van der Aalst* 2013). Originally, BPM approaches tended to be model-driven, targeting the design of explicit process models and process implementation (*van der Aalst* 2013; *van der Aalst* 2016). A process model can be considered a "map" describing the life cycle of a case of a particular process (*van der Aalst* 2016). It can be generally used to gain and visualise process insights, structure discussions between stakeholders, instruct people, document for certification procedures, find flaws in systems and procedures, perform performance analysis, specify requirements and configure supporting information systems (*van der Aalst* 2016). BPM has also started to focus more on the execution/monitoring, adaptation and diagnosis phases (*van der Aalst* 2016).

3.1.2 Data Mining

"Data mining is the analysis of (often large) observational datasets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner" (*Hand* et al. 2001). The datasets that are investigated with data mining approaches usually exceed the datasets that are handled with classical exploratory data analysis by statisticians (*Hand* et al. 2001). Data mining is data-driven and founded on statistics, databases, and algorithms (*van der Aalst* 2016). A table is usually given as input data and the output may include, for example rules, patterns, tree structures, clusters, graphs, equations (*van der Aalst* 2016).

A standard methodology for data mining projects is CRISP-DM (Cross Industry Standard Process for Data Mining) (*Schröer* et al. 2021; *Wirth & Hipp* 2000). According to CRISP-DM, the life cycle of a data mining project is divided into six phases from business understanding to deployment (make use of data in production/operation and continuous monitoring), as shown in Figure 3.1 (*Wirth & Hipp* 2000). CRISP-DM is especially useful for planning, documentation and communication (*Wirth & Hipp* 2000). The interested reader is referred to *Chapman* et al. (2000) and *Wirth & Hipp* (2000) for further information on CRISP-DM phases, the tasks involved and their outputs.

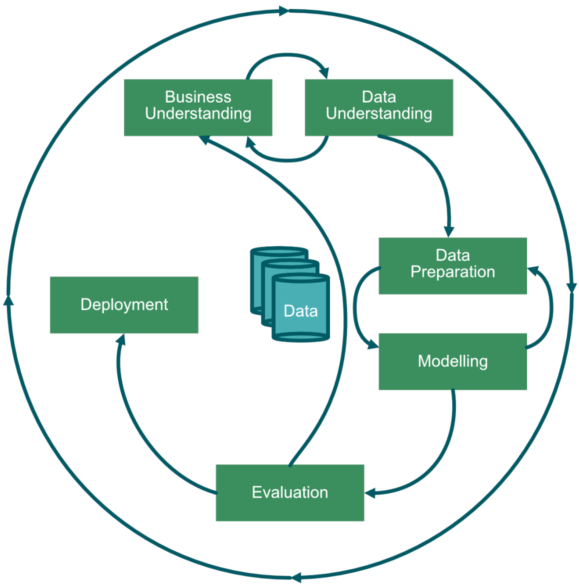

Figure 3.1: Phases of the CRISP-DM Reference Model for carrying out data mining projects. Adopted from *Wirth & Hipp* (2000).

In comparison to the discipline of statistics, the focus of data mining is on practical applications and scalability (*van der Aalst* 2016). However, data mining techniques are historically mainly not process-centric (*van der Aalst* 2016).

3.1.3 Business Intelligence

In literature, there doesn't exist a clear definition for business intelligence (BI) (*van der Aalst* 2016). It is a broad term encompassing anything that aims to provide actionable information for decision-making (*van der Aalst* 2016). In a broader sense, *Forrester* (2010) defines BI as "a set of methodologies, processes, architectures, and technologies that transform raw data into meaningful and useful information used to enable more effective strategic, tactical, and operational insights and decision-making" (*van der Aalst* 2016). A more narrow definition of BI, according to *Forrester* (2010), is "a set of methodologies, processes, architectures, and technologies that leverage the output of information management processes for analysis, reporting, performance management, and information delivery" (*van der Aalst* 2016). The focus of BI is on queries and and reports combined with simple visualisation methods to display dashboards and scorecards (*van der Aalst* 2016). Traditional BI tools are data-centric but do not understand the processes to which the data relates (*van der Aalst* 2016). They focus on basic forms of analysis rather than deeper process analysis (*van der Aalst* 2016).

3.1.4 Process Mining

Process Mining can be classified under the rubric of BI and is a technique that bridges the gap between BPM and data mining (*van der Aalst* 2016). Figure 3.2 visualises the process- and data-centric origins that process mining unites. An event log, which is a particular view of event data extracted from process-supporting information systems, is the basis for process mining methods (*van der Aalst* 2016). The event log needs to contain information on the executed activity and a case ID which matches the event to an individual case (*van der Aalst* 2016; *van der Aalst* et al. 2002). An activity represents a "well-defined step in the process", and a case is a representation of a sequence of events (*van der Aalst* 2016; *van der Aalst* et al. 2012). This sequence of events and respectively sequence of activities is also referred to as trace (*van der Aalst* 2016).

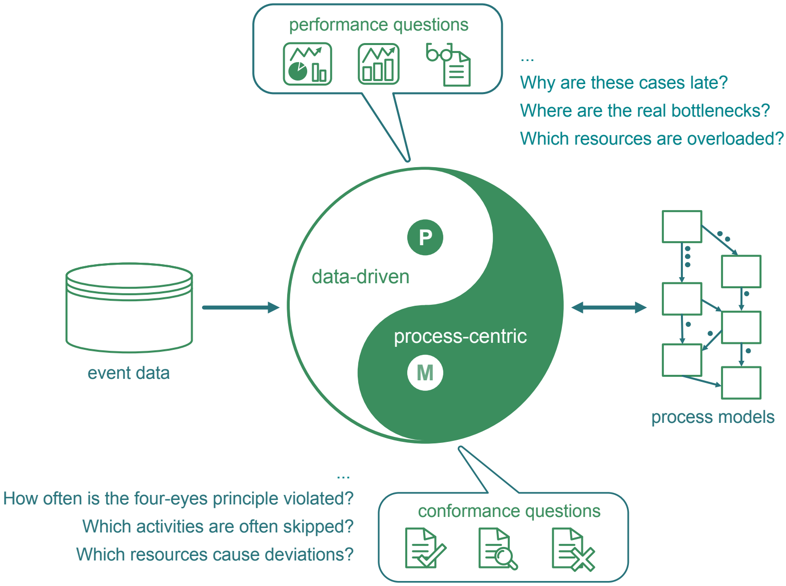

Figure 3.2: Complementation, interconnection and interdependence of process-centric and data-driven characteristics that process mining combines with exemplary conformance and performance questions. Adopted from *van der Aalst* (2016).

Figure 3.3 shows what an event log looks like using the IHPT (see subsection 2.2.2) process as an example. Performance analysis is possible when a corresponding timestamp per event exists in the event log (*van der Aalst* 2016). It is possible that events in the event log can be related to other attributes (from master/stock, process and other data, see also at the beginning of section 3), too (*van der Aalst* 2016; *van der Aalst* et al. 2012). For example, these can be costs, resources (like operating persons, related devices and systems, etc.) or other data elements (involved locations, sizes of products, etc.) (*van der Aalst* 2016; *van der Aalst* et al. 2012). In IHPT, other information can relate to, for example the patient ID (unique, anonymous patient identifier), which in turn could also be adopted as case ID, if process analysis from the patient's perspective is to be conducted. More possible information related to IHPT will be presented in subsection 5.1.

transport ID	activity	timestamp	transporter	patient ID
10001	transport request	01-01-2009, 8:35 am	Sara Lee	323557
10001	waiting list for dispatching	01-01-2009, 8:45 am	Sara Lee	323557
10001	assignment sent to device	01-01-2009, 8:55 am	Sara Lee	323557
10001	assignment accepted	01-01-2009, 9:15 am	Frank Turner	323557
10001	arrival at pick-up location	01-01-2009, 9:25 am	Frank Turner	323557
10002	transport request	02-02-2009, 1:17 pm	Sara Lee	133562
10002	waiting list for dispatching	02-02-2009, 2:17 pm	Sara Lee	133562
10002	assignment sent to device	02-02-2009, 2:25 pm	Sara Lee	133562
10002	assignment accepted	02-02-2009, 2:32 pm	Frank Turner	133562
10002	arrival at pick-up location	02-02-2009, 2:47 pm	Frank Turner	133562
10002	transport started	02-02-2009, 2:57 pm	Frank Turner	133562
10002	arrival at target location	02-02-2009, 3:12 pm	Frank Turner	133562
10002	transport completed	02-02-2009, 3:15 pm	Frank Turner	133562
10003	transport request	17-04-2009, 5:30 pm	Sara Lee	222451
10003	waiting list for dispatching	17-04-2009, 5:34 pm	Sara Lee	222451
10003	assignment sent to device	17-04-2009, 5:50 pm	Sara Lee	222451
…	…	…	…	…

event

trace

case ID

activity

timestamp

resources / other data

Figure 3.3: A fragment of an event log related to an IHPT process. Adapted from *van der Aalst* (2016).

Process mining allows for the creation of process models from event logs (see Figure 3.3) and the identification of sequential, temporal and resource patterns (*van der Aalst & Weijters* 2004). When appropriate data is available, it can be applied to any type of organisation or operational process (*van der Aalst* 2016). Many relevant sub-areas of process mining can currently be found in the literature. In the following, the three most historically established and fundamental ones are presented (*van der Aalst* 2016; *van der Aalst* et al. 2012):

- The first sub-area is process discovery. Based on the behaviour seen in the event log, a discovery algorithm develops a process model.
- The second sub-area is process conformance. The behaviour from the event log is compared with the existing process model of the same process in conformance checking. This technique helps to check the level of conformity of the discovered process behaviour with the facing model of the process.
- The third sub-area is process enhancement. The aim is to extend and improve the existing process model by continuously comparing the behavioural information that is captured in the event log.

Figure 3.4 shows a 4-phase model describing the different steps of process mining projects (*Aguirre* et al. 2017). Overall, such projects are characterised by a project definition phase, a data preparation phase, a process analysis phase and finally a process redesign phase. More detailed subphases are shown in Figure 3.4.

Even though the spectrum of process mining sub-areas has broadened substantially, the initial focus of process mining activities was on process discovery (*van der Aalst* 2016). In general, different algorithms, such as Alpha miner (*van der Aalst* et al. 2002), Heuristic Miner (*Weijters* et al. 2006), Inductive Miner (*Leemans* et al. 2013), Spilt Miner (*Augusto* et al. 2019) and Fuzzy Miner (*Günther & van der Aalst* 2007), can be used to discover process models from event logs, which can lead to different models.

Alpha Miner was the first process discovery algorithm, serving as the basis for the development of subsequent algorithms (*van der Aalst* 2016). The main limitation of Alpha Miner is that it can only be applied to event logs that do not contain noise (*de Koninck & de Weerdt* 2016). Noise is the occurrence of infrequent and sporadic behaviour in the event logs that is not representative of the usual behaviour of the process (*van der Aalst* 2016). Heuristic Miner

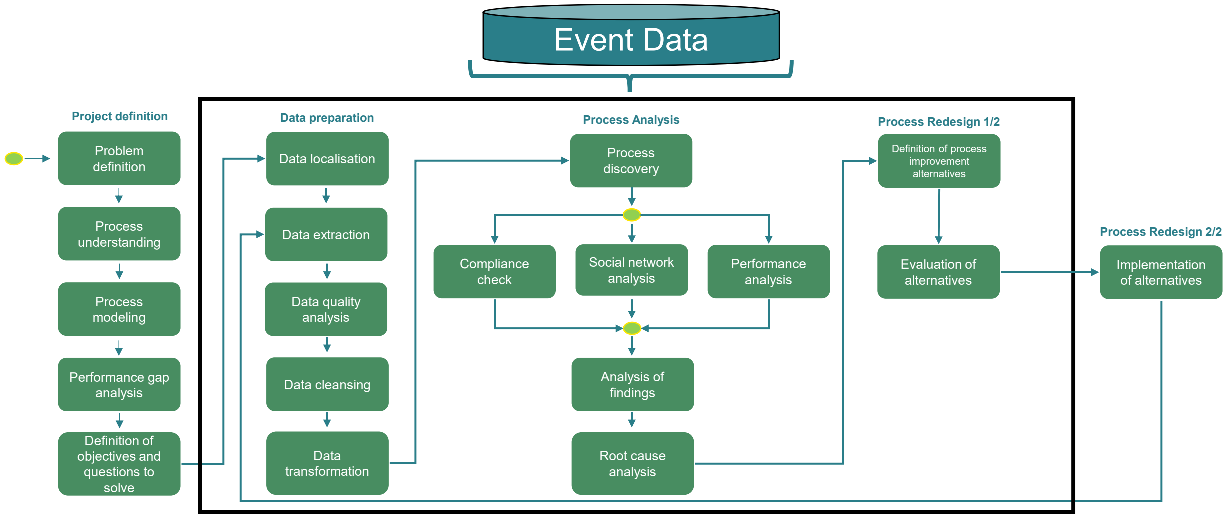

Figure 3.4: Process mining project methodology. Adapted from *Aguirre* et al. (2017).

discovery algorithm can deal with noise in event logs through the introduction of frequency-based metrics (*Conforti* et al. 2017). Inductive Miner has a special feature to preprocess an event log, discovering process trees by constructing directly-follows relationships (*Pegoraro* et al. 2019). However, Inductive Miner algorithms often oversimplify models (*Vidgof* et al. 2020). The Split Miner, like the Inductive Miner, extracts directly-follows relations (*Leemans* et al. 2018). In contrast to Inductive Miner, the Split Miner can discover process models more accurately representing the process behavior recorded in the event log, although it often produces complex models that are difficult to interpret (*Leemans* et al. 2018). A different approach to the previously mentioned ones is the Fuzzy Miner. By offering the flexibility to adjust user-defined levels of significance and correlation thresholds, this algorithm was developed to explore unstructured processes (*Günther & van der Aalst* 2007). Many process mining commercial software algorithms such as *Celonis®* Tools (*Lira* et al. 2019) and *Fluxicon® Disco* (*Günther & Rozinat* 2012) are based on the Fuzzy Miner. There are other process discovery algorithms, and the interested reader is referred to *van der Aalst* (2016) for more information.

There are a number of notations for describing process models, such as Directly-Follows Graphs (DFGs), Petri nets, Business Process Modeling and Notations (BPMN), and Unified Modelling Language (UML) (*van der Aalst* 2022). The latter three are sophisticated notations that can capture concurrent activities (*van der Aalst* 2022). However, they are perceived as too complicated for users and require considerable computation time (*Leemans* et al. 2019; *van der Aalst* 2020). DFGs, in contrast, offer simplicity and performance, making them more suitable when working together with stakeholders that are non-experts in the field of process mining (*Munoz-Gama* et al. 2022). As a result of this simplicity, however, concurrencies and causalities are typically not taken into account (*van der Aalst* 2020). Commercial tools also offer interactive filters in a BI (see subsection 3.1.3) environment and are user-friendly, which is why they are successful and gaining popularity in healthcare organisations, too. For further details on different process model notations, the interested reader is referred to *van der Aalst* (2022) and *van der Aalst* (2019).

The event log data used in process mining for process model discovery contains information about the execution of processes, which in general can be extracted and fed into process mining tools (*van der Aalst* 2016). The main advantage of process discovery is that it provides access to what was actually executed in volatile environments such as hospitals (*Rebuge & Ferreira* 2012). These advantages make process mining an attractive alternative to conventional process mapping methods, which are mainly based on interviews and thus depend on people's subjective understanding of the processes performed (*van der Aalst* 2016). Traditional process mapping methods are therefore time consuming and cannot provide accurate insights about the real processes (*van der Aalst* 2016). Process mining also allows a simplified and illustrative generation, as well as a demonstration of knowledge about processes, which differs from conventional attempts to examine abstract and seemingly infinite data tables (*Fernández-Llatas* 2021e).

While conformance checking measures the alignment between pre-developed models and reality, process enhancement aims to extend or improve an existing process model using information about the actual process recorded in information systems (*van der Aalst* et al. 2012). In this way, compliance and performance questions cannot only be answered with actual event data, but the underlying processes can also be improved by the identification of bottlenecks or non-compliance in process steps (*van der Aalst* 2018). However, "what if" questions cannot be answered as process mining is backward-looking (*van der Aalst* 2018). For this and the exploration of potential redesign measures, other approaches need to be consulted (*van der Aalst* 2018). Nevertheless, previously explored observations, made possible by process mining, support these measures as a starting point (*van der Aalst* 2022).

3.2 Process Prediction

In this subsection, the fundamentals of different techniques are presented that are suitable for carrying out process predictions. Simulation approaches are described in subsection 3.2.1. Since ML and in particular ANN will be of greater relevance for the main part of this thesis, subsection 3.2.2 will be more detailed. A comparison the different process prediction techniques using frameworks and case studies from the relevant literature, and the resulting focus on ANN in this thesis, is presented later, in subsection 4.3.

3.2.1 Knowledge-based Models - Simulations

In science and engineering, equation-based simulations (other types can be e.g. cellular automata, agent-based) are typically used to predict behaviour of a system or process for a particular situation (*von Rueden* et al. 2020).

Based on mathematical models (often in the form of differential equations), a deductive model that describes causal relationships is developed (*von Rueden* et al. 2020). Extensive research, for example, deriving from theoretical physics and continuing with numerous experimental validations, is needed to develop such knowledge-based simulation models (*von Rueden* et al. 2020). After development, the model can be applied to approximate solutions based on specific input parameters that are numerically computed within the given model (*von Rueden* et al. 2020). Figure 3.5 illustrates the mentioned simulation components.

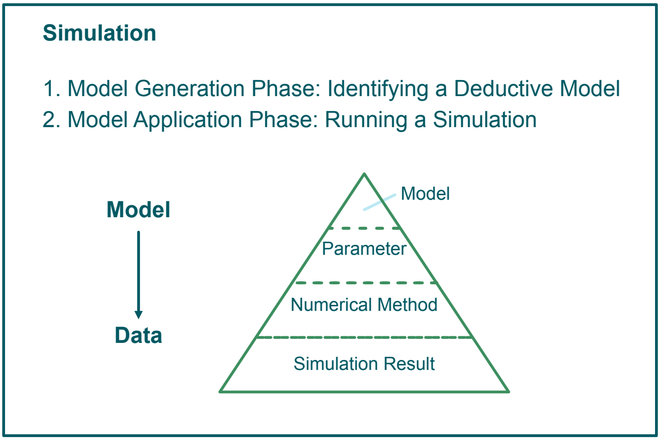

Figure 3.5: Components of Simulation. First a simulation model is developed and then the results of variants (i.e. data) can be simulated. Adopted from *von Rueden* et al. (2020).

To develop high-quality simulation models for business processes, extensive process information as input needs to be collected (*Depaire & Martin* 2022). Traditionally, this is done by investigating process documentation, conducting interviews, and process observations (*Depaire & Martin* 2022). *Depaire & Martin* (2022) summarise from literature the main limitations of these traditional sources of information for the development of simulation models as follows:

- process documentations describe usually as-planned processes, which can differ from the actual process behavior,
- interviews can result in contradictory information and the process perception might be influenced by recent process experiences,

- observational data could suffer from the Hawthorne effect (see also subsection 2.2.2), i.e. a performance increase of process executing staff because they know, that they are being under observation.

Subsection 3.2.1.1 presents fundamentals of different simulation approaches and subsection 3.2.1.2 provides recent applications of simulation approaches in connection with process mining literature.

3.2.1.1 Simulation Approaches

Brailsford (2014) and *Brailsford & Hilton* (2001) distinguish between two approaches of simulation modeling, namely discrete-event simulation (DES) and system dynamics (SD). According to *Brailsford* (2014) and *Brailsford & Hilton* (2001), Table 3.1 presents criteria on which the choice for simulation modeling should be made. SD adopts a holistic view and its complex nature lies in the dynamic interactions between the elements (on an aggregated level) of the system, whereas the difficulty of a DES model is in the detailed modeling of discrete events of the system (*Brailsford* 2014; *Brailsford & Hilton* 2001; *Law* 2013). DES is capable of modelling a high level of complexity and detail while the models remain transparent to users (*Brailsford & Hilton* 2001). Nevertheless, the development and execution of DES models are typically associated with significant effort, and the processing times can be long (*Brailsford & Hilton* 2001). SD models are capable of using judgmental or descriptive data as well as numerical data whereas DES relies on large amounts of quantitative, numerical data (*Brailsford* 2014; *Brailsford & Hilton* 2001).

Table 3.1: Criteria for selection of modelling approach. Adopted from *Brailsford* (2014) and *Brailsford & Hilton* (2001).

Criteria / Approach	DES	SD
Scope	Operational, tactical	Strategic
Importance of variability	High	Low
Importance of tracking individuals	High	Low
Number of entities	Small	Large
Control	Holding (queues)	Rates (flows)
Relative timescale	Short	Long
Purpose	Decisions: optimisation, prediction and comparison	Policy making: gaining understanding

SD tools are generally easy to use and do not require knowledge of computer programming while the overall emphasis is rather on policy understanding than on decision support (*Brailsford* 2014; *Brailsford & Hilton* 2001). Although the development and deployment are related to higher complexity, DES is rather suited for the purpose of process predictions than SD (*Brailsford & Hilton* 2001).

For further fundamentals on DES, SD and further simulation approaches, the interested reader is referred to *Brailsford* (2014), *Brailsford & Hilton* (2001), and *Law* (2013).

3.2.1.2 Applications of Simulations Connected with Process Mining

More recently, simulation models can also be retrieved automatically from the event logs from information systems that increasingly support business process execution (*Camargo* et al. 2020; *Depaire & Martin* 2022). The advantage over the traditional information gathering methods mentioned above is that the process data from information systems provide an objective view of the process (*Depaire & Martin* 2022). However, extracting necessary knowledge from the process data to develop accurate simulation models is a major challenge (*Depaire & Martin* 2022). According to *Camargo* et al. (2020) (based on *Dumas* et al. (2013)) the following elements are needed in addition to a process model to run a DES:

- "The mean inter-arrival time of cases and its associated probability distribution function, e.g. one case is created every ten seconds on average with an exponential distribution.
- The probability distribution of the processing times of each activity. For example, the processing times of an activity may follow a normal distribution with a mean of 20 minutes and a standard deviation of five minutes, or an exponential distribution with a mean of ten minutes.
- For each conditional branch in the process model, a branching probability (i.e. percentage of time the conditional branch in question is taken when the corresponding decision gateway is reached.
- The resource pool that is responsible for performing each activity in the process model. For example, in an insurance claims handling process, a possible resource pool would be the claim handlers. Each

resource pool has a size (e.g., the number of claim handlers or the number of clerks). The instances of a resource pool are the resources.

- A timetable for each resource pool, indicating the time periods during which a resource of a resource pool is available to perform activities in the process (e.g. Monday-Friday from 9:00 to 17:00).
- A function that maps each task in the process model to a resource pool."

With *Simod*, a tool for automated simulation model discovery from event logs is proposed that can evaluate and optimise the accuracy of the model (*Camargo* et al. 2020). New event logs can be generated based on historical ones with *Simod* (*Camargo* et al. 2020). A mentioned limitation for *Simod* is the requirement of an event log that incorporates events with both a start and end timestamps (*Camargo* et al. 2020). The focus of *Simod* is on the simulation of event sequence flows (i.e. process control flows) and durations (*Camargo* et al. 2020). The simulation model accuracy is determined by comparing the ordering and duration of activities in simulated event logs with historical ones (*Camargo* et al. 2020). Next to *Simod*, also other automated process simulation approaches focus mainly on activity durations and process control flows (*Camargo* et al. 2020; *Depaire & Martin* 2022). These factors mainly relate to the operational level (see Figure 2.4 in Subsection 2.3) of the processes.

3.2.2 Data-based Models - Machine Learning and Artificial Neural Networks

Machine learning (ML), a subfield of artificial intelligence (AI), can also be used to predict the behaviour of a system or process (*Goodfellow* et al. 2016; *von Rueden* et al. 2020). There are many definitions in the literature for AI. In a frequently cited source, *Russell & Norvig* (2010), AI is defined as "the study of agents that receive percepts from the environment and perform actions". AI "attempts not just to understand but also to build intelligent entities" (*Russell & Norvig* 2010). Historically, AI projects tended to hard-code knowledge about the world into formal languages, but have faced difficulties because people struggle to align rules to accurately meet the complexity of the world (*Goodfellow* et al. 2016). ML aims to help here out (*Goodfellow* et al. 2016). The relation of the concepts of AI, ML and furthermore Deep learning (DL) with respective examples of each concept are provided in Figure 3.6.

DL, that incorporates the concept of artificial neural networks (ANN), is a subfield of ML (*Goodfellow* et al. 2016). In the following the fundamentals of ML (see subsection 3.2.2.1) and DL (see subsection 3.2.2.2) will be described in more detail. Subsection 3.2.2.3 gives a brief overview of recent applications of process prediction tasks associated with process mining literature.

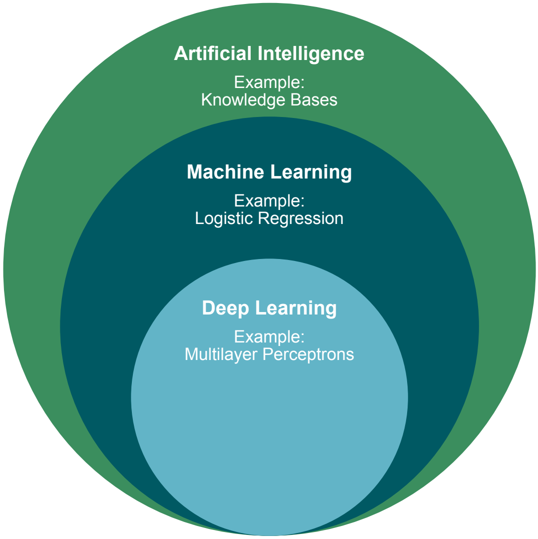

Figure 3.6: Relationship between the terms Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL). Adapted from *Goodfellow* et al. (2016).

3.2.2.1 Machine Learning

ML, a subfield of AI, can be defined as follows: "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E." (*Mitchell* 1997). In ML, the main goal is that a machine automatically learns a model to describe patterns in a given set of data (*von Rueden* et al. 2020). An inductive model is trained, which means that the model is built by drawing conclusions from data samples and to identify patterns (*von Rueden* et al. 2020). First, historical training data is prepared (*von Rueden* et al. 2020). Then a function class or network architecture that is assumed to map input features to target values is defined and tuned through a learning algorithm so that the performance of the mapping is maximised to result in the final desired model (*von Rueden* et al. 2020). This procedure can be repeated to achieve sufficient model performance through tuning of the model hyper-parameters (*von Rueden* et al. 2020). Figure 3.7 illustrates the aforementioned ML components.

It is not guaranteed that the trained model is able to reflect causal relationships (*von Rueden* et al. 2020). Therefore, the models are usually data-based rather than knowledge-based (*von Rueden* et al. 2020). This inductive model can ultimately be used on new data to predict or derive a desired target variable (*von Rueden* et al. 2020).

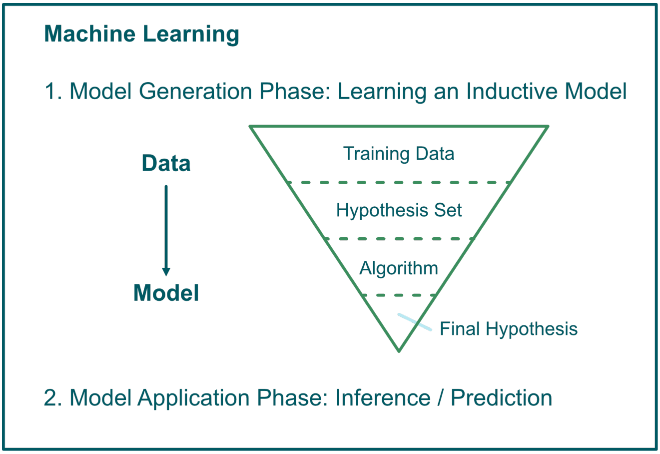

Figure 3.7: Components of machine learning. First, a machine learning model is developed from historical data, which can then be used to predict target variables. Adopted from *von Rueden* et al. (2020).

According to *Russell & Norvig* (2010), there exist three main different learning types in ML:

- unsupervised learning: the agent learns patterns in the input, even if no explicit feedback is provided i.e. no labeled examples have ever been given by a teacher; the most common task is clustering, which involves the autonomous allocation of values of a dataset into different subgroups,

- reinforcement learning: the agent learns from a set of reinforcements that either rewards or punishes, leaving it up to the agent to decide which of the previous actions was most responsible for the particular reinforcement,
- supervised learning: the agent studies a few sample input-output pairs and then learns a function that maps from input (i.e. features) to output (i.e. labels); if the output is a finite set of values (or just two), the learning problem is called (binary/boolean) classification. If the output is an indefinite number, it is called regression.

The key challenge in ML is that the trained ML model must perform well on new, previously unseen data (*Gardner & Dorling* 1998; *Goodfellow* et al. 2016). This ability is called generalisation (*Gardner & Dorling* 1998; *Goodfellow* et al. 2016). The error of the ML model when computing the training dataset is called training error (*Goodfellow* et al. 2016). The error of the ML model when computing a previously unseen test dataset is called test error (or generalisation error) (*Goodfellow* et al. 2016). If the goal is to just minimise the training error, we have simply an optimisation problem (*Goodfellow* et al. 2016). In ML problems both, training and test error are to be minimised (*Goodfellow* et al. 2016). The errors of a ML model, and thus the model performance, can be evaluated by so called loss functions (*Goodfellow* et al. 2016). In the following (see equations 3.1 to 3.3), some common ML loss functions are presented (*Russell & Norvig* 2021):

- Absolute-value loss:
$$L1(y, \hat{y}) = |y - \hat{y}| \tag{3.1}$$
- Squared-error loss:
$$L2(y, \hat{y}) = (y - \hat{y})^2 \tag{3.2}$$
- 0/1 loss (for discrete-valued outputs):
$$L_{0/1}(y, \hat{y}) = 0 \text{ if } y = \hat{y}, \text{ else } 1 \tag{3.3}$$

where y is the actual value that the ML model is attempting to predict and $\hat{y}$ is the predicted value. To evaluate the error over a set of predictions and actual values in a regression, and thus to estimate the performance of the ML model, the mean value of the set of samples calculated by a chosen loss function is usually obtained (*Goodfellow* et al. 2016).

A metric for evaluating the performance of regression models in terms of their ability to explain variance can be the coefficient of determination R^2 (*AlDahoul* et al. 2021; *Miles* 2014; *Muloiwa* et al. 2023; *Ozili* 2022). R^2 measures in a model how well the variance in the actual values y is explained by the input variables in the set of samples (*Mikut* 2008; *Miles* 2014; *Muloiwa* et al. 2023). R^2 is given by equation 3.4 (*Mikut* 2008; *Miles* 2014; *Muloiwa* et al. 2023).

$$R^2 = 1 - \frac{\sum_{i=1}^{m} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{m} (y_i - \overline{y})^2} \tag{3.4}$$

where m is the number of samples, y_i are the actual values, $\hat{y}_i$ are the predicted values, and $\overline{y}$ is the mean of the actual values y_i. This formulation evaluates the improvement in the regression estimate of the model relative to the simple mean of the actual values in the sample set (*Mikut* 2008). The values of R^2 range usually from 0.0 (no relationship) to 1.0 (deterministic relationship) (*Mikut* 2008).

For evaluating the performance of models with multiple input variables, there is also a so-called $adjusted\ R^2$, because in the literature an undesirable increase in R^2 could be observed with a rising number of input variables (*Miles* 2014). The $adjusted\ R^2$ is calculated according to equation 3.5 (*Miles* 2014).

$$adjusted\ R^2 = 1 - \frac{(1 - R^2)(N - 1)}{N - k - 1} \tag{3.5}$$

where R^2 is calculated according to equation 3.4, N is the sample size, and k is the number of input variables in the model. The higher R^2 is, the better a model is able to explain the variance in the actual data (*Miles* 2014). A model with a R^2 of 1.0, the highest possible value, is able to explain all of the variance in the sample set (*Miles* 2014). A R^2 of 0.0 (or a negative R^2, which could theoretically be observed) indicates that the prediction performance of a model is just as accurate (or even less accurate, if R^2 is negative) as the average value of the set of samples (*Ozili* 2022). In science domains, where researchers are concerned with objects, molecules, materials, or atoms whose characteristics are known and whose behaviour are predictable and do not change over time, a high R-squared model is expected (*Ozili* 2022). An acceptable value of R^2 for a prediction model dealing with human behaviour, which can change over time, is regarded to be between 0.5 and 1.0 (*Ozili*

2022). The mentioned properties of R^2 are also valid for $adjusted\ R^2$ (*Ozili* 2022). R^2 has linear underlying assumptions and can thus tend to mislead performance evaluations related to non-linear models (*Spiess & Neumeyer* 2010). For this reason, it should not be used as sole performance metric (*Spiess & Neumeyer* 2010). On non-linear models in the pharmacological and biochemical domain, *Spiess & Neumeyer* (2010) show, for example that using R^2 (and also $adjusted\ R^2$) could indicate the best performing model in only around 28-43% (depending on the underlying experimental noise in the data) of the experimental evaluations. However, R^2 (and also $adjusted\ R^2$) is a frequently used performance metric in the literature to evaluate ANN (mostly together with other performance metrics).

Classification models are usually evaluated with metrics such as accuracy, recall, precision and F1-score that calculate different ratios of correctly and incorrectly predicted instances (*Janiesch* et al. 2021).

One way to ensure a good generalisation performance of the model is to divide the dataset not only into training and test data but into training, validation and test data (*Gardner & Dorling* 1998). Thereby the training set can be used to actually train the model, the validation dataset is used to supervise the generalisation ability whilst training, and the test set is used to assess the overall performance of the trained model (*Gardner & Dorling* 1998). Figure 3.8 shows schematically how the training and validation error with increasing ML model training time (or training epochs) evolve and indicates the optimal generalisation ability where both training and validation error are relatively low. Before and after the optimal generalisation ability are the underfitting and overfitting zones (*Goodfellow* et al. 2016). Training should be stopped when the generalisation performance reaches a maximum (and respectively the validation error reaches a minimum), e.g. through an early stopping criterion when training and validation error start to diverge (*Gardner & Dorling* 1998; *Maleki* et al. 2020).

Error curves similar to the one displayed in Figure 3.8 evolve with the increasing capacity of a model (*Goodfellow* et al. 2016). The capacity of a model is its ability to fit a wide variety of functions (*Goodfellow* et al. 2016). The capacity of a ML model is dependent on different factors like the number of input features and their parameters or the functions that the learning algorithm can select from (*Goodfellow* et al. 2016).

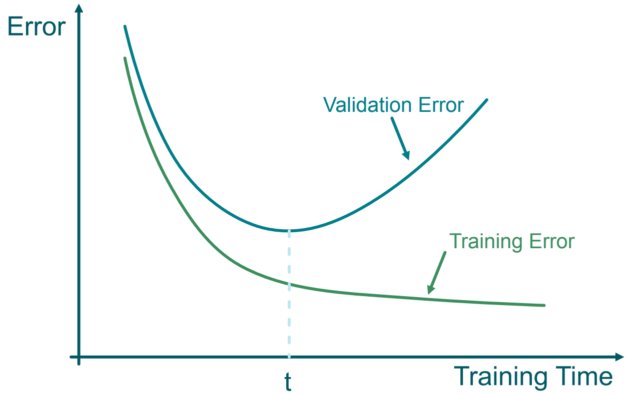

Figure 3.8: ML model training and validation error development during training. Adopted from *Gardner & Dorling* (1998).

3.2.2.2 Deep Learning

DL, according to *Goodfellow* et al. (2016), "is a particular kind of machine learning that achieves great power and flexibility by representing the world as a nested hierarchy of concepts, with each concept defined in relation to simpler concepts, and more abstract representations computed in terms of less abstract ones". As per *Goodfellow* et al. (2016), an ANN, e.g. in the form of multilayer perceptron (MLP), is an example for DL (see also Figure 3.6 in subsection 3.2.2).

An ANN is generally considered to be a massive parallel combination of simple processing units, also known as neurons, that can learn from the environment and store that knowledge in its connections (*Haykin* 1999). It is widely applied to cognitive tasks such as learning and optimisation (*Lawrence & Luedeking* 1994). The MLP is one type of ANN architectures (*Gardner & Dorling* 1998). MLP is a feed-forward network because information is processed from the input layer to the output layer in a forward direction (*Gardner & Dorling* 1998). It is the focus of the majority of ANN research (*Ncibi* et al. 2017) and the most common ANN (*Guneri & Gumus* 2008). Otherwise, ANN architectures can also be recurrent/feedback networks, like recurrent neural networks (RNN), that feed its outputs back into its own inputs (*Gardner & Dorling* 1998; *Russell & Norvig* 2010).

An MLP consists of an input layer, several hidden layers and an output layer (*Gardner & Dorling* 1998). Figure 3.9 illustrates an MLP schematically with example inputs and outputs. The input can be e.g. numbers, characters, audios, images, etc. which are decomposed into binary data processable by a computer (*Zhu* et al. 2023). Depending on the specific task, the output can be, for example continuous, binary, or categorical values (*Zhu* et al. 2023). Each layer of an MLP is composed of neurons that are each connected to the neurons of the next layer (i.e. they are fully-connected) (*Gardner & Dorling* 1998). The number of hidden layers and neurons also affects the MLP model's capacity and generalisation performance (*Gardner & Dorling* 1998; *Russell & Norvig* 2010). With the exception of the input neurons, each neuron within the MLP model can leverage a non-linear activation function (*Gardner & Dorling* 1998).

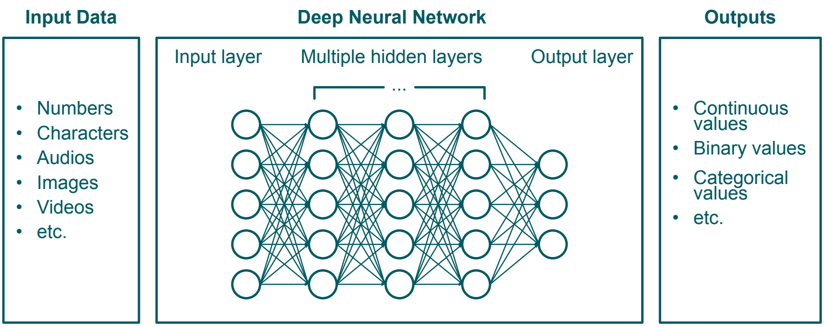

Figure 3.9: Diagram of an MLP-ANN. Adopted from *Zhu* et al. (2023).

Figure 3.10 shows the perception of a neuron (in the hidden or output layer). A neuron multiplies each of its inputs x_i by an associated weight w_i, and afterwards sums these weighted inputs, then adds a preset number b called the bias (*Russell & Norvig* 2010; *Zhu* et al. 2023). The result of this computation is then adjusted through an activation function to calculate the output $g(x)$ (*Russell & Norvig* 2010; *Zhu* et al. 2023).

In Figure 3.10 the activation function is a hard non-linear threshold function (*Russell & Norvig* 2010; *Zhu* et al. 2023). To activate the neurons other types of non-linear activation functions can also be used (*Russell & Norvig* 2021; *Zhu* et al. 2023). The four most popular non-linear activation functions will be presented in the following (see equations 3.6 to 3.9) and visualised in Figure 3.11 (*Russell & Norvig* 2021):

- Sigmoid:
$$g(x) = \frac{1}{1 + e^{-x}} \tag{3.6}$$
- ReLU (Rectified Linear Unit):
$$g(x) = max(0, x) \tag{3.7}$$
- Tanh (hyperbolic tangent):
$$g(x) = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{3.8}$$
- Softplus:
$$g(x) = log(1 + e^{x}) \tag{3.9}$$

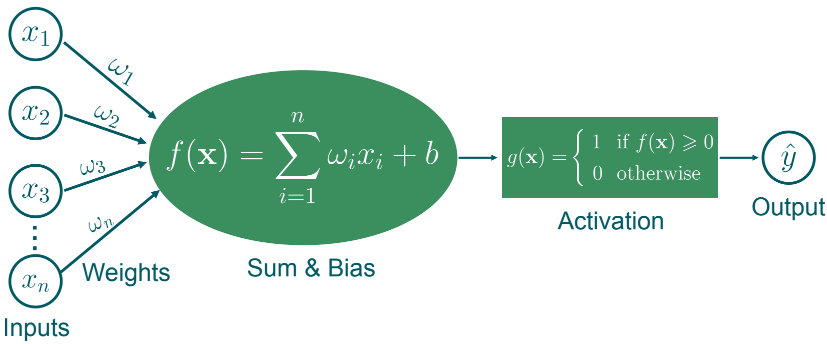

Figure 3.10: Diagram of a neuron's perception. Adopted from *Zhu* et al. (2023).

In each training epoch, the weights and biases between the neurons of the different layers are updated through back-propagation depending on the observed output layer error (*Russell & Norvig* 2010). With each weight-updating epoch, the aim is to decrease the training and the test error (*Russell & Norvig* 2010). However, as seen already in Figure 3.8 from subsection 3.2.2, fewer training epochs can lead to underfitting MLP models and more epochs can lead to overfitting MLP models (*Gardner & Dorling* 1998; *Maleki* et al. 2020). During

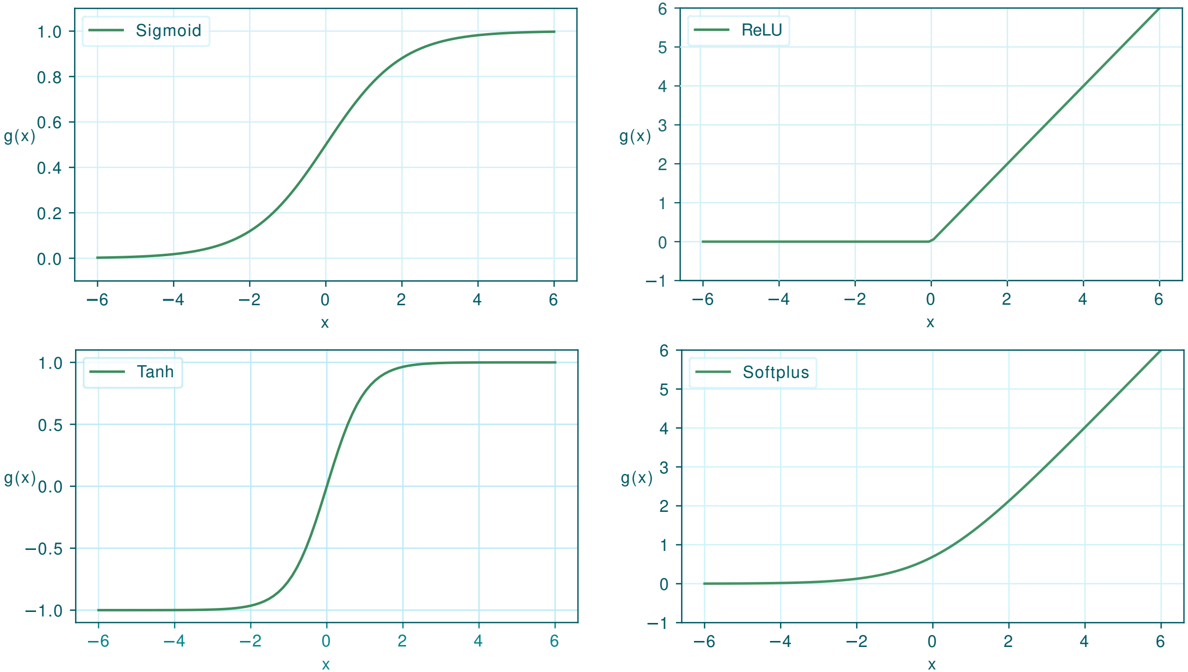

Figure 3.11: Most common non-linear activation functions. Adapted from *Russell & Norvig* (2021).

the back-propagation, the gradient of the output layer error is computed in a backward flow through the MLP to the first hidden layer by an optimisation algorithm (*Goodfellow* et al. 2016). This optimisation algorithm determines how to change the weights and biases to improve the error in the output layer and adjusts them accordingly (*Goodfellow* et al. 2016). Choosing the right optimisation algorithm is difficult because no single best algorithm has emerged (*Goodfellow* et al. 2016). The most popular optimisation algorithms are SGD (Stochastic Gradient Descent), SGD with momentum, RMSProp (Root Mean Square Propagation), RMSProp with momentum, AdaDelta (Adaptive Delta) and Adam (Adaptive Moment Estimation) (*Goodfellow* et al. 2016). Some of these optimisation algorithms use adaptive learning rates (*Goodfellow* et al. 2016). The learning rate reflects the size of the adjustment steps that the optimisation algorithm conducts (*Russell & Norvig* 2010). If the learning rate is too small, too many steps are required to find the optimal settings, while if the learning rate is too large, the optimal setting of the parameters may be overlooked (*Russell & Norvig* 2010). Adapting the learning rates aims to improve the learning process (*Goodfellow* et al. 2016).

In general, an MLP does not rely on prior assumptions about the distribution of data (*Gardner & Dorling* 1998). It is capable of modelling complex non-linear functions and can be trained to generalise accurately when confronted with previously unseen data (*Gardner & Dorling* 1998). These intrinsic properties of the MLP make it a compelling alternative to traditional mathematical models and a viable candidate when choosing between statistical methods (*Gardner & Dorling* 1998). Other ANN architectures, like RNN or convolutional neural networks (CNN), are also being successfully applied more recently on time series data in healthcare prediction tasks (*Morid* et al. 2023).

Even though ANN are able to handle complex learning tasks, there is no good theory to achieve an optimal ANN structure (*Russell & Norvig* 2010). Always, some degree of trial and error is required to achieve the right network structure for the underlying problem and data (*Russell & Norvig* 2010).

3.2.2.3 Applications of Machine Learning and Deep Learning Connected with Process Mining

In general, ML and DL techniques can be used for process prediction tasks (*Kratsch* et al. 2021). According to *Kratsch* et al. (2021) and *Marquez-Chamorro* et al. (2018), process prediction tasks that allow organisations to act proactively in fast-changing environments can be divided into the following types:

- performance predictions such as the remaining cycle time of running process instances,
- prediction of process compliance (business rule violations),
- prediction of the sequence of next process activities or events,
- prediction of the final or partial process outcome.

For classification and regression tasks, most of the process mining literature currently uses ML techniques (*Di Francescomarino & Ghidini* 2022). DL approaches are rather used for predicting next events (according to *Di Francescomarino & Ghidini* (2022), in current literature mostly applied through RNN, including its sub-type Long-Short Term Memory - LSTM) during process execution instead of process outcome prediction (*Kratsch* et al. 2021). However, the latter yields substantial savings in process related resources (*Kratsch* et al. 2021). It has recently been shown that DL also outperforms classical ML approaches when it comes to outcome predictions (*Kratsch* et al. 2021).

New research trends strive to take inter-case information for predictions into account because different cases running within the same time window can be dependent on limited resources (*Di Francescomarino & Ghidini* 2022; *Senderovich* et al. 2015; *Senderovich* et al. 2019). Nevertheless, extracting inter-case information is a challenging task (*Di Francescomarino & Ghidini* 2022). The goal is to capture as much information as possible, but for multiple features, this can lead to an explosion of the feature space, when there is a large number of concurrent cases (*Di Francescomarino & Ghidini* 2022). Further trends in process predictions are explainable predictions that help users understand the rationale behind predictions, and the incorporation of additional case-specific knowledge (a-priori knowledge) about the future that can improve the prediction power of models (*Di Francescomarino & Ghidini* 2022).

3.3 Process Redesign

Process redesign refers to specific implementable measures that aim to improve processes (*de Roock & Martin* 2022). A better process can generally be seen as one that better supports the achievement of an organisation's strategic objectives (*van der Aalst* et al. 2016). The wider context of a process, such as the time of day or month of the year, the workload and resources available, but also the friction between individuals, all have influence on the execution of a process (*van der Aalst & Dustdar* 2012). Thus, there are many possible factors to consider when working on the analysis and improvement of processes (*van der Aalst & Dustdar* 2012). Measures can be e.g. reconfiguring the as-planned activity sequence in the process, but can also relate to the adaptation of other contextual attributes in the process, such as increasing available resources for the process in terms of capacity planning (*van der Aalst* 2016).

To achieve better processes, decisions about process adaptation measures are often based on manual process investigations (e.g. interviews or observation) or by automatically exploiting event data (e.g. process mining) of processes (see subsection 3.1), both of which aim to enable analysts to estimate improvements in possible process adaptations (*van der Aalst* et al. 2016). Process prediction techniques (see subsection 3.2) further help to quantify the expected effects of measures and answer "what if" questions (*van der Aalst* 2016). However, improving or redesigning a process can be seen as a problem under certain constraints for which an optimised solution out of a variety of possible solutions needs to be found (*van der Aalst* et al. 2016). Many optimisation problems, both practical and theoretical, involve finding the best possible configuration of a set of variables to reach a certain objective (*Blum & Roli* 2003). KPIs (see subsection 2.3), typically targeted for improvement in a process include e.g. the use of time or resources (*van der Aalst* et al. 2016). This subsection will present first general optimisation methods in subsection 3.3.1. Then, metaheuristic optimisation algorithms, and thereby especially GA, are introduced in subsection 3.3.2, as they will be of particular interest for the main part of this thesis. Lastly, subsection 3.3.3 gives a brief overview of recent applications of process redesign tasks in process mining literature.

3.3.1 Optimisation Methods

In general, optimisation problems can be classified in two categories: problems where the solutions are encoded in real-valued variables, and problems where the solutions are encoded in discrete variables (*Blum & Roli* 2003). The latter can be addressed through combinatorial optimisations (*Blum & Roli* 2003). Combinatorial optimisation problems are popular for real-world problems, because the objective functions and constraints tend to be complex (e.g. non-linear, black-box) while the search space is finite and characterised by discrete decision variables (*Talbi* 2009). Examples for combinatorial optimisation problems are the Travelling Salesman problem, the Quadratic Assignment problem or Timetabling and Scheduling problems (*Blum & Roli* 2003). Combinatorial optimisation problems can generally be computed either through exact solving methods or through approximate methods (*Blum & Roli* 2003).

A classification of optimisation methods is given in Figure 3.12. It has to be mentioned, that no single method or algorithm can be certainly declared as a best choice being applied to all types of problems (*Janga Reddy & Nagesh Kumar* 2020). Important factors to choose the right method or algorithm, according to *Janga Reddy & Nagesh Kumar* (2020) and *Janga Reddy & Nagesh Kumar* (2012), are:

1. "complexity of the problem, and the character of the objective function whether it is known explicitly,
2. the number and nature of the constraints, equality and inequality constraints,
3. the number of continuous and discrete variables, etc."

As mentioned in subsection 2.2.2, long computation times for optimisation must be overcome in problems, like IHPT problems, that are typically characterised by complex models, to increase the practical applicability (*Klein & Thielen* 2024). Since exact methods for solving complex problems can consume exponential computing time, which is too high for practical purposes, approximate methods have received more attention in recent years (*Blum & Roli* 2003). Metaheuristic algorithms have emerged among these approximate methods (*Blum & Roli* 2003; *Talbi* 2009). Generally, they belong to the family of heuristic algorithms (see Figure 3.12) (*Talbi* 2009). On large-size problems, according to *Talbi* (2009), heuristics are able to find "good" solutions with acceptable performance and costs in a wide range of problems, but there is

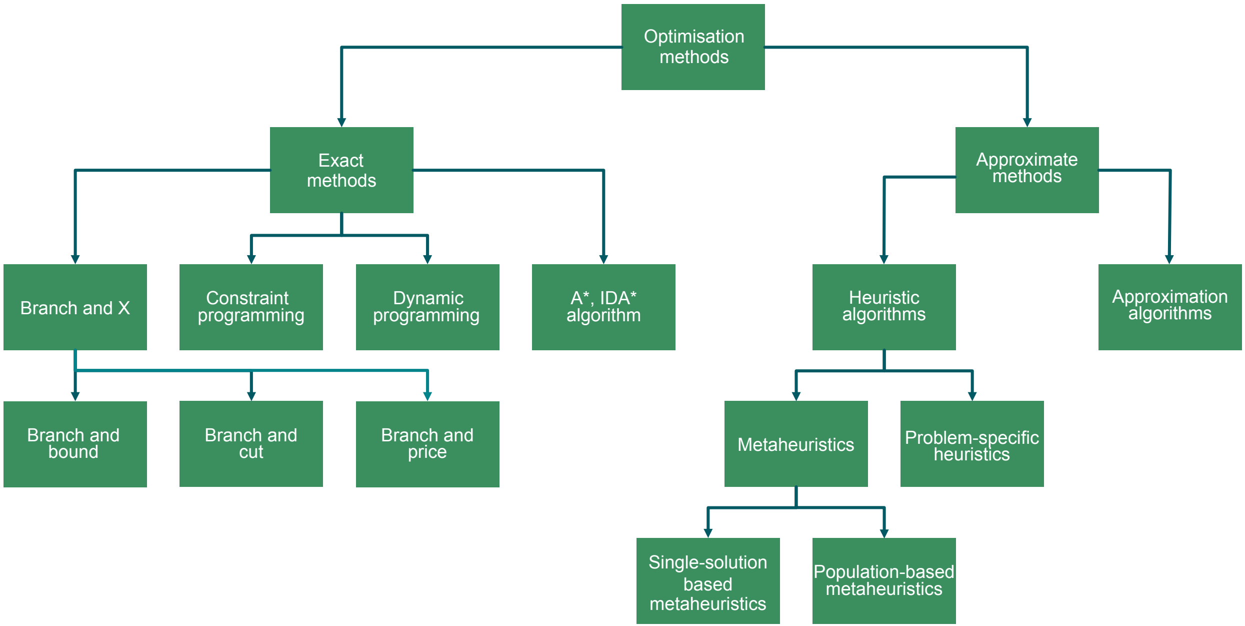

Figure 3.12: Classification of optimisation methods. Adapted from *Talbi* (2009).

no guarantee on the quality of the obtained solution. In contrast, the family of approximation algorithms (see Figure 3.12) can "provide provable solution quality and provable run-time bounds" (*Talbi* 2009). Nevertheless, they require a deeper problem understanding for the design and are problem-specific, which limits their applicability (*Talbi* 2009). Furthermore, for real-world applications these approximation algorithms tend to be less useful because their attainable solutions fall too far from the best global one (*Talbi* 2009). In contrast, "metaheuristic algorithms are general-purpose algorithms that can be applied to solve almost any optimisation problem" and they obtain "satisfactory solutions in a reasonable time" (*Talbi* 2009). The interested reader is referred to *Talbi* (2009) for more information on exact and approximate optimisation methods. The next subsection presents metaheuristic and especially its subclass GA in more detail.

3.3.2 Metaheuristic Algorithms - Genetic Algorithms

Metaheuristic algorithms essentially attempt to combine basic heuristic methods into a higher-level framework aimed at exploring a search space efficiently and effectively (*Blum & Roli* 2003). Like displayed in Figure 3.12 from subsection 3.3.1, they can broadly be classified into single-solution based and population based algorithms (*Katoch* et al. 2021). While single-solution based metaheuristics are more exploitation (intensification) oriented and thus tend to get stuck in local optima, the population-based metaheuristics are more exploration (diversification) oriented (*Katoch* et al. 2021; *Talbi* 2009). Population based metaheuristics use multiple candidate solutions in the search process to avoid solutions from being stuck in local optima (*Katoch* et al. 2021). A subclass of these population based metaheuristics are genetic algorithms (GA), the most popular evolutionary search algorithms taking natural genetics and natural selection as inspiration (*Goldberg* 1989; *Janga Reddy & Nagesh Kumar* 2020; *Katoch* et al. 2021).

Metaheuristic optimisation techniques, like the GA, have the advantage of finding near-optimal solutions for problems where exact, deterministic, mathematical modelling of the objective with respect to the decision variables is not possible (*Reynolds* et al. 2019). They are particularly useful when using black-box models and non-continuous decision variables (*Reynolds* et al. 2019).

GA are widely used to solve real-world complex problems (e.g. multi-objective problems) (*Goldberg* 1989; *Katoch* et al. 2021). Evolutionary algorithms can generally handle complicated search spaces and find near-optimal (or optimal) solutions in reasonable computational time, and provide solutions to any complex optimisation problem that is difficult to solve with conventional non-linear programming methods, e.g. those that by their nature may involve discontinuities in the search space, non-differentiable objective functions, imprecise arguments and function values (*Janga Reddy & Nagesh Kumar* 2020). GA search from a population of solutions and use reproduction, crossover and mutation of successful solutions (evaluated by an objective function) to iteratively improve performance towards an optimal point or points (*Goldberg* 1989). In this way, GA maintain the diversity of the population and prevent solutions from being stuck in local optima (*Katoch* et al. 2021). The performance (i.e. the speed of convergence) of a GA can be additionally improved by elitism selection that propagates an elitist individual or elitist individuals per generation (i.e. best performing solutions) to the next generation, whether or not they would be present in the next generation by the normal selection procedure (*Jebari & Madiafi* 2013; *Katoch* et al. 2021). Nevertheless, due to decreased genetic diversity within the population of solutions, elitism selection can lead to a risk of convergence to local optima (*Jebari & Madiafi* 2013).

Other population-based algorithms, like the more recently evolved swarm-intelligence algorithms, are outperformed by the GA when the computational budget is high (*Piotrowski* et al. 2017). Swarm-intelligence algorithms are also called behaviourally inspired algorithms, as they are inspired by the collective behaviour of species such as ants, bees, wasps, etc. (*Bonabeau* et al. 1999; *Janga Reddy & Nagesh Kumar* 2020; *Talbi* 2009).

According to *Goldberg* (1989) and *Talbi* (2009), GA are applicable to virtually any problem by exploiting widely available information. GA are also suitable for solving discrete or mixed discrete (mix of continuous and discrete design variables) optimisation problems, which are usually more computationally intensive, because GA are combinatorial (*Wu & Chow* 1994).

3.3.3 Applications of Process Redesign Methods Connected with Process Mining

A current research trend in process mining is called prescriptive process monitoring, which belongs to process redesign and actively supports stakeholders in making decisions by not only providing predictions but also by optimising process outputs or a certain measure of interest (*Di Francescomarino & Ghidini* 2022). This is evolving because most studies dealing with predictions fail to suggest concrete actions to improve the process, leaving it to the subjective assessment of a user (*G. Park & M. Song* 2019). According to *Kubrak* et al. (2022), mainly optimising the process outcome or optimising the process efficiency are the objectives of prescriptive process monitoring literature.

Research in relation to prescribing optimised next activities in running cases is conducted by *de Leoni* et al. (2020), *G. Park & M. Song* (2019), and *Weinzierl* et al. (2020). After developing an LSTM model based on a loan process data in the financial domain to predict the next event and the respective processing time of that event, *G. Park & M. Song* (2019) solve a min-cost-max-flow network problem for scheduling necessary resources during process execution by evaluating the total weighted completion time. ML is used by *de Leoni* et al. (2020) to predict if a customer found a new job before reaching the maximum service duration in running cases of a process of a reintegration company. For running cases with predicted, poor outcomes, any possible continuation of the running case is simulated to find and recommend the activity or activities that is or are predicted to optimally continue the process to maximise the percentage of customers finding a new job over all cases (*de Leoni* et al. 2020). *Weinzierl* et al. (2020) use an LSTM model to predict the next most likely activities and the resulting throughput time in running cases of a helpdesk ticketing management process and of a purchase order handling process of a company for paints and coatings. By evaluating the throughput time and checking process conformity using business process simulation (BPS) through DES, the next best activity is then proposed instead of the most likely activity if the most likely activity exceeds a certain throughput time threshold (*Weinzierl* et al. 2020).

Metzger et al. (2019) and *Teinemaa* et al. (2018) develop ML and DL based process adaptation strategies that recommend interventions during process execution taking cost models. These incorporate trade-offs between the cost of intervention, the benefit of preventing undesired outcomes, and the cost of compensating for unnecessary interventions induced by false alarms (*Metzger* et al. 2019; *Teinemaa* et al. 2018). *Metzger* et al. (2019) use an LSTM model to predict the occurrence of process violations in running processes on a airfreight forwarding process, a traffic fine process and a loan application process. *Teinemaa* et al. (2018) use ML cost-sensitive classification algorithms to predict outcomes and provide an intervention alarm mechanism during process execution in a loan application process in the financial domain, a traffic fine process and an unemployment benefits allocation process. An alarm mechanism, that can lead to interventions that mitigate or prevent undesired outcomes, is thereby developed (*Teinemaa* et al. 2018).

More applications of prescriptive process monitoring can be found in *Kubrak* et al. (2022). According to *Kubrak* et al. (2022) current literature focuses mainly on identifying cases in a process during execution that require intervention, and finding the point in time at which that intervention needs to be triggered. The interested reader is referred to *Kubrak* et al. (2022) for further information on prescriptive process monitoring and current research approaches.

4 Utilising Process Data in Intra-Hospital Patient Transport and Other Operational Healthcare Processes

This section builds on *Kropp* et al. (2023), *Kropp* et al. (2024a), and *Kropp* et al. (2024b).

According to *Martin* et al. (2020) and *van der Aalst* (2016), hospital information systems (HIS), and other software systems, can hold information about hospital processes, such as IHPT (see also section 3). As indicated by *Martin* et al. (2020) and *van der Aalst* (2016), the analysis of process data using process mining techniques can provide valuable insights into the execution of healthcare processes, allowing for the improvement of the services provided (see also subsection 3.1.4). Subsection 2.2.2 has already highlighted examples of the analysis of IHPT process data to identify process issues and improvement potentials.

Subsection 4.1 will present current research on process mining analysis in healthcare, elaborating on the state of the art in organisational healthcare processes including a view on IHPT. Subsection 4.2 will focus on data-based redesign of organisational healthcare processes, especially in the IHPT domain, because subsection 4.1 will indicate current shortcomings and research gaps in this field. Based on the identified challenges, the approach of thesis to reorganising the capacity planning of IHPT is outlined in subsection 4.3.

4.1 Process Mining Analysis in Healthcare

Process mining can be used to discover, analyse and improve processes from large amounts of data held in information systems (see also subsection 3.1.4). Process mining methods have been successfully applied in the healthcare context to various areas, like the analysis of patient pathways (*Agostinelli* et al. 2020; *de Oliveira* et al. 2020) or layout design (*Halawa* et al. 2021; *Rismanchian & Lee* 2016). It can assist resource planning in organisations including hospitals. For example, (*Alvarez* et al. 2018) applied process mining to discover how people interact and collaborate in emergency rooms (ER). Using a similar approach, *Lismont* et al. (2016) investigated the handover of work between general practitioners and specialists. *Stefanini* et al. (2020) estimate the resources needed by a particular group of patients by combining process mining and time-driven activity-based costing to support the planning of healthcare services.

Despite the benefits that process mining offers, there remain challenges in the healthcare context that need be addressed. *Kaymak* et al. (2012) discussed shortcomings of early process mining methods in medical contexts. According to *Kaymak* et al. (2012), the use of process mining may lead to false sequences of medical activities, when medical knowledge is not incorporated into process mining tools. *Rojas* et al. (2015) argue that in addition to the need to incorporate medical knowledge, there are other challenges and limitations to the use of process mining methods in healthcare, such as data quality and the integration of data from other resources. *Lismont* et al. (2016) mentioned issues regarding data irregularity, data abstraction levels, data abundance and general data quality in healthcare. *Munoz-Gama* et al. (2022) identified ten specific challenges to the use of process mining in healthcare which are also addressed in this thesis. These challenges (*Munoz-Gama* et al. 2022) are ranked qualitatively in the following according to the degree of emphasis attached to them in this work (1. - more emphasis; 10. - less emphasis):

1. "Take Care of Privacy and Security - Methods to preserve patients' privacy and security when conducting process mining for healthcare methods analyses are needed.

2. Deal with Reality - If it does not work with real data, it does not work.

3. Design Dedicated/Tailored Methodologies and Frameworks - Developments to foster the use of process mining by healthcare professionals are required.
4. Discover Beyond Discovery - Conformance Checking and Enhancement types can provide new knowledge to the Process mining for healthcare domain.
5. Mind the Concept Drift - Healthcare processes change over the time.
6. Do It Yourself (DIY) - Developments to foster the use of process mining by healthcare professionals are required.
7. Pay Attention to Data Quality - Addressing quality issues make results trustable.
8. Look at the Process through the Patient's Eyes - New knowledge can emerge looking the process from the patient' perspective.
9. Evolve in Symbiosis with the Developments in the Healthcare Domain - Process mining for healthcare methods should provide ongoing support to the constantly changing healthcare domain.
10. Complement HISs with the Process Perspective - How to incorporate the process perspective in the HIS is a challenge to be addressed."

To overcome the previously mentioned challenges, *Fernández-Llatas* (2021a) and *Munoz-Gama* et al. (2022) emphasise the need for continuous integration of expert knowledge and involvement of multidisciplinary teams when dealing with process mining in healthcare. To facilitate fast stakeholder involvement, it is important to consult user-friendly techniques that do not require extensive process mining expertise and provide simple visualisations (*Munoz-Gama* et al. 2022). To this end, *Fernández-Llatas* (2021a) introduces interactive process mining, which aims to merge data-driven techniques with knowledge-driven approaches to provide a comprehensible way to study processes. Coordination steps between the involved parties enable the generation of interactive process models (*Fernández-Llatas* 2021e). They can also be automatically formalised and learned, and they overcome conventional numerical KPIs by offering contextual and personalised views to support the assessment of perceptual issues (*Fernández-Llatas* 2021e). Interactive process models display views on the status of the current processes and can be filtered and tailored according to specific criteria available in the underlying process data (*Fernández-Llatas* 2021e). Data rodeos - recurring joint meetings with all the relevant stakeholders (e.g., data analysts, process managers, executing personnel, patients) - are held to interactively analyse the data and latest performance indicators (*Fernández-Llatas* 2021e; *Lull* et al. 2022). Through these interactive sessions, adjustments such as data cleaning, filtering and adding metadata are performed to make the interactive process models understandable and valuable for hospital stakeholders (*Fernández-Llatas* 2021a; *Lull* et al. 2022).

Ibanez-Sanchez et al. (2019) apply interactive process models to support the application of value-based healthcare through the study of stroke emergency processes. Based on the HIS data in a cardiology outpatient department, *Lull* et al. (2022) utilise interactive process models to examine primary care services. In *Fernández-Llatas* (2021c) further applications of interactive process models in healthcare can be found.

Overall, the application of interactively designed process models in healthcare unite data and knowledge-driven worlds and increase the technology acceptance of the stakeholders, enabling them to understand how processes are deployed (*Fernández-Llatas* 2021d). However, in healthcare, the patient is the central stakeholder (see also subsection 2.2), and to support high quality care, process mining experts and researchers need to explicitly take the patient's perspective into account (*Munoz-Gama* et al. 2022).

Although the support for healthcare resource planning through process mining has been demonstrated in the literature, similar applications in secondary (i.e. organisational, supporting; see also subsection 2.2.1) healthcare processes contexts are rare (*de Roock & Martin* 2022).

Based on the analysis of 263 papers on process mining in healthcare, *de Roock & Martin* (2022) highlight that only about 7.6% of the papers deal with analysis of organisational processes and only another 15.2% deal with organisational processes in part. Most of the literature deals with medical treatments (*de Roock & Martin* 2022). In addition, *de Roock & Martin* (2022) conclude that current research tends to focus mainly on the analysis stage, but that the ability to translate analysis results into concrete actions that drive process improvement within healthcare organisations is where the real value lies. The process redesign phase (see also subsection 3.1.4), which is the last stage of a process mining project, is barely addressed (*de Roock & Martin* 2022).

Little research has been reported on the application of process mining to resource planning in IHPT services. *Kropp* et al. (2023) perform process discovery and conformance analysis on an IHPT dataset, that covers one year of operation, to demonstrate the capability of process mining analysis on event data captured in the case study hospital's logistics system (i.e. a smaller dataset from the same case study hospital of this thesis). However, the solutions presented in *Kropp* et al. (2023) are at an early stage and no capacity analysis is carried out. This highlights the importance of the approach of this thesis that proposes specific adjustments to the allocation of IHPT resources to optimise process efficiency. *Kropp* et al. (2024a) analyse a larger IHPT dataset, containing 3.5 years of operational information (i.e. the case study dataset of this thesis), with process mining techniques, also incorporating capacity evaluations. The main results from *Kropp* et al. (2024a) and further analysis will be presented in section 6. These provide the necessary process knowledge for the novel process redesign approach in IHPT presented in section 7, which is based on the investigations of *Kropp* et al. (2024b). *Kropp* et al. (2024b) use the same dataset (i.e. the case study dataset of this thesis) as *Kropp* et al. (2024a).

4.2 Data-based Process Redesign in Healthcare

Different techniques can be used for process predictions and process redesign (see subsections 3.2 and 3.3). Literature shows that ANN (see subsection 3.2.2.2) are able to model complex behaviour (that usually requires domain knowledge) without having to assume certain function forms and degrees of non-linearities in advance (*Gardner & Dorling* 1998; *Mitrea* et al. 2009). There are already several applications of ANN in primary healthcare processes to optimise process redesign. For instance, *Amato* et al. (2013) regard ANN as an essential tool to assist doctors in diagnosis and analysis, involving tasks such as data processing, reducing the likelihood of overlooking relevant information and shortening diagnosis time, thereby adding to the reliability of doctors' ultimate diagnostic decisions. Based on a logistic regression model, *Yang* et al. (2017a) and *Yang* et al. (2017b) develop a process recommender system to provide data-driven, step-by-step treatment recommendations. The framework introduced in *Yang* et al. (2017a) and *Yang* et al. (2017b) starts by clustering treatment procedures of trauma resuscitation patients according to context attributes (patient attributes and hospital factors). Then it generates a proposal for the execution of the patient treatment process, when a new set of context attributes is inserted into the trained regression model (*Yang* et al. 2017a; *Yang* et al. 2017b).

In general, as indicated by *de Roock & Martin* (2022) (see subsection 4.1), there are few studies that provide insights on process mining-based process redesign of organisational processes in hospitals. Furthermore, in the literature review of *de Roock & Martin* (2022) (see subsection 4.1), there are no studies identified that analyse process data for IHPT processes to be able to automatically derive process improvements. *Nas & Koyuncu* (2019) additionally highlight that there are few studies found in the literature for hourly patient arrival problems.

Subsection 4.2.1 presents literature that focuses on optimising the process redesign phase of organisational healthcare processes in a data supported way. Subsequently, subsection 4.2.2 particularly reviews approaches using ANN for capacity optimisation, as they promise capabilities for complex behaviour modeling.

4.2.1 Data-supported Process Redesign in Organisational Healthcare

Agostinelli et al. (2020) investigate patient care flows in a case study with process mining on real-world data. *Agostinelli* et al. (2020) evaluate the temporal distribution of abandonments from ER and examinations without reservations as well as the value of recent investments. *Agostinelli* et al. (2020) suggest starting points for future improvements to address some of the problems identified in the care flow process, but no specific improvement measures have been developed or evaluated.

Andrews et al. (2020) analyse transport pathways identified during the time-critical pre-hospital care phase of road crash victims. With the assistance of domain experts, improvement concepts are proposed that target both data quality improvement and future automated decision support, e.g. through AI (*Andrews* et al. 2020). However, no evaluation of specific measures and their impact is carried out.

Badakhshan & Alibabaei (2020) examine data from an automation system of a pre-hospital ER. Based on previous bottleneck identification following process discovery and compliance checks, several specific improvement ideas are provided (*Badakhshan & Alibabaei* 2020). There is no quantitative evaluation of the effects of the proposed measures, and no alternatives to those proposed in *Badakhshan & Alibabaei* (2020) are investigated.

To improve the care process for patients with arthrosis to better match available facilities and resources, *Canjels* et al. (2021) use process mining techniques. The knowledge gained from the process mining analysis of historical data is used to cluster and redistribute potential patient pathways according to the required complexity of patient care between two hospital sites (a university medical centre and an outpatient city clinic) (*Canjels* et al. 2021). This potentially allows more patients to be treated fully or partially in the cost-effective outpatient clinic environment in the future (*Canjels* et al. 2021).

Stefanini et al. (2017) propose a methodology that takes advantage of process mining techniques related to healthcare systems to support service reconfiguration. *Stefanini* et al. (2017) apply their method in a case study with historical data of a lung cancer unit. The evaluations unveil the average demand of activities and associated resource consumption of an average patient and support managers in decision-making about the establishment of a new lung cancer unit (*Stefanini* et al. 2017). Process improvement ideas and what-if analysis are suggested within *Stefanini* et al. (2017), but not carried out or evaluated.

Antunes et al. (2019) optimise waiting times, queue length and queue occurrences in an emergency department by rescheduling the weekly and hourly number of available physicians using a mixed-integer programming (MIP) mathematical model. The derived, adapted schedule is tested to evaluate the success of the mathematical optimisation, using a DES model designed and validated with the historical process data and knowledge gained from process mining analysis (*Antunes* et al. 2019).

To optimise organisational healthcare processes *Abohamad* et al. (2017), *Pourbafrani & van der Aalst* (2023), *van Hulzen* et al. (2022), and *Zhou* et al. (2014) develop DES models based on process mining analysis. Improvement alternatives of capacity management decisions in the radiology department are evaluated in *van Hulzen* et al. (2022) through data-driven process simulation based on DES. Recommendations regarding the size of the waiting area, reception staffing, and the required number of radiology devices are derived (*van Hulzen* et al. 2022). However, *van Hulzen* et al. (2022) conclude, that the conformity of a developed simulation model relies highly on the modeller. It is important to include domain knowledge during the data-driven development and validation of a simulation model (*van Hulzen* et al. 2022). A reference model for data-driven simulation, with DES, in process mining for production systems is presented in *Pourbafrani & van der Aalst* (2023). In particular, literature on practical approaches for generating DES models of processes is reviewed in *Pourbafrani & van der Aalst* (2023) to develop the reference model. *Pourbafrani & van der Aalst* (2023) also emphasise on the influence of human factors in producing accurate simulation models of processes. *Zhou* et al. (2014) use DES to evaluate the impact of the number of receptionists, nurses, and doctors to improve the performance of an outpatient clinic. In *Zhou* et al. (2014) the DES model is based on knowledge gained from process mining analysis. Specific scenarios are quantitatively investigated to assess the effects of operational changes, and sensitivity analysis is carried out to determine when an increase in the number of specific personnel resources reaches a limit of improvement (*Zhou* et al. 2014). To identify performance bottlenecks and to explore improvement strategies to reduce patients' length of stay in the emergency department (ED LOS), also *Abohamad* et al. (2017) use DES with a simulation model developed using process mining based knowledge. Specific scenarios for varying medical staffing, increasing clinical assessment space, or incorporating a policy of discharging patients who wait longer than a certain time threshold to be admitted to a hospital bed, are simulated and quantitatively evaluated (*Abohamad* et al. 2017).

Akbari et al. (2023), *Li* et al. (2021), and *Yazır* et al. (2023) optimise the routing and scheduling of home healthcare services using mathematical models and metaheuristic algorithms. A level-based integer programming (IP) mathematical model for smaller instances, and a generalised variable neighborhood search-based (GVNS) metaheuristic algorithm for larger instances are used in *Akbari* et al. (2023). The solutions proposed by *Akbari* et al. (2023) optimise the planning of multiple teams of home healthcare providers who should visit a given set of patients in their homes according to the service urgency, the severity of the condition of the patients, and location. To optimise the planning of the weekly routes of nurses visiting patients located at a scattered geographic area, *Yazır* et al. (2023) formulate a MIP mathematical model and use an adaptive large neighborhood search-based (ALNS) metaheuristic algorithm. The optimisation is accomplished by minimising the total costs that incorporate e.g. wage costs, charging costs of used vehicles, further transfer costs, and the costs of patients left unserved (*Yazır* et al. 2023). To optimise the routing and scheduling of home healthcare with consideration of outpatient services, a MIP mathematical model is developed in *Li* et al. (2021)

to improve travel costs, waiting times and patients' preference satisfaction under constraints on time windows, workload and skill requirements. Furthermore, for larger instances a hybrid GA for the optimisation is developed and proposed (*Li* et al. 2021).

Using a multi-directional local search (MDLS) metaheuristic algorithm, *Molenbruch* et al. (2017) optimise service quality and operational costs with improved driver schedules for a service provider conducting demand-responsive transportation between patients' homes and healthcare locations.

In *Naesens & Gelders* (2009) a data analysis of the IHPT process is carried out to propose process improvements. This results in a partial decentralisation of the IHPT organisation (*Naesens & Gelders* 2009). In *Naesens & Gelders* (2009) no quantitative evaluation of the redesigned process is conducted.

To optimise IHPT, several authors[1] solve mathematical models. To optimise specifically IHPT routing and scheduling, *Kallrath* (2005) solves MIP mathematical models, uses a branch-and-bound approach, a column enumeration approach and (meta-)heuristic algorithms (recommended for larger problem instances). A general, theoretical framework, incorporating the different solution approaches mentioned is presented by *Kallrath* (2005). *Kallrath* (2005) also carries out comparative experiments using real-world instances from a German hospital to reduce e.g. patient waiting times, transport delays and uneven occupancy of transport vehicles. A MIP mathematical model to optimise the hourly staff planning per day of the week and to reduce completion times of transports or patient waiting times is developed by each, *Gopal* (2016), *Kuchera & Rohleder* (2011), and *Séguin* et al. (2019). *Séguin* et al. (2019) achieve a 16% reduction in daily staff capacity. Possible delay minutes of transports per specific hour could, at the same time, be mainly decreased between 27% and 71% (in contrast, less active scheduled transporters could also partly lead to an increase of up to 58% in possible delay minutes per hour) (*Séguin* et al. 2019). *Kuchera & Rohleder* (2011) validate their optimisation proposal with positive observations of the patient service quality in real operation, saving two full-time equivalent (FTE). There are no reports in *Kuchera & Rohleder* (2011) on the relative improvement in FTE. *Gopal* (2016) uses DES to validate that the proposed solution does not have adverse effects on the IHPT service quality by examining the resulting average time from pending to completion

[1] (*Bouabdallah* et al. 2013; *Elmbach* et al. 2015; *Gopal* 2016; *Kallrath* 2005; *Kuchera & Rohleder* 2011; *Maka* et al. 2022; *Séguin* et al. 2019; *Turan* et al. 2011)

of the transports. The approach of *Gopal* (2016) reduces process throughput times by up to 13% (and by up to 25% in sub-processes), depending on the underlying scenario. Between around 1% and 8% FTE could be saved at the same time, depending on the scenario (*Gopal* 2016). To minimise the total cost of operation, also *Maka* et al. (2022) develop a MIP mathematical model for an optimised planning of IHPT. The approach helps first to select a minimum number of depots with the best locations from a choice of locations within a hospital and then to allocate different resources to each depot accordingly, like wheelchairs, stretchers, oxygen tanks, staff etc. (*Maka* et al. 2022). To minimise the sum of the empty stretcher moves between IHPT assignments, *Bouabdallah* et al. (2013) present a MIP mathematical model. By solving a weighted sum mathematical model, *Turan* et al. (2011) provide optimised IHPT planning for patient routing with fixed randomly generated appointments. The aim of *Turan* et al. (2011) is to minimise patient transporters' travel time and the patients' waiting time. The mathematical model also takes factors like the number of different transporters per patient and empty runs of transporters between transportation assignments into account (*Turan* et al. 2011). Compared to schedules that minimise transporters' travel time and the patients' waiting time, the patients' inconvenience of having to deal with different transporters could be improved by reducing the number of different transporters per patient by 27%, however at the cost of around 12% increased transporters' travel times (*Turan* et al. 2011). Furthermore it is pointed out, that the developed model has computational limitations and that optimised planning incorporating more than 40 transport requests per hour require the development and use of (meta-)heuristic approaches (*Turan* et al. 2011). For the scheduling of IHPT with consideration of the transporters' ergonomic stress, *Elmbach* et al. (2015) develop a mathematical model and investigate optimisation solutions by the use of dynamic programming (for small instances) and beam search-based heuristic algorithms (for small and large instances). Compared to simple decision rules of a human decision maker, the ergonomic liability at the case study hospital could theoretically be improved by an average of around 36% (and a maximum of around 79%) for large (real-world) instances by applying the beam search-based heuristic algorithm (*Elmbach* et al. 2015).

Various authors[2] use (meta-)heuristic algorithms to optimise IHPT. In addition, *Hanne* et al. (2009) and *Vancroonenburg* et al. (2016) incorporate DES in their approach. To optimise IHPT routing and scheduling, *Beaudry* et al. (2010), *Fröhlich Von Elmbach* et al. (2019), and *Kergosien* et al. (2011) utilise tabu search. While using fewer vehicles, *Beaudry* et al. (2010) reduce waiting times for patients. Through the approach of *Kergosien* et al. (2011) the case study hospital could theoretically handle around 10% more requested transports independently, thus requiring fewer subcontracted transports to handle all transports and meet all suggested time windows. *Kergosien* et al. (2011) also compare their approach with integer linear programming (ILP). In comparison to the simple decision rules of a human decision maker, *Fröhlich Von Elmbach* et al. (2019) achieve average staff savings of about 8% while improving ergonomic liability of transporters. The performance of the tabu search approach in *Fröhlich Von Elmbach* et al. (2019) is also compared with a MIP solver. To optimise IHPT routing and scheduling with respect to resource- and client-centred perspectives, *Schmid & Doerner* (2014) develop a hybrid large neighbourhood search (LNS)-based algorithm. Exact MIP solutions for smaller instances and ten hour runtime MIP solutions for larger (real-world) instances are compared with the algorithm's performance (*Schmid & Doerner* 2014). To maximise the possible task throughput in IHPT scheduling, *Fiegl & Pontow* (2009) present a heuristic algorithm which is based on scheduling and graph theory. Compared to usual scheduling in a hospital case study, around 17% reduction in task flow time could be theoretically achieved (*Fiegl & Pontow* 2009). To optimise IHPT routing and scheduling, *Xiao* et al. (2022) develop and compare a greedy and a column generation-based heuristic algorithm. For solving subproblems, the latter integrates additionally either MIP or GA-based metaheuristics (*Xiao* et al. 2022). A lexicographic branch-and-bound column generation-based approach is developed in *Bärmann* et al. (2024) for the optimisation of IHPT routing and scheduling in terms of transport delays, walked distances of transporters between transportation assignments and equal transporter utilisation. Using large instances from two European hospitals, *Bärmann* et al. (2024) conduct performance evaluations of their approach against a standard branch-and-bound column search approach, classical column generation-based methods and MIP. The approach of

[2] (*Bärmann* et al. 2024; *Beaudry* et al. 2010; *Fiegl & Pontow* 2009; *Fröhlich Von Elmbach* et al. 2019; *Hanne* et al. 2009; *Kergosien* et al. 2011; *Schmid & Doerner* 2014; *Vancroonenburg* et al. 2016; *Xiao* et al. 2022)

Bärmann et al. (2024) is also tested in comparison to the commercial routing and scheduling software used by the hospitals, showing an improvement of approximately 20% in both transport delays and empty runs by transporters. Lastly, *Bärmann* et al. (2024) implement and evaluate their approach in the operation of a German hospital for nine months, with promising performance results. To optimise the scheduling and assignment of IHPT to transporters, *Vancroonenburg* et al. (2016) utilise a cheapest insertion and a local search heuristic algorithm, along with DES. Multiple scenarios are designed and compared to a baseline scenario, using various KPIs (*Vancroonenburg* et al. 2016). These KPIs are, for example, the evenly weighted sum of delayed transport time, transporters' windows of availability without carrying out transports, and the total transporters' travel time carrying out assignments (*Vancroonenburg* et al. 2016). Depending on parameters like transport request arrival rates and the number of transporters, the approach of *Vancroonenburg* et al. (2016) improves the sum of these three factors by up to 31%. According to *Vancroonenburg* et al. (2016), the process could be even further improved in scenarios that allow transporters combining different transports (i.e. multiple pick-ups in sequence, before performing deliveries). By the use of different metaheuristic algorithms (GA and others) and DES aiming to optimise the scheduling and assignment of transports to vehicles or transport teams, *Hanne* et al. (2009) improve patient waiting times in IHPT. For example, average patient waiting times could theoretically be decreased by around 20% to 26% and average patient travel times by around 10% through the approach of *Hanne* et al. (2009). In a German hospital, the approach is furthermore deployed and evaluated in practice, leading to decreased transportation costs of around 20% while contributing to improved patient satisfaction (*Hanne* et al. 2009).

To find the best scenario among 20 different improvement strategies of IHPT, *Meephu* et al. (2023) use DES. Mean patient waiting times could be reduced by around 22% in the best scenario (*Meephu* et al. 2023).

To model the vendor selection process for university health centres, a hybrid analytical hierarchy process and artificial neural network (AHP-ANN) model is developed in *Fashoto* et al. (2016). Based on the determination of a priority sequence of five selection criteria (service, delivery, cost, risk, quality), the approach of *Fashoto* et al. (2016) aims to provide data-supported recommendations for decision-making.

The following subsection explicitly presents ANN approaches for optimising capacity planning in healthcare, since ANN approaches are effective in offering a high level of capability to model complex problems (see also subsection 3.2.2.2) (*Abiodun* et al. 2018).

4.2.2 Artifical Neural Networks to Optimise Capacity Planning in Healthcare

In *Rajakumari & Madhunisha* (2020) no case study is conducted, but a four staged framework to create and use a CNN to predict and assess improvement options for a patient appointment scheduling system is presented at a schematic and theoretic level. After completing the first stage ("data preparation") and the second stage ("process mining analysis"), in the third stage ("simulation modeling and evaluation"), a CNN is to be developed and the conformity of the model predictions towards reality is to be evaluated (*Rajakumari & Madhunisha* 2020). Improvement options are to be explored in the last stage ("Experiments and decision support") of the framework of *Rajakumari & Madhunisha* (2020) to support decisions with the best available option.

To support complex decision-making processes around hospital staff planning for improved resources handling, a framework is proposed by *Mesabbah* et al. (2019) to offer an accurate and process mining-based auto-generated DES model utilising healthcare event logs. Based on different patient features and process information, activity durations and next activities in the DES model are to be predicted by a ML model within the proposed framework (*Mesabbah* et al. 2019). In *Mesabbah* et al. (2019), the ML model is neither specified nor implemented yet, so no specific case study is investigated with the presented holistic framework.

To optimise emergency department capacity planning, *Nas & Koyuncu* (2019) use a RNN and DES approach. The RNN is used to predict patients' arrival rates that serve as an input parameter for the DES model (*Nas & Koyuncu* 2019). The route of the patients in the emergency department is extracted from the analysis of the hospital's data, which serves as another input to the DES model (*Nas & Koyuncu* 2019). With the help of the hospital experts, treatment and service times, which also serve as input to the DES model, are determined from observations (*Nas & Koyuncu* 2019). After running simulations, the number of beds are identified as one of the process bottlenecks affecting the waiting time of patients at the emergency department (*Nas & Koyuncu* 2019). Additional exploratory simulations help *Nas & Koyuncu* (2019) to determine the optimal number of beds. *Nas & Koyuncu* (2019) emphasise that ML methods could also substitute the simulation part in the case study.

Gul & Guneri (2015) use an ANN considering different sets of variables with the aim of modeling and forecasting the patient ED LOS to tackle the high patient demand faced by the emergency department during peak hours. Nevertheless, no predictions are presented after the modeling phase and *Gul & Guneri* (2015) emphasise that there is still room for improvement in the accuracy of the prediction results.

4.3 Research Gaps and Research Questions

The literature on process redesign of organisational healthcare processes is summarised in Table 4.1 and the literature specifically on process redesign of IHPT processes in Table 4.2. Some of the literature identified provides only qualitative optimisation ideas.

Andrews et al. (2020) already point out that the automatic, data-driven, derivation of improvement opportunities will be necessary in the future. In summary, DES models[3], mathematical models[4] and (meta-)heuristic algorithms[5] are most commonly developed and used to simulate and evaluate scenarios, when an optimisation is approached quantitatively in the process redesign literature. In subsection 4.2.1 it was already shown, that the conformity of simulation models with reality are highly dependent on modelers and the provided domain knowledge. The same applies to mathematical models and metaheuristic algorithms. This is where ANN can provide a remedy because they can, according to *Gardner & Dorling* (1998) and *Mitrea* et al. (2009),

[3] (*Abohamad* et al. 2017; *Antunes* et al. 2019; *Gopal* 2016; *Hanne* et al. 2009; *Meephu* et al. 2023; *Nas & Koyuncu* 2019; *Pourbafrani & van der Aalst* 2023; *van Hulzen* et al. 2022; *Vancroonenburg* et al. 2016; *Zhou* et al. 2014)

[4] (*Akbari* et al. 2023; *Antunes* et al. 2019; *Bärmann* et al. 2024; *Beaudry* et al. 2010; *Bouabdallah* et al. 2013; *Elmbach* et al. 2015; *Fiegl & Pontow* 2009; *Fröhlich Von Elmbach* et al. 2019; *Gopal* 2016; *Kallrath* 2005; *Kergosien* et al. 2011; *Kuchera & Rohleder* 2011; *Li* et al. 2021; *Maka* et al. 2022; *Molenbruch* et al. 2017; *Schmid & Doerner* 2014; *Séguin* et al. 2019; *Turan* et al. 2011; *Xiao* et al. 2022; *Yazır* et al. 2023)

[5] (*Akbari* et al. 2023; *Bärmann* et al. 2024; *Beaudry* et al. 2010; *Elmbach* et al. 2015; *Fiegl & Pontow* 2009; *Fröhlich Von Elmbach* et al. 2019; *Hanne* et al. 2009; *Kallrath* 2005; *Kergosien* et al. 2011; *Li* et al. 2021; *Molenbruch* et al. 2017; *Schmid & Doerner* 2014; *Vancroonenburg* et al. 2016; *Xiao* et al. 2022; *Yazır* et al. 2023)

Table 4.1: Literature overview - redesign phase of organisational healthcare processes. Adopted from *Kropp* et al. (2024b).

Literature	Type	Presented evaluation of process improvement alternatives	Used main approach to create and evaluate process improvement alternatives	Comments on process redesign and process improvement alternatives
(*Agostinelli* et al. 2020)	Case study	Qualitative	Knowledge from PM Analysis	Only ideas, no evaluation of alternatives.
(*Andrews* et al. 2020)	Case study	Qualitative	Domain experts, Knowledge from PM Analysis	Only ideas, no evaluation of alternatives.
(*Badakhshan & Alibabaei* 2020)	Case study	Qualitative	Knowledge from PM Analysis	Only ideas, no evaluation of alternatives.
(*Canjels* et al. 2021)	Case study	Quantitative	Domain experts, knowledge from PM Analysis	Specific optimisation proposed, but only one alternative is evaluated.
(*Stefanini* et al. 2017)	Framework/ Case study	Qualitative	Domain experts, knowledge from PM Analysis	Only ideas, no evaluation of alternatives.
(*Antunes* et al. 2019)	Case study	Quantitative	MIP mathematical model and DES	Alternatives are evaluated to find best solution.
(*van Hulzen* et al. 2022)	Case study	Quantitative	DES	Alternatives are evaluated to find best solution.
(*Pourbafrani & van der Aalst* 2023)	Framework	Quantitative	DES	Framework for data-based model developing, no evaluation of alternatives.
(*Zhou* et al. 2014)	Case study	Quantitative	DES	Specific alternatives are evaluated to find the best solution among them and sensitivity analysis towards personnel resources is conducted.
(*Abohamad* et al. 2017)	Framework/ Case study	Quantitative	DES	Specific alternatives are evaluated to find the best solution among them and sensitivity analysis of different resources is conducted.
(*Akbari* et al. 2023)	Case study	Quantitative	IP mathematical model and meta-heuristic algorithm (GVNS)	Alternatives are evaluated to find best solution, both approaches are compared.
(*Yazır* et al. 2023)	Case study	Quantitative	MIP mathematical model and meta-heuristic algorithm (ALNS)	Alternatives are evaluated to find best solution, both approaches are compared.

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Table 4.1 – continuation

Literature	Type	Presented evaluation of process improvement alternatives	Used main approach to create and evaluate process improvement alternatives	Comments on process redesign and process improvement alternatives
(*Li* et al. 2021)	Case study	Quantitative	Convex MINLP mathematical model and metaheuristic algorithm (hybrid GA)	Alternatives are evaluated to find best solution, both approaches are compared.
(*Molenbruch* et al. 2017)	Case study	Quantitative	Metaheuristic algorithm (MDLS)	Alternatives are evaluated to find best solution.
(*Fashoto* et al. 2016)	Case study	Quantitative	AHP-ANN	Specific alternatives are evaluated to find the best solution among them.
(*Rajakumari* & *Madhunisha* 2020)	Framework	Quantitative	CNN	Coarse framework without providing details on implementation, no alternatives are evaluated.
(*Mesabbah* et al. 2019)	Framework	Quantitative	DES and ML approach	Coarse Framework without providing details on implementation, no alternatives are evaluated.
(*Nas* & *Koyuncu* 2019)	Case study	Quantitative	ML approaches (RNN etc.) and DES	Specific alternatives are evaluated by a simulation model that uses ML results as input parameter to find best solution among them.
(*Gul* & *Guneri* 2015)	Case study	Quantitative	ANN	Focus is on development of ANN that allows for evaluation of alternatives, no alternatives are evaluated.

Table 4.2: Literature overview - redesign phase of IHPT processes. Adapted from *Kropp* et al. (2024b).

Literature	Type	Presented evaluation of process improvement alternatives	Used main approach to create and evaluate process improvement alternatives	Comments on process redesign and process improvement alternatives
(*Haldar* et al. 2019)	Case study	Qualitative	Process analysis	Specific optimisation implemented, but only one alternative is evaluated (see subsection 2.2.2).
(*Naesens & Gelders* 2009)	Case study	Qualitative	Process analysis	Only ideas, no evaluation of alternatives.
(*Kallrath* 2005)	Framework/ Case study	Quantitative	MIP mathematical model, branch-and-bound, column enumeration, (meta-)heuristic algorithms	Alternatives are evaluated to find best solution.
(*Séguin* et al. 2019)	Case study	Quantitative	MIP mathematical model	Alternatives are evaluated to find best solution.
(*Kuchera & Rohleder* 2011)	Case study	Quantitative	MIP mathematical model	Alternatives are evaluated to find best solution.
(*Gopal* 2016)	Case study	Quantitative	MIP mathematical model and DES	Alternatives are evaluated with MIP model to find best solution. DES is used to validate the found solution.
(*Maka* et al. 2022)	Case study	Quantitative	MIP mathematical model	Alternatives are evaluated to find best solution.
(*Bouabdallah* et al. 2013)	Case study	Quantitative	MIP mathematical model	Alternatives are evaluated to find best solution.
(*Turan* et al. 2011)	Case study	Quantitative	Weighted sum mathematical model	Alternatives are evaluated to find best solution.
(*Elmbach* et al. 2015)	Case study	Quantitative	Heuristic algorithm (beam search-based) and dynamic programming	Alternatives are evaluated to find best solution.
(*Beaudry* et al. 2010)	Case study	Quantitative	Metaheuristic algorithm (tabu search)	Alternatives are evaluated to find best solution.
(*Kergosien* et al. 2011)	Case study	Quantitative	Metaheuristic algorithm (tabu search) and ILP	Alternatives are evaluated to find best solution.
(*Fröhlich Von Elmbach* et al. 2019)	Case study	Quantitative	Metaheuristic algorithm (tabu search) and MIP	Alternatives are evaluated to find best solution.
(*Schmid & Doerner* 2014)	Case study	Quantitative	Metaheuristic algorithms (LNS-based hybrid algorithm) and MIP	Alternatives are evaluated to find best solution.

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Table 4.2 – continuation

Literature	Type	Presented evaluation of process improvement alternatives	Used main approach to create and evaluate process improvement alternatives	Comments on process redesign and process improvement alternatives
(*Fiegl & Pontow* 2009)	Case study	Quantitative	Heuristic algorithms (based on scheduling and graph theory)	Alternatives are evaluated to find best solution.
(*Xiao* et al. 2022)	Case study	Quantitative	Heuristic greedy or heuristic column generation-based algorithm (with integrated metaheuristic GA or integrated MIP)	Alternatives are evaluated to find best solution.
(*Bärmann* et al. 2024)	Case study	Quantitative	Heuristic (lexicographic) branch-and-bound column generation-based algorithms, classical column generation-based algorithms and MIP	Alternatives are evaluated to find best solution.
(*Vancroonenburg* et al. 2016)	Case study	Quantitative	Heuristic algorithms (cheapest insertion and local search) and DES	Alternatives are evaluated to find best solution.
(*Hanne* et al. 2009)	Case study	Quantitative	Metaheuristic algorithms (GA, etc.) and DES	Alternatives are evaluated to find best solution.
(*Meephu* et al. 2023)	Case study	Quantitative	DES	Specific alternatives are evaluated to find the best solution among them.

model complex behaviour without the burden of having to make prior assumptions (see also subsections 3.2.2.2 and 4.2). In addition, by comparing the relative accuracy for generating activity durations and process control flows, *Camargo* et al. (2021) derive that ANN models, when trained with large logs, outperform simulation models automatically derived from process data (i.e. *Simod*, see subsection 3.2.1.2). Dependencies that cannot be captured by the process discovery algorithms (which are the basis of data-driven process simulation approaches, see also subsection 3.2.1.2), may be understandable for ANN (*Camargo* et al. 2021).

Where (non-linear) relationships are difficult to capture and describe, ANN offer predictive capabilities superior to traditional statistical or mathematical methods, as several authors[6] conclude. If sufficient data covering a wide range of all variables is present, ANN are able to model multi-variable dependent and complex processes (*Izadifar & Abdolahi* 2006).

Fashoto et al. (2016), *Gul & Guneri* (2015), *Mesabbah* et al. (2019), *Nas & Koyuncu* (2019), and *Rajakumari & Madhunisha* (2020) already provide research on the use of ANN, and ML approaches more broadly, for automated process redesign of organisational healthcare processes. Interrelationships between different process-relevant entities in the system can automatically be detected and understood by ANN (*Abiodun* et al. 2019; *Sharma & Kaur* 2013).

Whether the combination of an ANN and a metaheuristic algorithm is applicable in terms of practical performance metrics to exploit process data to optimise the capacity planning in the IHPT through more efficient allocation of resources involved is a major research question. The aim of this thesis is to assess if and how the combination of both methods, that is applied in section 7, can lead to a substantial, reliable improvement of the IHPT process. To optimise the total number of delayed cases per day of the week by optimising resource planning, hourly predictions of delayed IHPT as a function of several resource conditions are provided in this thesis. Subsection 2.2.2 and 2.3 already indicated that, according to *Sibbel* (2004), next to personnel and material/infrastructural factors also organisational aspects influence the capacity of services in hospitals. A key challenge is that, prior to analysing historical data, little is known about the pick-up and delivery locations, the

[6] (*Al-Waeli* et al. 2019; *Dumitru & Maria* 2013; *Izadifar & Abdolahi* 2006; *Neto & Fiorelli* 2008; *Nikzad* et al. 2012; *Salami* et al. 2016; *West* et al. 1997)

daily patient transport assignments and the required transporter capacity. Therefore, a detailed multi-perspective IHPT process analysis using process mining is conducted in section 6 to understand the key factors influencing the process.

The approach of this thesis is to develop an MLP (see subsection 3.2.2.2), i.e. an ANN, to automatically model the dependencies between selected attributes within the IHPT process based on a historical dataset to accurately predict delayed cases. A GA (see subsection 3.3.2), which uses the MLP to predict the effects of resource adjustments, is then applied to optimise the resource allocation of the involved capacities (e.g. transporters). IHPT, as mentioned in subsection 2.2.2, is a process characterised by complexity due to the heterogeneous organisation of hospitals (*Klein & Thielen* 2024). The GA, as a metaheuristic, evolutionary algorithm, has proven to produce effective solutions in complex environments (see subsection 3.3). The practicality of the proposed optimisation that is obtained by the GA (see subsection 7.2) is determined by the predictive performance of the MLP model (see subsection 7.1.2). The effectiveness of the GA is further validated in subsection 7.2.3 using a problem of reduced complexity. In summary, the contribution of this thesis is to show, using the example of the IHPT process, that optimisations in capacity planning within the healthcare domain are possible by combining MLP and GA. In this regard, how the raw data for the two techniques must be prepared and made available, will also be addressed (see subsection 7.1.1).

In other domains, some research combining ANN and metaheuristics for automated process redesign could be identified. *Sette* et al. (1996) use the combination of an ANN (i.e. MLP) and the GA to optimise the spinning production process of fibre-yarn in the textile industry. The reason for this approach is that the relationship between the input (i.e. machine settings and fibre quality parameters) and output (i.e. yarn strength and elongation) dimensions is complex, and it was not possible to develop an exact mathematical model for the interdependencies (*Sette* et al. 1996). Through an ANN, the production process is modeled and subsequently the GA adapts the input parameters to receive optimised output parameters (*Sette* et al. 1996). *Reynolds* et al. (2018) also develop ANN (i.e. MLP) to predict energy consumption and indoor temperature in buildings for future timesteps by using weather, occupancy, set point schedule, and previous indoor temperature as model inputs. With a GA, optimised heating setpoint schedules for different zones in a small office building are derived using the ANN as an evaluation engine to calculate the energy consumption over 24 hours (*Reynolds* et al. 2018). In *Reynolds* et al. (2019), similarly, ANN (i.e. MLP) are used to predict, hourly building energy demand, indoor temperature and solar photovoltaic generation of a district's buildings. Based on this, GA are utilised to determine optimal operating schedules for heat generation equipment, thermal storage, and heating set point temperature, resulting in increased profits (*Reynolds* et al. 2019). In *Reynolds* et al. (2019) and *Reynolds* et al. (2018) the building user behaviour and weather conditions are assumed and simulated to allow for the comparison of different strategies. Further literature in the building energy optimisation domain can be found in the related work sections of *Reynolds* et al. (2018) and *Reynolds* et al. (2019).

According to *Ozili* (2022), in environments that are mostly dependent on human behaviour (like the IHPT), the modeling of systems or processes tends to be even more challenging than in the science domain, dealing with objects, molecules, materials, or atoms (see also subsection 3.2.2.2). In this thesis, real-world data will be used to improve and evaluate the predictive performance of the developed MLP models. This exceeds the scope of the reviewed IHPT literature, which mostly does not use real-world data or only uses broader statistics of real-world data to feed instances into simulations or mathematical models. Only the approaches of *Bärmann* et al. (2024), *Hanne* et al. (2009), and *Kuchera & Rohleder* (2011) are so far transferred into practice, deployed and tested. Predictive performance is rarely evaluated in detail in the IHPT literature, and when evaluated, it is almost exclusively qualitative. Only *Meephu* et al. (2023) examine disparities in mean ratings between historical and simulation data by applying the two-sample T-test and confidence interval. For manually developed models that are not validated with historical process data, no statement is possible on the real-world significance. In contrast, this thesis will evaluate and present various relevant predictive performance metrics for the developed MLP model (see subsection 7.1.2). Validated by these performance metrics, the MLP model will be able to reflect real-world interdependencies.

The redesign results of this thesis will further contribute as an input at a tactical or strategic level (see subsection 2.3) to the IHPT literature dealing with detailed routing and scheduling at an operational level (see subsection 4.2.1 and also Table 4.2). The overall goal of this thesis is to demonstrate and communicate the advantages of redesigning IHPT capacity planning by combining an ANN and a metaheuristic algorithm in IHPT with techniques recommended in the literature using knowledge derived via process mining from real-world IHPT data. In particular, the research questions this thesis aims to solve are defined as follows:

- Research questions towards process analysis of IHPT (*Kropp* et al. 2024a):

  RQ 1: How can process mining in real-world datasets with multiple case- and event-related attributes help to analyse capacity planning in IHPT beyond process discovery?

  RQ 2: What are the important factors and limitations to consider when proposing capacity improvement measures in IHPT based on real-world datasets with multiple attributes related to case and event?

- Research questions towards process redesign of IHPT (*Kropp* et al. 2024b):

  RQ 3: Is a combination of an ANN and a metaheuristic algorithm applicable to reliably improve capacity planning in the IHPT in terms of practical performance metrics through more efficient allocation of resources?

  RQ 4: What are the important factors and limitations to consider when applying the combination of an ANN and a metaheuristic algorithm to derive a reliable improvement of the IHPT process?

Part III

Case Study

5 Materials and Methods

This section builds on *Kropp* et al. (2023), *Kropp* et al. (2024a), and *Kropp* et al. (2024b).

Real-world IHPT process data from the German hospital “Klinikum Magdeburg gGmbH” with approximately 700 to 800 beds and 75,000 inpatient and outpatient cases per year are used and investigated in this case study. The 4-phase model of *Aguirre* et al. (2017) (see subsection 3.1.4) describing different steps of process mining projects is adopted to situate the investigations (see Figure 5.1). As mentioned in subsection 3.1.4, process mining projects aim to exploit event data to improve processes (*van der Aalst* 2016). Section 6 will present the results of a detailed multi-perspective process analysis (process discovery and process conformance analysis) before a novel approach is developed in section 7 to provide decision support for the last stage in a process mining project, the process redesign phase (see Figure 5.1). In this thesis, 3.5 years of event data from the IHPT of a German public hospital are first analysed with process mining to understand the process and key elements. The event data is then processed for an artificial neural network (ANN) prediction model to subsequently allow improved transport capacity planning by solving an optimisation problem with a GA. The implementation of the derived optimisation in real operation (see “Process Redesign 2/2” in Figure 5.1) will not be investigated in this thesis, but remains a central task for future work (see section 10).

Within this section, background information on the case study and the underlying raw data will be provided in subsection 5.1. The methods associated with the process analysis (see section 6) are described in subsection 5.2 and the methods associated with the novel process redesign approach (see section 7) is described in subsection 5.3.

In conducting this research, ethical guidelines and data protection standards were strictly followed to ensure patient and transporter information remain

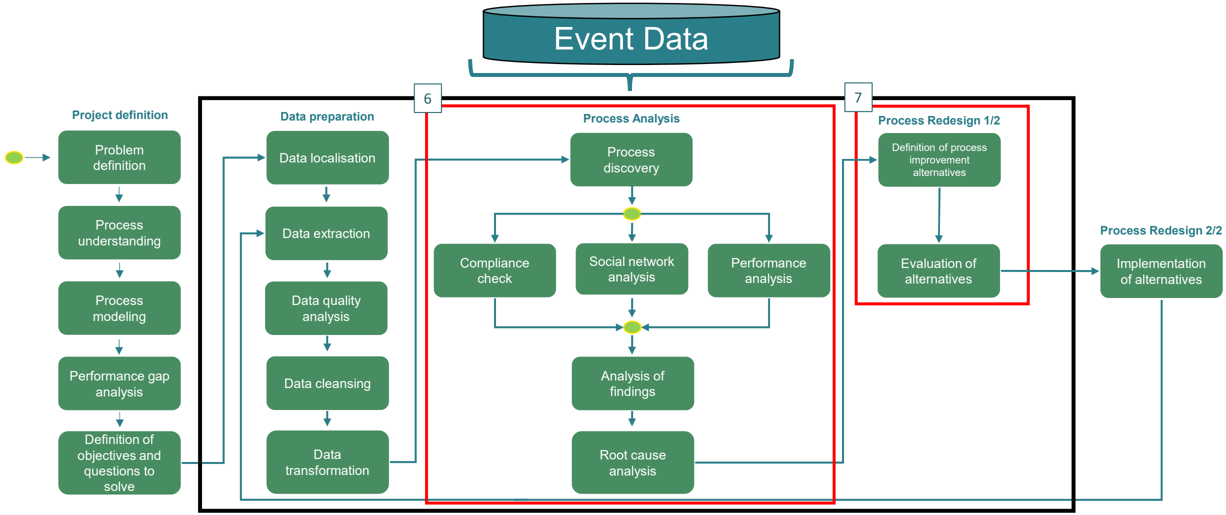


Figure 5.1: Classification of this thesis in the process mining methodology. The focus of this work is on process analysis and process redesign. Section 6 presents investigations on process analysis and section 7 on process redesign. Adapted from *Aguirre* et al. (2017).

confidential and secure. The data used in this thesis were provided in a de-identified format, preventing the identification of individual patients or transporters. Specifically, transport staff were de-identified through unique device IDs according to the used portable devices for receiving assignments, and no personal names were included in the provided dataset. Each patient was given a de-identified, unique patient ID, preventing the identification of individuals. The data was limited to logistics information, such as timestamps of various activities, types of transportation vehicles, priorities, or locations (see subsection 5.1 for more details) involved in the IHPT process. Importantly, the data did not include any information about medical diagnoses or health conditions. No personal data related to individuals were processed or stored in the created research database. In addition, the research results that will be presented throughout this thesis only contain aggregated information, which do not allow for any conclusions about individual transports or other individuals. These measures ensure compliance with data protection regulations and maintain confidentiality in the processing and use of health-related data. The IHPT process has been supported and documented by a logistics software system in the hospital for a couple of years. For the case study a consistent subset of 3.5 years of historical information was provided, which does not differ in terms of recording from the regular ongoing data recording of the IHPT process in the hospital. In this way, the Hawthorne effect (marked differences in performance of people involved in a process due to observation and documentation, see subsection 4.2.1) is eliminated in the case study.

5.1 Background and Raw Data

The hospital logistics software system logs the IHPT process and associates specific information regarding each transport case. Figure 5.2 visualises the usual IHPT process flow. In the hospital, there are transports from wards to functional areas and vice versa. Transports also take place between wards or between functional areas. The case study hospital has different ways of dispatching transport assignments. Once requested and added to the waiting list for dispatching, a transport can be assigned manually (by an employee in the hospital) or automatically (directly by the logistics software system). When a transporter has been selected, the transport assignment is sent to the transporter's device and the rest of the process goes on. A transporter can

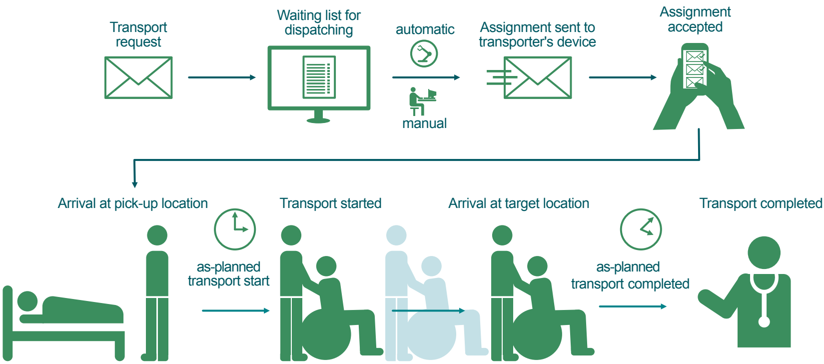


Figure 5.2: Exemplary patient transport in the case study hospital (*Kropp* et al. 2024b).

receive up to three different transport assignments on their mobile device at the same time.

The information logged on the IHPT process is provided by the hospital in the form of two CSV files. Both datasets used for the investigations cover a period with transport cases where the first activity occurred between 01/01/2019, and 30/06/2022. A couple of transport cases had some activities on 01/07/2022, although their first registered activity occurred earlier. In consultation with the hospital process managers, the data for further investigation should include only fully accompanied, completed transports with the patient as subject of transport, with no additional specialised services provided other than transport. To consider only these transport cases, the datasets originally containing 302,400 transport cases were filtered down to 256,266 transport cases. Transports of goods, transports with specialised services, unaccompanied transports and uncompleted transports were removed in this filtering. All further investigations address these remaining 256,266 transport cases.

One of the provided CSV files presents an event log (see subsection 3.1.4). The event log displays the events that occurred within the IHPT process with the corresponding activities that occurred during each transport, along with the timestamps indicating the date and time each event and associated activity happened. Table 5.1 displays the various activities and indicates the number of transport cases in which each activity occurs. It also provides information on the overall frequency of activities, taking into account that they may occur multiple times within a single case, or may not occur at all. In total there are

2,329,635 events, each of which records an activity, timestamp and transport ID (each transport has a unique ID) per row in the event log.

Table 5.1: Statistics on all activities. Statistics are sorted by case count and, within the same case count, alphabetically according to the German activity name. Adopted from *Kropp* et al. (2024a).

Activity (German - in System)	Activity (English translation)	case count	activity count
Auftrag abgeschlossen	transport completed	256,266	257,205
Auftrag an Endgerät	assignment sent to device	256,266	282,505
Auftrag angenommen	assignment accepted	256,266	262,262
Transport begonnen	transport started	256,266	256,556
Warteliste Kommissionierung	waiting list for dispatching	256,266	302,271
an Abholort	arrival at pick-up location	256,265	257,334
an Ankunftsort	arrival at target location	256,265	256,376
Anforderung	transport request	256,261	317,641
Vorgemerkt	transport is pre-registered	111,906	127,579
Verfall - nicht zugestellt	expiration - not delivered	6,021	9,714
Dispo	transport assignment	145	153
Storniert	transport canceled	33	39

The second file is a master table that contains more information on the total of 256,266 transport cases, with each row representing an individual case, along with 125 attribute categories that contain case-specific information. Of these 256,266 transport cases, around 34.2% were completed with a delay of ten minutes or more. This threshold, beyond which transports are regarded as significantly delayed, was set in consultation with the hospital process managers. They also view the percentage of delayed transports as critical. Therefore, there is a need to reduce the number of delayed IHPT cases using the knowledge gained from the data provided.

Both the event log and the master table can be connected through the transport IDs present in both tables. Together, they provide the raw data for the process mining analysis (see section 6). For the process redesign phase, the raw data needs to be further preprocessed to develop the MLP prediction model (see subsection 7.1.1). Figure 5.3 shows example information from the event log and the master table, as well as specific interdependencies. Figure 5.3 (upper part) also presents the as-planned process according to the hospital process managers.

More information on the raw data (event log and master table) is summarised in Figure 5.4. As mentioned, there exist 125 case-related attribute categories in the master table for all of the transport cases. In total, the master table

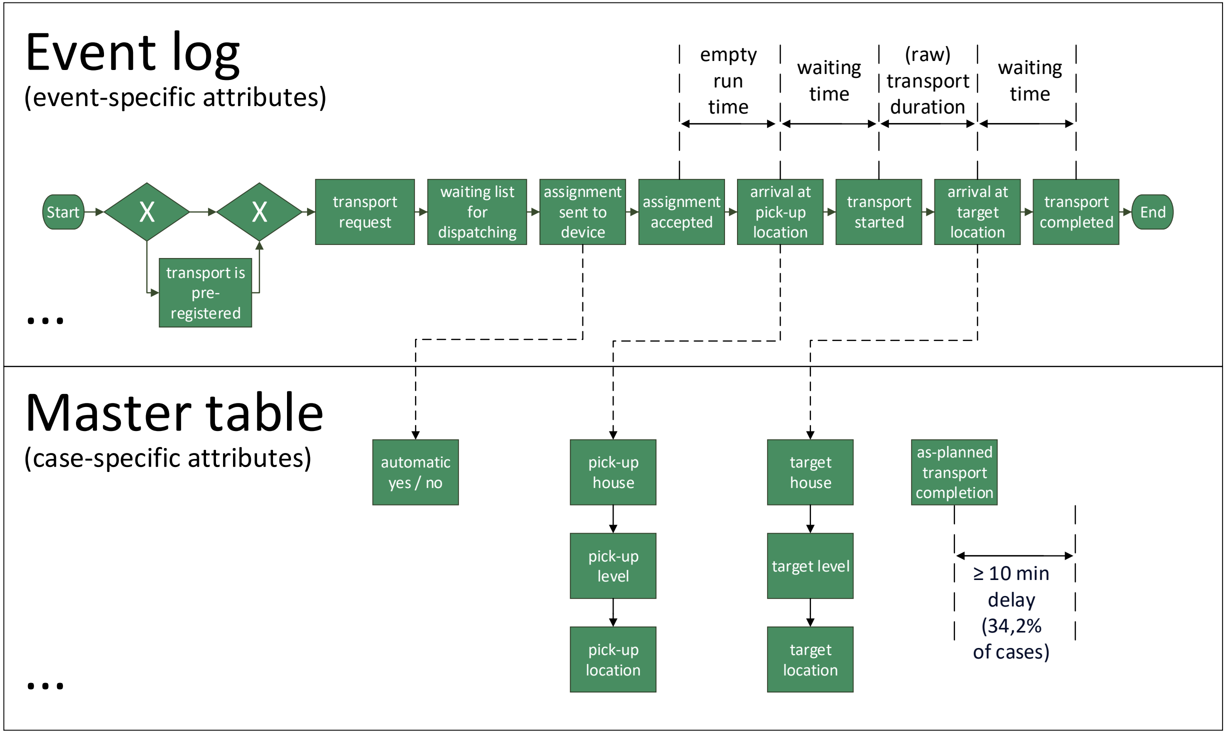


Figure 5.3: Event log (upper part) and master table (lower part) with exemplary information. The event log visualisation shows the as-planned process control flow in BPMN (own visualisation).

consists of 32,033,250 data cells (256,266 cases multiplied by 125 attribute categories), out of which 5,506,348 cells are empty or have non-interpretable information (NULL/NA values).

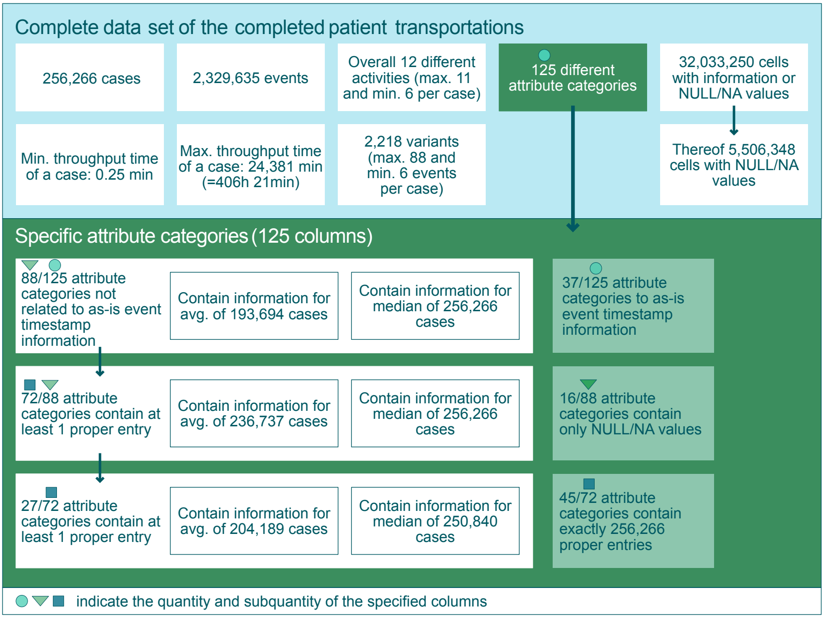


Figure 5.4: Information on underlying raw data within a data collection period of around 3.5 years (*Kropp* et al. 2024b).

Figure 5.4 further breaks down the attribute categories, showing the mean and median number of entries with relevant information (i.e. attributes) for each of the attribute category clusters. Subtracting these entries with interpretable information from the 256,266 possible entries per attribute category gives the average or median number of missing attributes per category cluster. Of the 125 attribute categories in the original dataset, 37 are related to the associated event timestamps (e.g. month, day of the week, calendar week, pre-calculated time differences between process steps). The remaining 88 attribute categories provide further general organisational information related to transport cases (e.g. pick-up location, target location, pick-up house, target house, pick-up level, target level, pick-up room, target room, pick-up room number, target room number, priority, pick-up priority, target priority, route

ID, requesting centre, assignment centre, cost centre, last control station, first control station, description, remarks, service provider, operator, tour, type of transport vehicle, patient ID, route, distance, complaint text, complaint category). These attribute categories can hold valuable information for deeper investigations into the root causes of process issues because organisational interrelationships can be revealed from them. For example, the types of transport vehicles used in the IHPT process are shown with their respective transport frequencies in Table 5.2.

Table 5.2: Statistics on transport vehicle types used in the IHPT process (own table).

type of transport vehicle	case count
patient in bed	144,189
patient in wheelchair	60,090
patient on stretcher	35,042
patient just accompanied	13,568
other	3,377

However, in the master table provided, not all transport cases have consistent information among these attribute categories (see Figure 5.4). Of the 88 attribute categories with further organisational information, 16 do not contain any relevant information, while the remaining 72 categories have varying degrees of information. More specifically, 45 of these 72 attribute categories are fully filled with assessable information, while the remaining 27 categories are inconsistently filled and therefore of limited use for further exploration. Table A.1 (statistics on attribute categories) in appendix A.1, as well as Figures A.1 to A.11 (histograms on example attribute categories) in appendix A.1 show more detailed information on the attribute categories from the master table. The example histograms (A.1 to A.11 in appendix A.1) are plotted in R with the library “ggplot2” (*Wickham* 2016). *ChatGPT* (versions 3.5 and 4; https://chat.openai.com/) was used to search for and explain certain methods of the used library or R functionalities. In the rest of this thesis, the event log and the master table are treated together as raw data or event log, since both datasets can be linked via the transport ID, thus forming a large joint pool of data.

To provide a general understanding of the layout of the hospital, Figure 5.5, that is created with *SketchUp® Free* by *Trimble®* (https://www.sketchup.com/en/plans-and-pricing/sketchup-free), shows the main campus of the hospital with its different buildings. Figure 5.6 shows another simplified view with

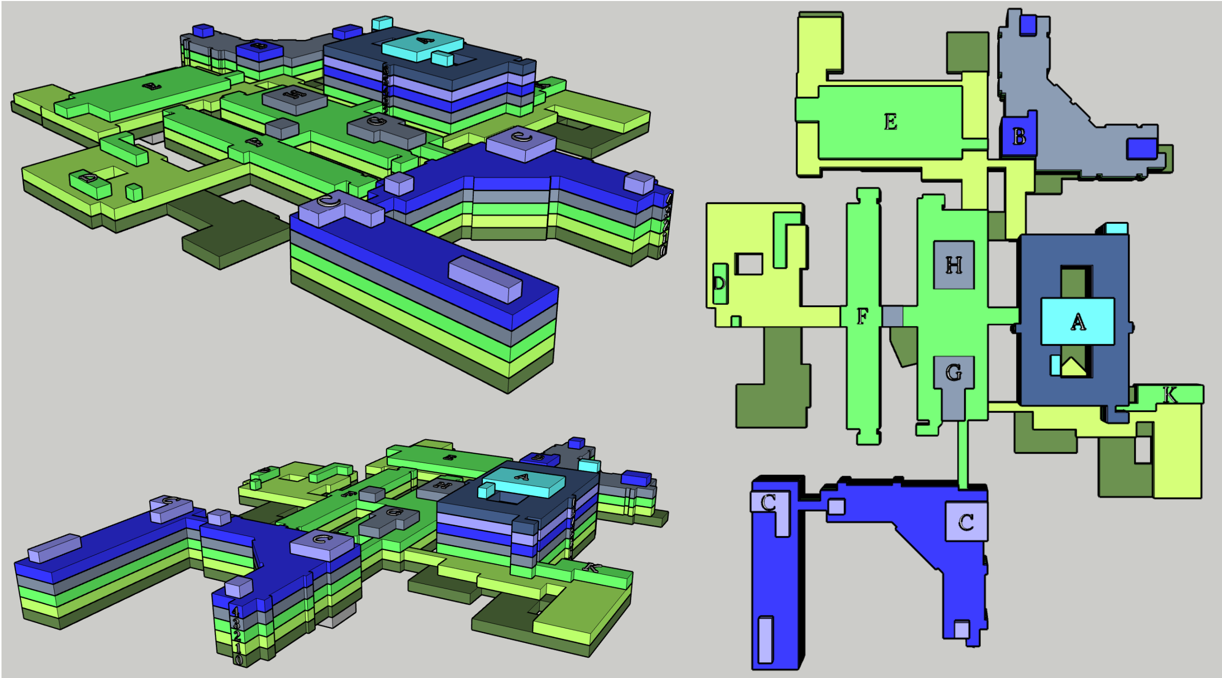
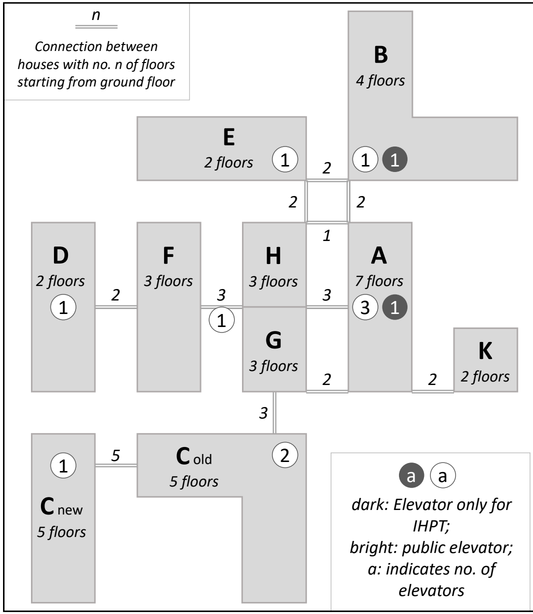


Figure 5.5: Simplified views on the hospital campus (created with *SketchUp*® *Free* by *Trimble*®). Adapted from *Hertenstein* (2024).



A (0)	post office
A (1)	endoscopy, functional diagnostics, IHPT control station, inpatient admission, outpatient clinics
A (2-5)	wards
A (6)	cesarean section OR, delivery room, milk kitchen, wards
B (0)	ER, IHPT ER control station, ER radiologies, wards
B (1)	OR holding, wards
B (2-3)	wards
C (0)	psychiatry, psychotherapy, social service
C (1-2)	psychiatry, psychotherapy
C (3)	art therapy, psychiatry, psychotherapy, work therapy
C (4)	psychiatry, psychotherapy
D (0)	pain therapy, palliative care, tonsillectomy
D (1)	wards
E (0)	facility service centre, intensive care units
E (1)	anesthesiology, central OR, pediatrics, recovery room
F (0)	dialysis, medical care centre
F (1)	wards
G (0)	physical therapy
G (1)	angiography radiology, cardiac catheterisation laboratory
G (2)	OR urology endoscopy, outpatient clinic urology
H (0)	pathology
H (1)	radiologies
H (2)	laboratories
K (0)	central kitchen

Figure 5.6: Simplified view on the hospital campus (without technical equipment floors) with additional infrastructural information. Only the information contained in the underlying IHPT data on pick-up and target locations is included on the right side. Adapted from *Hertenstein* (2024).

additional information about functional areas and wards in the hospital. Only the information contained in the underlying IHPT data on pick-up and target locations is included on the right side in Figure 5.6. It should be noted that there are certain elevators in the hospital that are dedicated exclusively to the IHPT.

With regard to the timestamps contained in the two underlying datasets, it should be mentioned that these are partly dependent on the manual confirmation of the transporters via their devices within the IHPT process. It is therefore possible that some of the timestamps do not accurately reflect reality. However, for the purposes of this thesis, it is assumed that all timestamps captured in the datasets reflect reality and no further quality analysis of timestamps is carried out. The implications of this assumption and suggestions for improving the reliability of the data can be found as part of the detailed process analysis in section 6.

5.2 Methodology - Process Analysis

The event log is processed with a discovery algorithm to create the process models (see subsection 3.1.4) and to further exploit the event log information. For this, the academic version of the *Celonis® Execution Management System* (https://www.celonis.com/ems/platform/) is utilised in this thesis. The rationale for choosing this tool was that the case study hospital had already used *Celonis® 4.7* (https://help.celonis.de/cpm47/en/celonis-process-mining-4-7), that allows for similar analysis as with *Celonis® Execution Management System*, to investigate on other internal processes. The hospital process managers involved in this case study were therefore to some extent familiar with the process mining tool. The *Celonis®* process discovery algorithm is built on the fuzzy miner and leverages properties of the heuristic algorithms (see subsection 3.1.4) (*Lira* et al. 2019). Based on process discovery, simple visualisations using DFGs (see subsection 3.1.4) can be generated by the *Celonis® Execution Management System*. For non-experts in the field of process mining at healthcare facilities, this type of visualisation can be easily accessed (*Munoz-Gama* et al. 2022). When interpreting the results, it is important to be cautious about the limitations of DFGs in terms of concurrencies, as mentioned in subsection 3.1.4. However, in the IHPT process the activities in reality are directly followed, as shown in Figure 5.7. It visualises the as-planned process

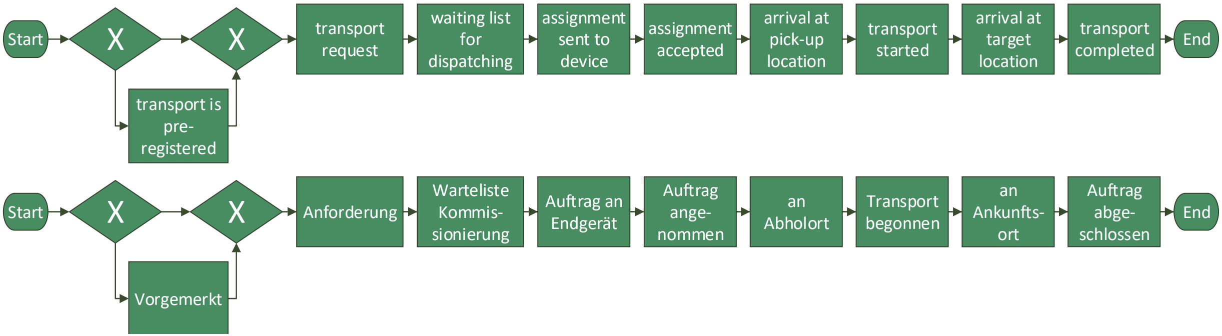


Figure 5.7: As-planned IHPT process control flow (at the bottom process model, the respective activity declarations of the logistics software system of the hosptial, that are based on German, are shown) in BPMN (own visualisation).

of the IHPT with English activity declarations (corresponding to the control flow visualised in Figure 5.3 from subsection 5.1) and also with the original German activity declarations captured in the logistics software system of the hospital. There are no activities occurring in parallel. To ensure that there is no concurrency in the presence of identical timestamps, a unique sorting number corresponding to the executed activity is assigned to each event during data preparation. Hence, if there are events with concurrent timestamps within a transport case, the order of the activities is specified by the sorting. This procedure addresses the problem with concurrencies in DFGs.

The *Celonis® Execution Management System* allows for process conformance analysis (see subsection 3.1.4. For example, discovered process variants can be compared with the as-planned process control flow. Additionally, throughput times of the whole process and process parts can be analysed and compared to planned times to find root causes for process issues in the data. In section 6, results of the process discovery and conformance analysis are presented. Improvement ideas are pointed out, too (see subsection 6.3).

COVID-19 also had an impact on the IHPT process, but the investigations in this thesis are aggregated over a longer period of time and are therefore not COVID-19 specific. There may have been other influences related to COVID-19 that are not explicitly recorded in the data (e.g. possible detours due to contamination prevention). This makes an analysis and interpretation even more complex. The aim of the process mining analysis in this thesis is to obtain information on the IHPT process over a large number of transport cases exceeding the COVID-19 affected period to make meaningful and general statements. Comprehensive investigations into the effects of COVID-19 on the IHPT process require particular attention to concept drift and information not captured in the data. This requires extensive research beyond the logistics data provided, which cannot be adequately addressed within the feasible scope of this thesis. However, these investigations are encouraged for future research to gain an understanding of the key factors in exceptional situations in the IHPT process.

5.3 Methodology - Process Prediction and Redesign

A novel, quantitative approach to real-world data-based process redesign (i.e. process improvement) is presented and investigated in section 7 taking the example of IHPT capacity planning. The procedure of the approach is schematically displayed in Figure 5.8.

General information about the underlying raw data of the IHPT process in the investigated German hospital is already provided in subsection 5.1. Subsection 7.1 presents in detail the methodological preparations for the real-world data-based optimisation of IHPT capacity planning. Subsection 7.1.1 describes data preprocessing steps to prepare the data adequately for the MLP model (see subsection 3.2.2.2), which predicts hourly delayed transport cases in the IHPT using multiple process information as input. The results of the process analysis in section 6 are particularly relevant, as they provide a basic understanding of the process and point to the key factors of the process. Subsection 7.1.2 presents the development of the MLP model, as well as various validation methods that address the predictive performance of the MLP model. An automated optimisation of the IHPT capacity planning is performed in subsection 7.2. Here, a GA (see subsection 3.3.2) is used to reallocate resources on a day of the week basis so that the MLP predicts fewer delayed daily transport cases. Furthermore, a validation of the optimisation performance is carried out using a simplified problem with a less complex solution space. The overall aim of the approach is to create better conditions for IHPT using an automated, data-driven hybrid MLP and GA combination to support optimised capacity planning. The approach must also be transferable to other areas of application in IHPT or more generally to other organisational processes in hospitals.

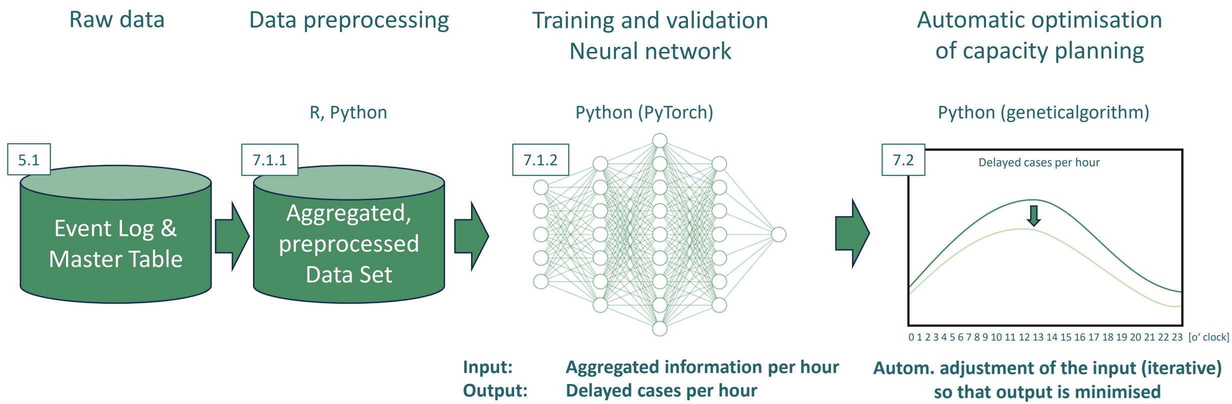


Figure 5.8: Procedure of the process redesign approach in this thesis: From raw data to automated resource optimisation (with subsection indication). Adapted from (*Kropp* et al. 2024b).

6 Multi-Perspective Process Analysis

This section builds on *Kropp* et al. (2023) and *Kropp* et al. (2024a)[1].

Within this section a detailed process mining analysis with process discovery and conformance methods is conducted to understand the IHPT process and identify improvement ideas. Subsection 6.1 describes general process information on the investigated IHPT process from different perspectives. Observations on a range of topics and tailored improvement opportunities are presented in subsection 6.2. The key findings that emerged from the process mining analysis are summarised in subsection 6.3.

6.1 General Process Information from Different Perspectives

This subsection builds on *Kropp* et al. (2024a).

The period analysed covers transports where the first activity occurred between 01/01/2019 to 30/06/2022 (i.e. 3.5 years), which covered a timespan of almost 1,278 days (i.e. 182.5 weeks) from the first to the last recorded event (a couple of transport cases had some activities on 01/07/2019 even though their first registered activity took place beforehand). Only transports that were fully completed, where the patient was the subject of the transport and there was no special additional service other than the transport, are considered (see subsection 5.1). To perform the multidimensional analysis, different elements are considered as case IDs: transport ID to provide insights into the transport processes, patient ID to examine the processes from patients' perspective, and transporter ID to inspect the processes from transport staff's perspective. A transporter ID is a composition of a unique number associated with a mobile device in use (receiving transport assignments) and the date when that particular device appeared in the logs so that a unique transporter ID can be built and equated with a transporter on a specific day.

Transport ID is Case ID

In total, 256,266 patient transport cases were carried out and completed. As mentioned in subsection 5.3, 34.2% of all transports were delayed by ten or more minutes. This limit, above which transports are considered significantly delayed, was defined in consultation with the hospital process managers (see subsection 5.3). The event log under investigation contains different activities per transport case. Table 5.1 from subsection 5.1 presented in how many cases particular logged activities appear and how often the particular activities appear in total across all cases (within a case, activities can appear multiple times). Figure 6.1 shows different views on the average distribution and delay information of planned transport starts per day of the week. It is visible, that there are peaks in planned transports from Monday to Friday between 07:00 and 13:59 (see top part in Figure 6.1). The delayed cases build from 07:00 until they peak between 12:00 and 12:59 (see middle part in Figure 6.1). After 13:00 they begin to decrease again. On weekends, i.e. on Saturdays and Sundays, there are generally fewer transports planned and conducted, and thus fewer delayed cases per day. Additionally, the overall delay rate on weekends is lower than from Monday to Friday (see lower part in Figure 6.1). From Monday to Friday, the peaks of the delay rate are generally between 6:00 and 6:59 in the morning and around noon (see lower part in Figure 6.1). A more in-depth analysis considering the transport ID as case ID, also based on the days of the week, is presented in subsection 6.2.

Patient ID is Case ID

As there could be 69,810 unique patient IDs identified in the dataset, there were on average around 3.7 transports per patient in the study period (derived

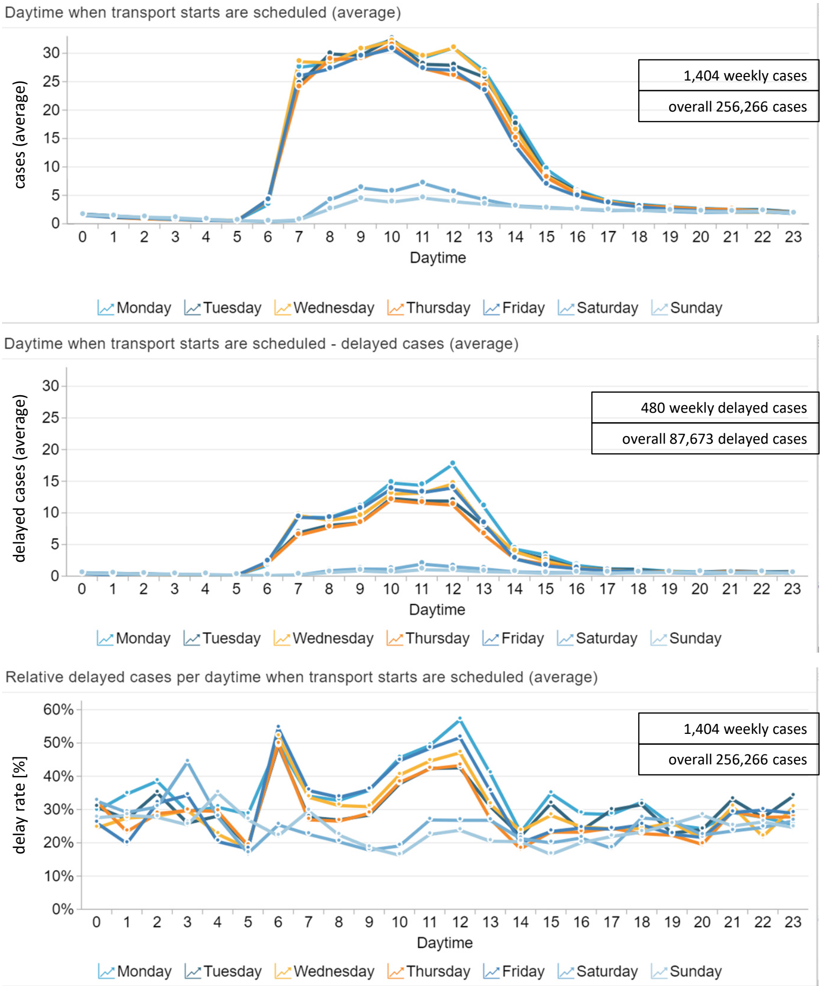


Figure 6.1: Transports (top part), delayed transports (middle part), and delay rate of transports (lower part) per day of the week and hour ordered by planned transport start (the minutes of each timestamp are rounded down to zero, e.g., 14:49 becomes 14:00) (own visualisation created with *Celonis*®).

from 256,266 transport cases in total). However, there were also close to 20,000 transports that had no patient IDs assigned, indicating that there may have been rather fewer transports than an average of 3.7 per patient. Per day, there were on average around 47 different patients transported. On average, for all patients, the time between the first transport request and the end of the last transport was seven days. However, considering the range between the 5th and 95th percentile, the adjusted average time was around three days. This observation fits the statement of the process managers that say that the usual length of stay in the hospital per patient is around 5.5 days, as the transports must take place in a shortened period of this time frame.

Transporter ID is Case ID

There were, in total, 10,089 different transporter IDs (unique IDs derived from a combination of a unique device ID and the date the particular device was being present) involved in the IHPT process. 23 different devices were identified in the event log. On average, around ten different transporters per day were involved in the IHPT process from Monday to Friday and around three different transporters per day from Saturday to Sunday. The daily average was 25.4 transports per transporter. Across all transporters, it took an average of 570 minutes and with a median value of 446 minutes from the start of their first transport (i.e. first found activity “transport started”) to the end of their last transport (i.e. last found activity “arrival at target location”).

6.2 Process Analysis - Deep Dive

This subsection builds on *Kropp* et al. (2024a).

In this subsection, a more detailed analysis is carried out from the perspective of the transports (the transport ID of a transport is the case ID). To this end, multiple KPIs are presented. Different process variants and activity intervals are first investigated in subsection 6.2.1. Then, critical transport routes are examined in subsection 6.2.2. Subsequently, it will be studied how the manual and the automatic dispatching of the transport assignments work. The interdependencies of these two types of transports will be presented in subsection 6.2.3. Capacity evaluations are provided in 6.2.4. Lastly, different departments with their respective incoming and outgoing transports will be evaluated in subsection 6.2.5.

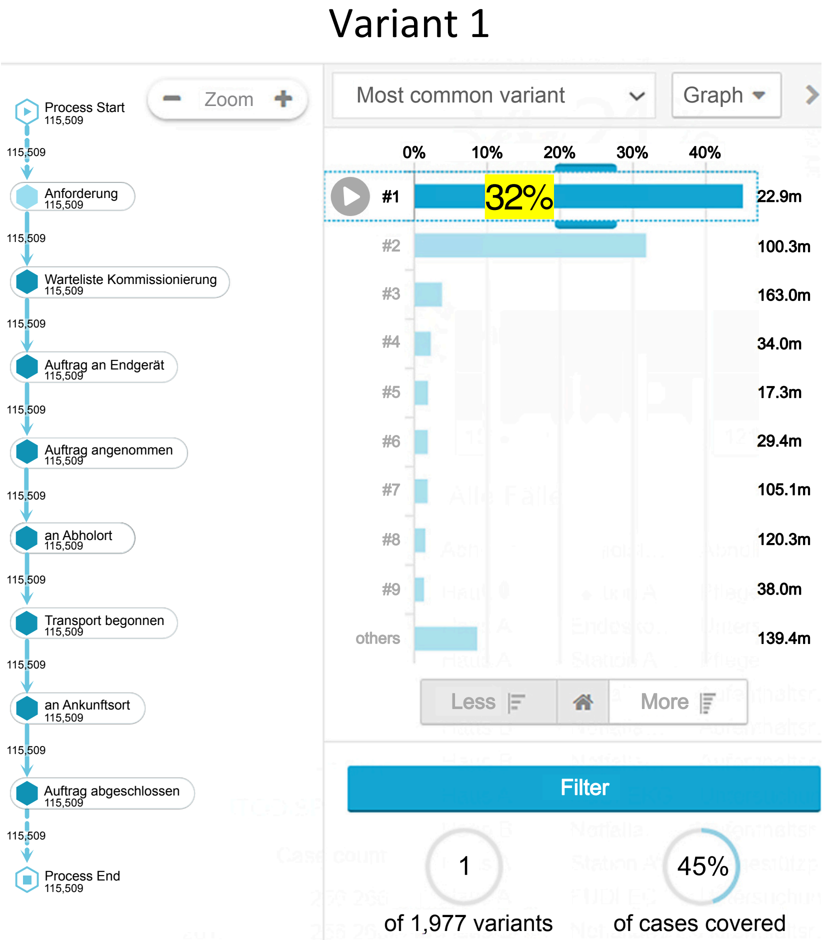
6.2.1 Process Variants and Activity Intervals

This subsection builds on *Kropp* et al. (2024a).

There are 1,977 different variants in the activity control flow among the 256,266 IHPT cases. The main variant (first part) and the first nine variants (second part) both are shown in Figure 6.2. Furthermore, Figure 6.2 displays the delay rate of each provided variant. Presenting all variants in a process model would result in an unstructured model that is hardly interpretable and therefore not shown here.

Variant 1, that covers around 45% of all cases and thus reflects the main variant, is composed of eight activities. The sequence of the activities is as follows: “transport request”, “waiting list for dispatching”, “assignment sent to device”, “assignment accepted”, “arrival at pick-up location”, “transport started”, “arrival at target location”, “transport completed”. The first nine variants together show loops and variations exclusively in the first half of the process. The number of affected cases is shown on the path connections in the process models in Figure 6.2. *Variant 4* and *Variant 8* are particularly outstanding for their increased delay rate.

Figure 6.3 shows the control flow of *Variant 4* (see first part in Figure 6.3) and *Variant 8* (see second part in Figure 6.3). In addition to the case-specific attributes, which provide information about the case as a whole, detailed event-specific attributes are also available. This allows root cause analysis to be performed at the event level, in addition to general activity and throughput time analysis. Analysis of the event-specific attributes reveals, that in *Variant 4*, it is mainly the transporter’s non-response that leads to a new transport request before the same process as in the first variant starts. In addition, some cases were also closed and re-requested manually by a dispatcher. *Variant 4* led to a delay rate of over 61% over all affected cases. *Variant 8* shows a similar activity sequence to *Variant 4*, however, there is also the step “transport is pre-registered” as the first activity in *Variant 8*. A transport can be pre-registered if, for example, it is a return transport that is required after an initial transport



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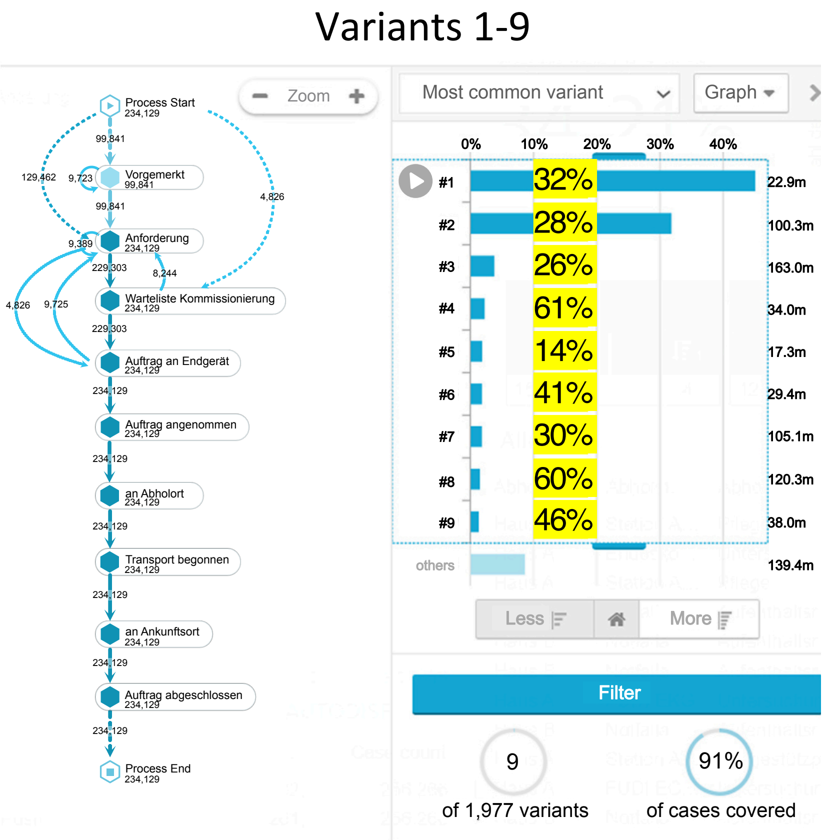
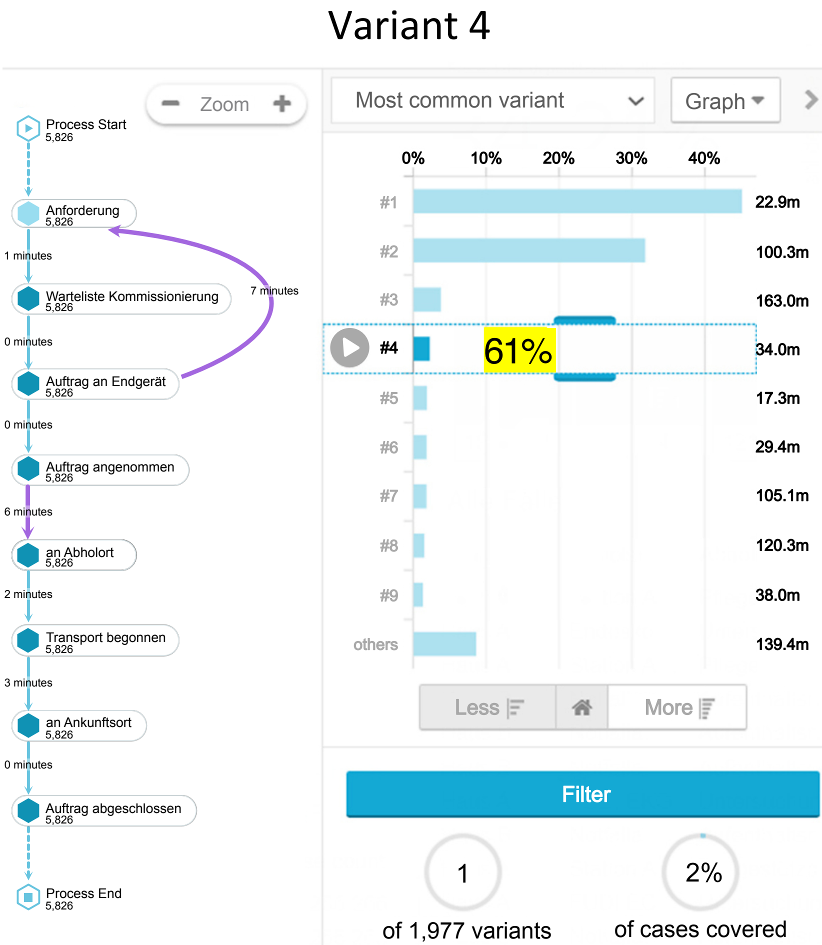


Figure 6.2 part 2/2

Figure 6.2: Process model of the most frequent variant (first part, representing 45% of all cases) and process model of the first nine variants (second part, representing 91% of all cases) with case counts on paths and activities (corresponding English activity names are shown in Table 5.1 from subsection 5.1). Delay rates of the respective process variants are shown in yellow highlighted percentages. Bar charts reflect relative frequency, and the numbers to the right of the bar charts reflect the median throughput time of the variants (created with *Celonis*®). Adopted from *Kropp* et al. (2024a).



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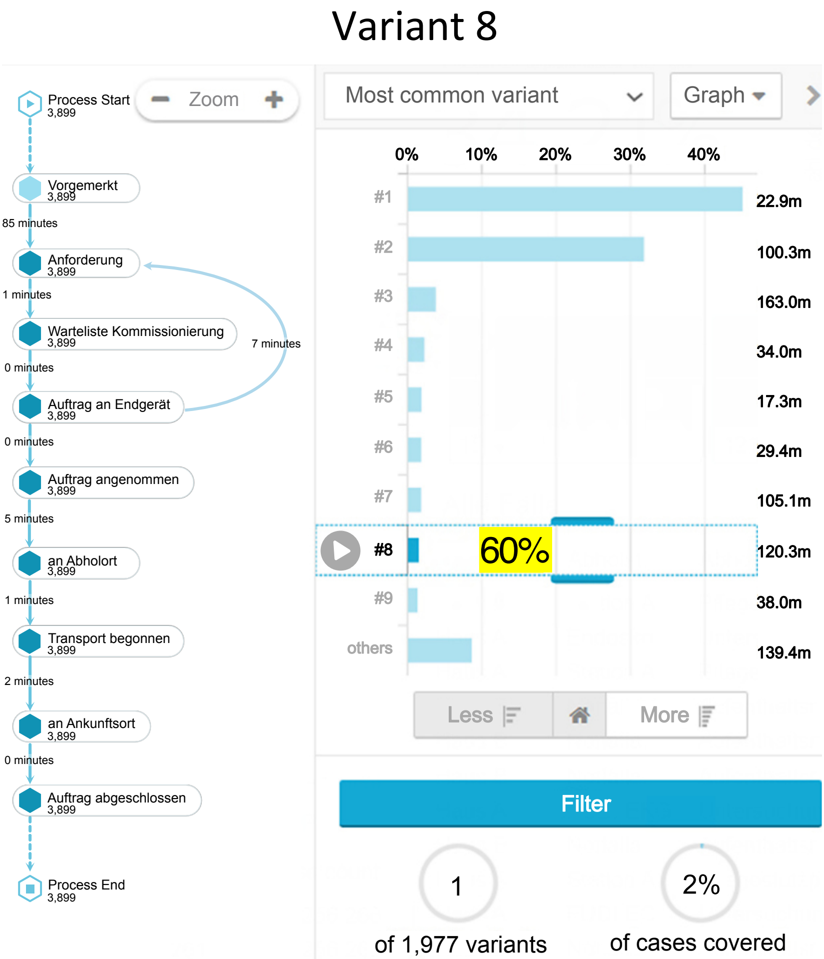


Figure 6.3 part 2/2

Figure 6.3: Process model of the variant 4 (first part) and variant 8 (second part) with median throughput times on the paths and case counts on the activities (corresponding English activity names are shown in Table 5.1 from subsection 5.1). Delay rates of both variants are represented in yellow percentages. Bar charts reflect relative frequency and the numbers to the right of the bar charts reflect the median throughput time of the variants (created with *Celonis*®). Adopted from *Kropp* et al. (2024a).

has been requested. A pre-registration of a transport can also occur in other occasions. *Variant 8* has a delay rate of over 60%. After examining the relevant activity intervals, improvement ideas to decrease the delay rates are given.

The activity “transport is pre-registered” occurs overall 127,579 times in 111,906 cases (see Table 5.1 in subsection 5.1). Pre-registering transports has mostly positive effects on the delay rate of transports. This can also be observed from the indicated delay rates in Figure 6.2 (second part). *Variant 2* starts with the activity “transport is pre-registered” before the activity “transport request” occurs and further proceeds as *variant 1*. The delay rate of *Variant 2* is slightly lower than that of *Variant 1*. *Variant 1* and *Variant 2* correspond to the as-planned process flow (see Figure 5.7 in subsection 5.2). All other variants (they cover around 23% of all cases) are regarded as non-conforming in discussions with the hospital process managers.

Multiple activity intervals can be examined in more detail. Initially, the process is analysed from start to completion, regardless of which process step is the first or last in each case. Transport assignments take an average of about 219 minutes from the first step until they are completed. The median is approximately 43 minutes, indicating that some cases take an exceptionally long time to complete, increasing the average throughput time. Some transports are also pre-registered a longer time before they are requested, contributing to longer average throughput times. Just from the activity “transport request” (first occurrence in a case; there can be loops in the process where activities are conducted multiple times) to the process end, a transport needs on average, 48 minutes and a median of 22 minutes.

From the activity step “assignment sent to device” (first occurrence in a case) to process end, the average throughput time is 22 minutes and the median is 16 minutes. To examine in more detail how the integration of the transporters looks within the process, the interval can be further trimmed to the interval from “assignment accepted” to process end. This reflects the process part in which the transporter’s actions are decisive. From both, the first and the last occurrence of the activity “assignment accepted” to the process end, on average, 19-20 minutes (median is 14 minutes) elapse.

Between the activity “assignment sent to device” (first occurrence in a case) and the acceptance of the assignment by the transporter (last occurrence of “transport accepted” in a case), there is an average of about two to three minutes and a median of around 0.25 minutes in throughput time, indicating that the acceptance of the assignment is immediate in most cases. Furthermore, after being ultimately sent to a device (last occurrence of “assignment sent to device” in a case), 89% of all transport cases are accepted (last occurrence of “transport accepted” in a case) in up to three minutes. This observation was also confirmed by the hospital process managers, who observed in practice that the transporters were already taking on new assignments while carrying out previous ones. If a transporter does not respond and the transport has to be re-requested, this will almost always cause delays (see the delay rates in Figure 6.3). To reduce this problem, the planned buffer time between “assignment sent to device” and a transporter not responding, resulting in a re-request, needs to be decreased. A reasonable buffer timespan before immediately initiating a re-request to avoid greater loss of time in the process seems to be around three minutes, as 89% of all cases, after being sent to a device, are currently accepted within three minutes.

In around 80% of all transports (transports of all variants), the interval between “transport request” (first occurrence in a case) and “waiting list for dispatching” (first occurrence in a case) consumes up to eight minutes. If the throughput time of this interval is between zero and four minutes, the delay rate for transports results in about 25%. The resulting delay rate is already around 40%, if the throughput time of this interval is between four and eight minutes. For the transport cases, where the interval between the “transport request” and “waiting list for dispatching” consumes more than eight minutes, the delay rate is 66%. To counteract this negative observation, an alarm could be set if more than four minutes elapse between “transport request” and “waiting list for dispatching” so that the affected transports can be re-requested immediately and the delay rates will be minimised.

The actual median transport time from the step “transport started” (first and last occurrence in a case) to “transport completed” (first and last occurrence in a case) recorded in the data is around three minutes, which is considerably shorter than the planned transport time, that is set at a median of ten minutes. The planned time from an initial “transport request” to “transport started” is set to a median of around 5 minutes. However, in the actual recorded data of the conducted transports, this interval covers in the median about 18 minutes. This interval (from first occurrence of “transport request” to first or last occurrence of “transport started” in a case) therefore appears to have a considerable impact on potential delays. The data also shows that in about 50.8% of all cases there is a delay of ten or more minutes already at the patient’s pick-up location. This likely leads to patient waiting times and, as described in subsection 2.2.2, can have negative effects not only on patient satisfaction but also on patient health. Compared to the planned completion time of transports, approximately 34.2% are still delayed by the time the actual transport completion is logged (see subsection 6.1). This demonstrates that overall, despite being delayed at the pick-up location, certain transports are able to arrive on time at the target location. The later activities in the control flow, which represent the actual accompanied (physical) transportation, seem to be less critical in terms of delays or throughput times. This raises the question of whether transport capacities and the distribution of transport assignments have been managed efficiently, as the initial activities up to 'arrival at pick-up location' appear to cause problems in the flow of the process.

It should be noted, that data quality in part of the IHPT process in the case study hospital, and hence the delay rates, depend on transporters manually confirming individual work steps via their devices (see also subsection 5.1). This implicates that the logged data may not always reflect the correct timestamp of when an activity took place. It is possible to try to filter out implausible data, but for the purposes of further investigation it is assumed that the timestamps logged are correct. Subsection 8.1 discusses further measures for this issue.

6.2.2 Critical Routes

This subsection builds on *Kropp* et al. (2024a).

Overall there were 109 different pick-up and 118 different target locations resulting in a total of 2,821 different observed transport routes. Figure 6.4 displays the six most frequent transport routes that make up approximately 10% of all cases. For comparison, the 100 most frequent transport routes account for almost 60% of all cases. The most frequent pick-up location, as in 45,394 cases, was the emergency department (German: Notfallambulanz). Around 40,600 of these cases targeted a ward and around 4,800 cases targeted another functional unit within the hospital. With 20,160 transport cases, the radiology (German: Radiologie) was the most frequent target location in the dataset. Of these, around 18,200 transports started from a ward, around 1,700 from another functional unit within the hospital and around 300 from the emergency department.

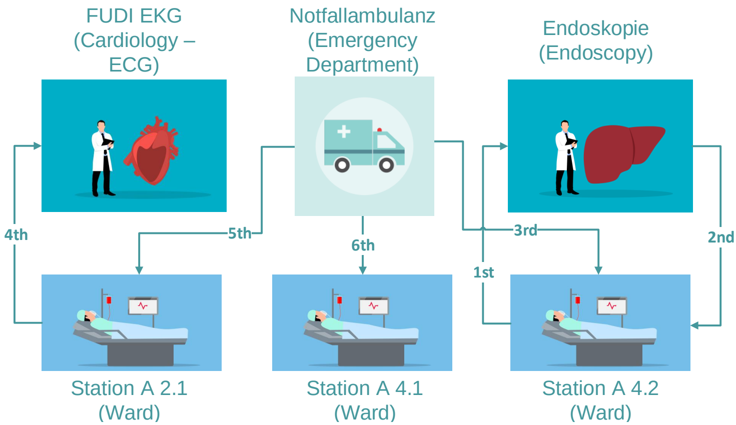


Figure 6.4: Visualisation of the six most frequent transport routes, displaying 26,617 of the 256,266 cases (the order of frequency is indicated on the connections between locations) (own visualisation).

Table 6.1 shows the most critical transport routes in terms of their delay time at the end of the transport process. They are ordered according to the total number of delay minutes that occurred on each route. By multiplying the average delay minutes per case on each transport route by the number of delayed cases, the sum of delay minutes is calculated. Only those transports with a delay of ten minutes and more are taken into account for this calculation and displayed in Table 6.1. By ranking according to the highest sum of delay minutes on the given routes, the Table 6.1 shows the most problematic routes from all cases considered. In addition, the respective houses of locations are shown in Table 6.1. The connection between "Station A4.2" and "Endoscopy" (both in the same building House A) stands out in the first and fourth row (both rows represent opposite routes). Overall, the scheduled transport times for the transports on these routes, as well as on the other routes identifiable in Table 6.1, are suggested to be increased.

Another analysis also revealed that transports with floor changes are more likely to have higher throughput times and to arrive delayed than transports on the same floor, even if the pick-up and target locations are in different houses (*Hertenstein* 2024). This observation has also been confirmed in practice by hospital process managers. Although there are elevators specifically for the IHPT (see Figure 5.6 in subsection 5.1), there may be a shortage of elevator availability at certain times. Subsection 6.2.5 presents in more detail analysis results on different functional departments (e.g. endoscopy, OR, radiology).

Table 6.1: Critical routes (only delayed cases) that lead overall to a high sum of delayed minutes. Adopted from *Kropp* et al. (2024a).

pick-up house	pick-up location	target house	target location	delayed cases	avg. delay per case [min]	sum of delay [min]
House A	Station A4.2	House A	Endoscopy	2,871	37.68	108,175.80
House B	Station B2.2	House H	Radiology	1,776	40.55	72,012.82
House A	Station A2.1	House A	FUDI EKG	1,972	36.09	71,538.31
House A	Endoscopy	House A	Station A4.2	1,492	39.99	59,664.18
House B	Emergency department	House A	Station A4.2	1,267	37.25	47,191.63
...	...	...	...	...	...	...

6.2.3 Manual vs. Automatic Transport Assignment

This subsection builds on *Kropp* et al. (2024a).

At the hospital, patient transports are dispatched partially manually and partially automatically (see subsection 5.1). Manual dispatchers and the automatic dispatching system try to select a transporter who does not have any assignment or selects a transporter whose target location of his current transport to be processed is closest to the pick-up location of the new assignment. Overall, the automatic assignment is used in 31% of all transport assignments. The automatic dispatching system (delay rate of 30%) performs slightly better than the manual process (delay rate of 36%). However, the automatic dispatching system operates mainly at times of lower IHPT demand (usually at weekends and outside core working hours Monday to Friday). Figure 6.5 and Figure 6.6 show different views on manually and automatically dispatched transports, respectively. The automatic process is less reliable during times when it runs concurrently with the manual process (i.e. Monday to Friday between 06:00 and 15:59) than during times when it runs alone (see lower part of Figure 6.6).

Although the automatic process seems to perform better than the manual process, a higher automation rate has historically resulted in increased delays

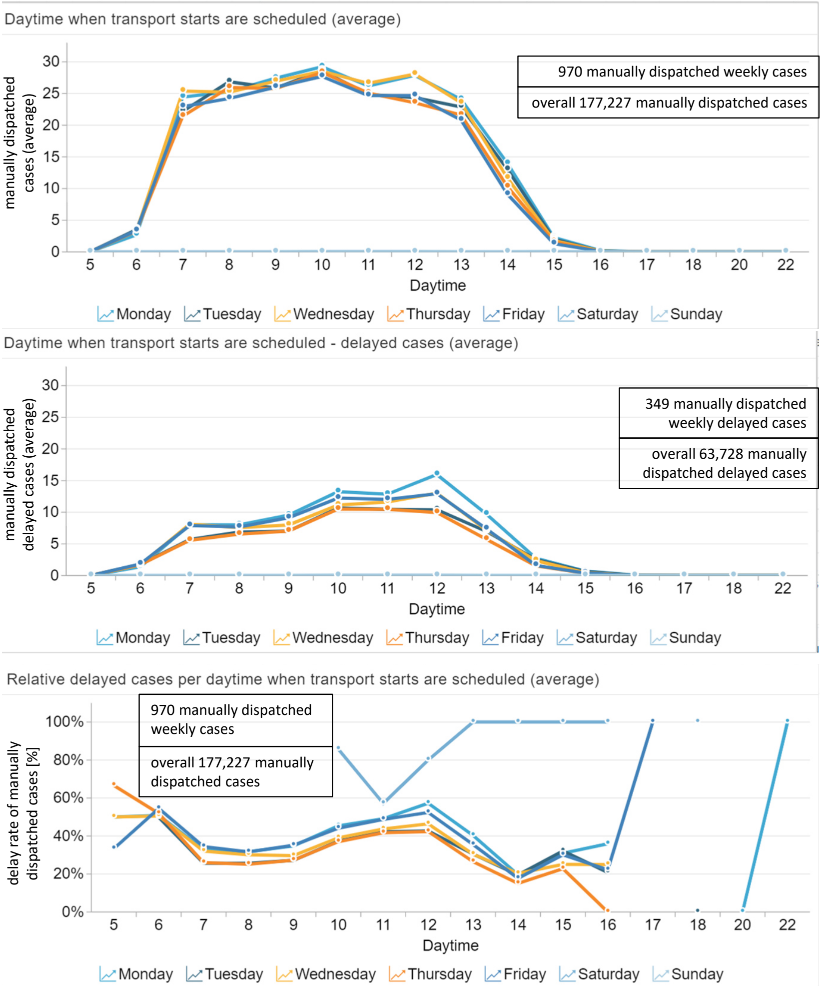


Figure 6.5: Manually dispatched transports (top part), manually dispatched delayed transports (middle part), and delay rate of manually dispatched transports (lower part) per day of the week and hour ordered by planned transport start (the minutes of each timestamp are rounded down to zero, e.g., 14:49 becomes 14:00) (own visualisation created with *Celonis*®).

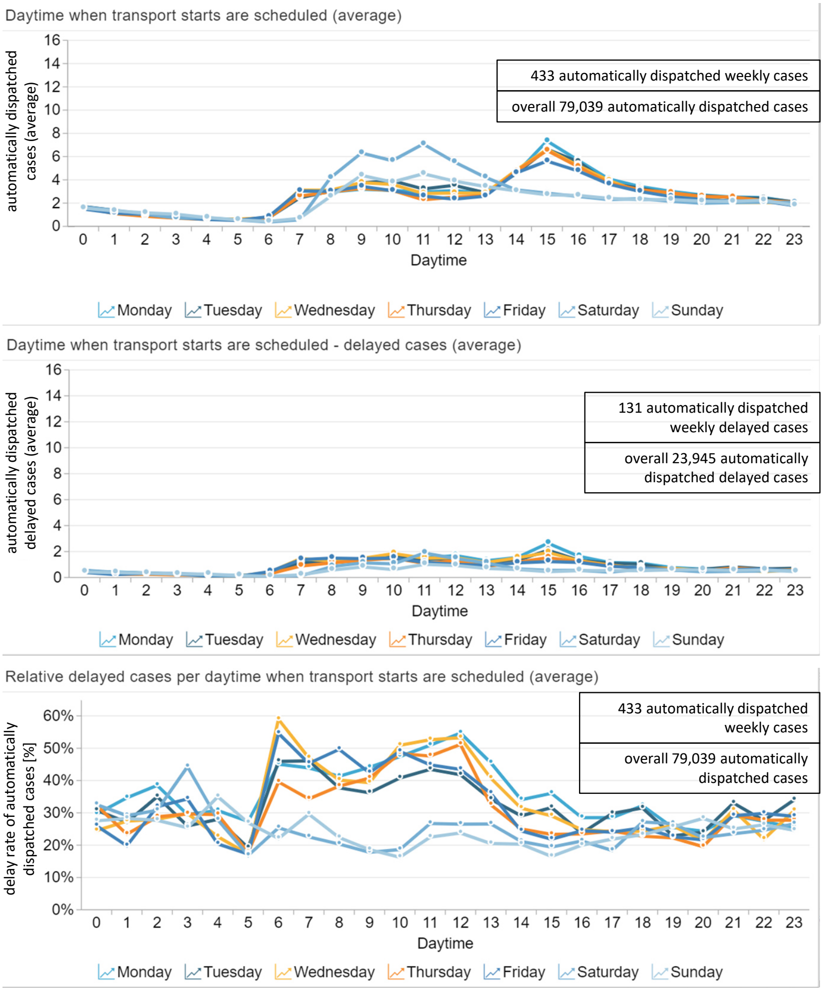


Figure 6.6: Automatically dispatched transports (top part), automatically dispatched delayed transports (middle part), and delay rate of automatically dispatched transports (lower part) per day of the week and hour ordered by planned transport start (the minutes of each timestamp are rounded down to zero, e.g., 14:49 becomes 14:00) (own visualisation created with *Celonis*®).

across all cases. Between 01/02/2021 and 01/08/2021, the automation rate was as high as 74%. However, this led to delays in 45% of manual assignments and 39% of automatic assignments. Delays occurred primarily when transports were assigned manually and automatically in parallel. Therefore, it is recommended to set time periods during which the automatic process should not be used, such as from Monday to Friday between 06:00 and 15:59. Or the automatic process should be tested fully independently, even during peak periods, to determine its ability to handle more than 20 requested transports per hour, as currently do the manual dispatchers mainly during core working hours from Monday to Friday.

6.2.4 Capacity Evaluation

This subsection builds on *Kropp* et al. (2024a).

Table 6.2 shows the absolute number of cases and also the average number of cases per day of the week. The average number of different transporters (transporter IDs) that can be discovered from the log is displayed per day of the week and the average peak number of transports requested per active transporter per hour is shown. Finally, the resulting rate of delayed cases is given in Table 6.2. Delayed transports are more likely to occur on Mondays and Fridays compared to the other days of the week. In general, Mondays are the busiest days in terms of transport cases. There are fewer transports conducted on Saturdays and Sundays than during the rest of the week, and the delay rate is also lower at weekends.

Between 10:00 and 12:59 delays can be observed most frequently (see middle part in Figure 6.1 from subsection 6.1). The reason behind these delays can be identified in the event-specific data. Due to the transporters' devices being full (they can receive up to three assignments at the same time, see subsection 5.1), no assignments can be sent to them. Already from 07:00 onwards, this observation begins to increase. A generally high number of delayed cases occurs between 07:00 and 13:59 (see middle part in Figure 6.1 from subsection 6.1). Mainly, there needs to be either a regulation of the number of planned transport starts, or more transport capacities (i.e. transporters) should be available between 07:00 and 13:59. Peaks in relatively delayed cases (i.e. high delay rate, see lower part in Figure 6.1 from subsection 6.1) between 06:00 and 06:59 could be observed, too. As the number of cases during this time period

Table 6.2: Day of the week statistics. Adopted from *Kropp* et al. (2024a).

Day of the week	absolute cases per day	average cases per day	average number of transporters per day	average peak number of transports requested per available transporter per hour	rate of delayed cases [%]
Monday	49,105	269	9.65	4.6	39.30
Tuesday	47,484	260	10.31	4.4	32.55
Wednesday	48,364	265	10.55	4.2	34.98
Thursday	45,286	248	10.18	4.3	31.41
Friday	44,532	244	9.44	4.6	37.70
Saturday	11,641	64	3.25	3.9	23.74
Sunday	9,854	54	3.16	2.8	22.61

is not high, it seems to be more reasonable to increase the transport capacities rather than to set a limit to the number of transports to be scheduled. Table 6.2 reveals that although Mondays have the highest average number of transports per day, the average number of transporters per day is only the fourth highest in comparison to the other days of the week. Using Monday as an example, Figure 6.7 presents a comparison between planned transport starts (upper part) and active transporters by the time they start transports (lower part) per hour. For any other day of the week similar comparative analysis could be conducted.

In Figure 6.7 (upper part) it can be observed, that there is a peak in assignments between 10:00 and 10:59. Simultaneously, there is a peak of about 4.6 assignments per active transporter in this hour (derived by dividing the number of cases by the number of different active transporters between 10:00 and 10:59). To avoid a backlog of assignments, the number of transporters needs to be increased in the morning (until 12:00/13:00), because the peak of assignments per hour is reached until 10:59 and the number of assignments per hour mainly decreases afterwards. For a lower delay rate, no more than three to four transports per active transporter per hour should be requested (considering the 19-20 minutes average and 14 minutes median time from assignment acceptance to the end of the transport, see subsection 6.2.1), which will reduce delays caused by a backlog of assignments throughout the day. Similar observations were being made on the days from Tuesday to Friday. The solutions suggested apply to these days, too. Furthermore, Table 6.2

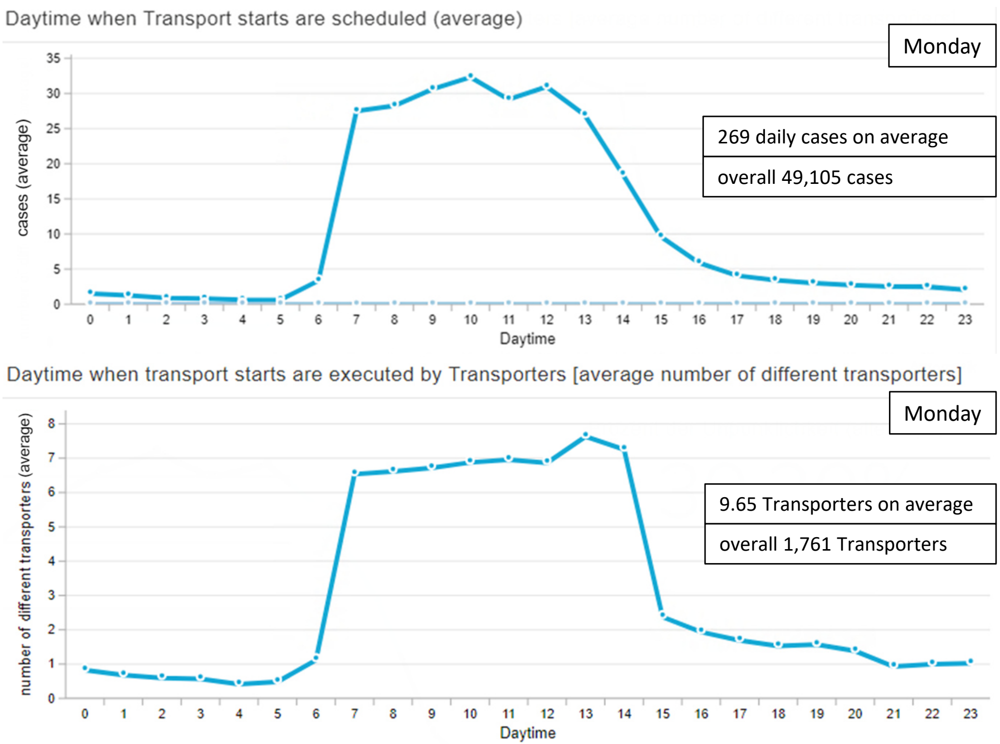


Figure 6.7: Comparison of planned transports (upper part) and active transporters (lower part) on average on Mondays (the minutes of each timestamp are rounded down to zero, e.g., 14:49 becomes 14:00) (created with *Celonis*®). Adopted from *Kropp* et al. (2024a).

shows that, despite the highest delay rates, there are fewer transporters active on Mondays and Fridays than from Tuesday to Thursday. On Mondays, a slight increase in transporter capacity should be taken into account as there is the highest number of assignments per day. The workload of the transporters in terms of the transports to be carried out is on average lower on the weekend than during the week, with a peak of 3.9 requested transports per active transporter per hour on Saturdays and 2.8 on Sundays (see Table 6.2). This KPI has a considerable impact on the delay rate. In the data, over 97% of all transports were declared as regularly scheduled transports. In consultation with hospital process managers, this high rate is questionable and probably due to incorrect use of the supporting logistics software system. A detailed analysis distinguishing between urgent and regular transport cases are not carried out due to the lack of reliability and the low number of reported urgent cases. However, further analysis in relation to different functional departments of the hospital, such as the emergency department, is provided in subsection 6.2.5.

6.2.5 Functional Departments

In this subsection, the transports to and from different selected departments in the hospital are examined in more detail. Table 6.3 shows general statistics on the different departments of the hospital (i.e. departments from and to which transports took place) as well as specific observations.

For endoscopy, specialist outpatient clinics, functional diagnostics (FUDI), cardiac catheterisation laboratory, operating rooms (OR) and radiology the process managers have provided information on working time planning of the departments' staff. For this reason, these departments are addressed first in Table 6.3. In addition, there were also other locations from and to which transports took place. These are denoted in Table 6.3 under "Other". These "Other" transports mainly included around 40,000 cases for which the emergency department was the pick-up location. Hence, the emergency department is included in Table 6.3 as a separate department from and to which transports took place. The emergency department is in constant operation. In relation to the observations, Table 6.3 presents qualitative improvement ideas in IHPT regarding the departments. An estimate of the cost impact of the IHPT can be made taking the example of OR. Out of the 25,938 transports related to OR, 20,293 transports had OR as target location. Among these transports

Table 6.3: Statistics of functional and other departments in the hospital (own table).

Department	absolute cases	rate of delayed cases [%]	observations
Endoscopy	25,367	39.27	Endoscopy represents the functional department with the highest delay rate. Transports from and to Endoscopy should be planned with longer throughput times between activities.
Specialist outpatient clinics	1,702	37.31	After 15:00, appointments are rarely scheduled, even though service hours continue until 17:00. Service times between 15:00 and 17:00 should be more evenly occupied by transportation scheduling.
FUDI	56,414	37.83	Transports to and from FUDI with planned start between 06:00 and 07:00 are almost always late (especially when the planned end is before 07:00). Transport capacity in this period must be increased.
Cardiac catheterisation laboratory	8,232	34.35	No special findings beyond general findings from previous observations.
OR	25,938	21.64	Between 11:00 and 12:59, there are many delays despite moderate order volumes. As the general transport volume (over all routes) is high in this period, the capacity needs to be increased and the OR transports need higher prioritisation due to important tasks and high costs in this functional department.
Radiologies	89,772	34.73	The latest service time for radiology is midnight. No special findings beyond general findings from previous observations.
All functional departments (from above)	199,234	34.91	Some transports went from functional department to functional department, so some transports above are double counted (e.g. transport from FUDI to Endoscopy would be counted in FUDI as well as in Endoscopy; about 10,000 cases were double counted in the categories mentioned above).
Other	57,032	31.77	Does not include transports from and to any of the above mentioned departments.
Emergency department	48,267	25.90	Cases are regularly and continuously distributed throughout a day on all days of the week (24/7). A steep increase in scheduled starts of transports can be observed in the morning between 09:00 and 12:59. Then it drops slightly depending on the day of the week, or is somewhat constant until 22:59, before the assigned transports drop again under less than two transports per hour and even lower until around 06:59 to 08:59 the next day. Between 02:00 and 04:59 there is on average less than one transport per hour from or to the emergency department, however the delay rate at the same time is up to almost 40% depending on the day of the week. Therefore, the capacity must be slightly increased at night.

3,851 (rate of 18.98%) were delayed ten or more minutes. Subsection 2.2.2 highlighted already, that OR costs are around 46 US dollar per minute. If the fully-staffed OR cannot be used for ten minutes due to a delayed transport, this corresponds to a loss of 460 US dollar. Over the 3,851 cases, this loss scales up to more than 1.77 million US dollar. That is more than 500,000 US dollar per year (1.77 million US dollar divided by the 3.5 years of observation in the case study hospital) just for transports to the OR. In addition, other hospital departments also generate unnecessary costs if they are run inefficiently. However, the potential costs will not be discussed further at this point, as this would require more in-depth investigations. For the present case study, only logistics data on the IHPT process are available, and no data on the previous or subsequent processes in the wards or functional departments. This data would be necessary to better assess the impact of the IHPT.

6.3 Key Observations

This subsection builds on *Kropp* et al. (2023) and *Kropp* et al. (2024a).

The data-based analysis using process mining methods described in subsections 6.1 and 6.2, can be used to find out how transport delays and patient waiting times are related to other circumstances. These can include e.g. suboptimal allocation of transport assignments to active transporters (through manual or automated dispatching), transport route-specific problems, resource bottlenecks, or general misplanning when requesting a transport. The dissatisfaction of personnel involved, due to problematic processes flows, can also have a negative effect on the patients' hospital experience. Problematic process flows can be caused by, for example, waiting times of transporters at pick-up (waiting for patients who are not yet ready) or target locations (when handing over the patient takes long). Inappropriate combination of assigned transport routes can also lead to increased distances with low patient throughput per transporter.

There are both organisational (also regarding personnel resources) and infrastructural elements that can affect the IHPT process (see also subsection 2.2.2). Organisational problems are, for example, inadequate resource planning or poor allocation of transports to transporters. Infrastructural issues are, for example, the availability of elevators or spatial conditions. While assessing compliance with predefined workflows and temporal performance aspects, process mining analysis on real-world data can help to identify starting points for process improvements. Some qualitative strategies are suggested below to reduce delays and waiting times in IHPT.

It has been observed that during the lunch time, transport starts are scheduled which eventually lead to delays (see Figure 6.1 in subsection 6.1). Problems can arise from conflicts between IHPT and simultaneous meal transport. It should be checked if there are any problems with the availability of elevators around noon. In the long term, it might make sense to add an elevator. Relocating wards or functional departments, where feasible, could also have a positive effect. However, there may be infrastructural barriers to adding an elevator or changing wards and departments that also need to be considered. In general, redesigning operational strategies to make workflows more efficient or adjusting resources during lunchtime can have a positive impact on delays and waiting times. For example, a possible solution might be to define precise rules about which elevators or routes should be used for IHPT and which ones for food or other goods.

Another issue that needs to be addressed is the adequate preparation of patients for transport. This probably contributes to the current delays around midday. Preparing the patient for transport requires the implementation of comprehensive communication procedures between different hospital units. Subsection 2.2.2 has already pointed out the positive effects of summoning patients via telephone prior an upcoming transport (*Haldar* et al. 2019).

Depending on the patient's condition and the types of necessary tests, different examinations could be strategically combined to save travel time. Not only can this strategy have a positive impact on patients' perceptions of the quality of service, but it can also reduce waiting and travel times for the transporters by reducing travel distances, and it can increase the patient throughput per transporter.

Transport delays are related with certain spatially centralised examination departments (see subsections 6.2.2 and 6.2.5), e.g., endoscopy, FUDI EKG and radiology. Decentralising these departments may achieve greater time savings in IHPT.

Another helpful strategy is providing real-time information about the IHPT process to the personnel involved, such as visualisations of the analysis performed in subsections 6.1 and 6.2, to help them adjust their procedures and anticipate complications.

Efficient planning and allocation of assignments to the transporters is also an important issue. The evaluations showed in over 50% of all cases the transporter was already delayed ten or more minutes at the pick-up location of the patient (see subsection 6.2.1). This indicates, for example, that there is not enough lead time in the transport request or that the transports were not assigned to the transporter with the closest distance to the patient's pick-up location. It has also been observed that pre-registering transports has a positive effect on the delay rate (see subsection 6.2.1). Thus, pre-registering the transports should not only be conducted for return transports, but for all transports where possible.

Capacity evaluations are carried out so that improvement measures can be developed through root cause analysis. The investigations from subsection 6.2.4 show the distribution of transportation assignments and active transporters across times of day and days of the week. The average peak number of requested transports per available transporter per hour needs to be decreased in certain hours per day by, for example, rescheduling shifts, to reduce the load on the transporters and the number of delayed transports (see subsection 6.2.4). The use of the automatic dispatching system to manage transports has proven to be beneficial in many cases (see subsection 6.2.3). However, it has been shown that there are increased delays when a manual dispatcher and the automatic dispatching system operate in parallel. Furthermore, it remains unclear how the automatic system deals with a larger number of simultaneously handled transports (e.g. more than 20 transports per hour), because it mainly operates on weekends and outside core working hours. Further testing of the automatic dispatching system is required, with process mining to monitor and interpret the resulting data.

In summary, the continuous use of analytical methods, such as process mining, help to create an understanding of the status quo of processes to identify root causes of process problems and starting points for process improvements. In addition, dashboards provide visibility into consistent feedback loops that can lead to automation measures.

The interactive process models and associated KPIs make it easier for analysts and domain experts to investigate process incidents in more detail and derive questions and objectives (*Fernández-Llatas* 2021e; *Lull* et al. 2022). All the relevant information can be retrieved interactively, as opposed to just numerical KPI analysis (see also subsection 4.1) (*Fernández-Llatas* 2021e; *Lull* et al. 2022). The process models, enriched with further process information, provide a comprehensible and holistic process view that helps to classify and understand relationships in process attributes (*Fernández-Llatas* 2021e;

Fernández-Llatas 2021f). Discussions with domain experts ensure the relevance and validity of the investigations and help all stakeholders to properly interpret process data.

Possible process adjustments that can be made are numerous, and it is difficult to commit to specific measures in advance. Many of the possible improvement measures arise from individual attribute filtering of the analysis and customised KPI assessments. Naturally, these are highly dependent on the expertise of the data analysts and the contribution of the domain experts. Now, it is necessary to put the identified individual measures into practice and to monitor the results with analogous analysis based on the identified KPIs, as has been conducted in subsections 6.1 and 6.2. However, it would be beneficial to have predictive models, e.g. simulation or ML models (see subsection 3.2), to forecast the potentially resulting KPI developments after adjusting certain process parameters. Ideally, these are validated with historical data and expert knowledge. Such models could support decision-making in process redesign by allowing several adaptation variants to be run prior to practical implementation, and only the best one to be implemented in practice, backed by quantitative analytics. Section 7 proposes a solution approach to this challenge that incorporates predictive capabilities for the specific example of IHPT capacity planning to support process redesign prior to the practical implementation of improvement measures. Other potential use cases for data-driven decision-making using IHPT logistics data could include, for example optimising IHPT on identified critical routes, or the hospital layout.

7 Enabling Decision Support - Process Prediction and Redesign

This section builds on *Kropp* et al. (2024b).

In this section a novel, quantitative approach to process redesign in the context of the IHPT process is presented using IHPT capacity planning as an example. Subsection 5.3 with Figure 5.8 already displayed the general procedure of the approach. First, subsection 7.1 presents in detail the methodological preparations, including data preprocessing and MLP prediction model development. Subsequently, an automated optimisation of the IHPT capacity planning on a day of the week basis using a GA, that incorporates the MLP model predictions, is performed in subsection 7.2. The aim is to develop a data-driven forecasting and optimisation method that combines an MLP and a GA to enable decision support for the hospital managers in IHPT capacity planning. This quantitative approach enables measures to be evaluated prior to practical implementation, ensuring that only the most promising solutions are adopted to improve the IHPT process.

7.1 Methodological Preparations for Optimising the Resource Planning

This subsection provides information on the preparations for the real-world data-based optimisation of the IHPT capacity planning, that is conducted in subsection 7.2. Subsection 7.1.1 describes data preprocessing steps to prepare the raw data accordingly for the MLP model, which aims to predict hourly delayed transport cases in the IHPT. Subsection 7.1.2 describes in detail the development of the MLP model, as well as different validation methods that address the model's predictive performance. The predictions of the MLP model are incorporated in the optimisation procedure in subsection 7.2.

7.1.1 Preprocessing the Data for MLP Model Development

For further investigations, the following information becomes particularly relevant as it pertains to improved resource planning: planned day of the week (Monday to Sunday) of transports as well as the as-planned and as-is starting time (specific to the hour between 0 and 23) of transports. To make future hourly predictions with greater detail based on the days of the week, new attribute categories are being created that are assigned to individual hours within each date and will serve as data basis for the MLP model development.

Figure 7.1 shows the data preprocessing approach, using colours to illustrate the derivation and processing of specific information from the raw data (first table) and its placement in the individual rows of the first step preprocessed table (second table). New attribute categories were generated using a self-developed script in R, with libraries "data.table" (*Barrett* et al. 2024), "dplyr" (*Wickham* et al. 2023) and "lubridate" (*Grolemund & Wickham* 2011), and Python, with libraries "numpy" (*Harris* et al. 2020) and "pandas" (*McKinney* 2010; *The pandas development team* 2023). Data visualisations are conducted using the R library "ggplot2" (*Wickham* 2016). During the preprocessing *ChatGPT* (versions 3.5 and 4) was used to search for and explain certain methods of the used libraries or R and python functionalities. The following information is calculated based on the raw data for each hour from January 1, 2019 to July 1, 2022 (total timespan of 30,672 hours):

1. "As-planned number of transports in same hour": Number of transports planned for the same date and at the same starting time (specific to the hour between 0 and 23).
2. "Delayed transports according to as-planned hour": Number of transports planned for the same date and at the same starting time (specific to the hour between 0 and 23) being delayed more than ten minutes.
3. "Amount of Transporters in same as-is hour (equals unique device IDs)": Number of transporters that are active for the same actual date and at the same actual time (specific to the hour between 0 and 23).

raw data - one transport case per row with case-specific information

256,266 Transports

transport ID	as-planned start	as-planned start hour	as-is start	as-is start hour	device ID	as-is transport completed	as-planned transport completed	Automatic (1=yes, 0 = no)	delayed ≥ 10 min
1210816	2019-01-01 00:15:00	0	01.01.2019 00:34:10	0	PTD05H	01.01.2019 00:50:05	2019-01-01 00:25:00	1	1
1210944	2019-01-01 00:51:00	0	01.01.2019 01:11:50	1	PTD06H	01.01.2019 01:22:41	2019-01-01 01:01:00	1	1
1210945	2019-01-01 01:01:00	1	01.01.2019 00:53:24	0	PTD05H	01.01.2019 01:23:15	2019-01-01 01:11:00	1	1
1210946	2019-01-01 01:20:00	1	01.01.2019 01:23:01	1	PTD06H	01.01.2019 01:41:01	2019-01-01 01:30:00	1	1
1210947	2019-01-01 01:50:00	1	01.01.2019 01:50:44	1	PTD05H	01.01.2019 02:17:36	2019-01-01 02:00:00	1	1
1210948	2019-01-01 02:02:00	2	01.01.2019 01:58:57	1	PTD06H	01.01.2019 02:00:06	2019-01-01 02:12:00	1	0
1210949	2019-01-01 02:39:00	2	01.01.2019 02:50:14	2	PTD06H	01.01.2019 02:53:35	2019-01-01 02:49:00	0	0
1210950	2019-01-01 03:15:00	3	01.01.2019 03:26:44	3	PTD05H	01.01.2019 03:35:26	2019-01-01 03:25:00	1	1
1210951	2019-01-01 03:29:00	3	01.01.2019 03:38:27	3	PTD06H	01.01.2019 03:49:54	2019-01-01 03:39:00	1	1
1210953	2019-01-01 03:59:00	3	01.01.2019 04:22:40	4	PTD05H	01.01.2019 04:44:06	2019-01-01 04:09:00	1	1
1210954	2019-01-01 04:19:00	4	01.01.2019 04:27:51	4	PTD06H	01.01.2019 04:35:10	2019-01-01 04:29:00	1	0
1210955	2019-01-01 04:39:00	4	01.01.2019 04:44:08	4	PTD05H	01.01.2019 05:17:12	2019-01-01 04:49:00	1	1
1210957	2019-01-01 07:42:00	7	01.01.2019 07:55:27	7	PTD01H	01.01.2019 07:55:36	2019-01-01 07:52:00	0	0

...

Figure 7.1 part 1/2 - continuation on following page

Data collection period of 30,672 hours

Date	Day of the week	Hour	**As-planned** number of transports in same hour	Delayed transports according to **as-planned** hour	Amount of Transporters in same **as-is** hour (equals unique device IDs)	Automatic rate according to **as-planned** hour
01.01.2019	2	0	2	2	1	1
01.01.2019	2	1	3	3	2	1
01.01.2019	2	2	2	0	1	0.5
01.01.2019	2	3	3	3	2	1
01.01.2019	2	4	2	1	2	1
01.01.2019	-	5	-	-	-	-
01.01.2019	-	6	-	-	-	-
01.01.2019	2	7	1	0	1	0

...

Preprocessed data - one hour per row with hour-specific information on transports

Cleaned data collection of 25,662 hours

Day of the week	Hour	**As-planned** number of transports in same hour	Delayed transports according to **as-planned** hour	Amount of Transporters in same **as-is** hour (equals unique device IDs)	Automatic rate according to **as-planned** hour
2	0	2	2	1	1
2	1	3	3	2	1
2	2	2	0	1	0.5
2	3	3	3	2	1
2	4	2	1	2	1
2	7	1	0	1	0

...

MLP input | MLP label | MLP input

MLP data with hour-specific information

Figure 7.1 part 2/2

Figure 7.1: Subset of the data preprocessing approach. Adopted from *Kropp* et al. (2024b).

This information is generated based on the timestamp associated with the “transport started” activity (German: “Transport begonnen”, see also Table 5.1 from subsection 5.1 and Figure 6.2 from subsection 6.2.1), in conjunction with the device ID managed by each transporter.

4. “Automatic rate according to as-planned hour”: Automation rate for the same planned date and at the same planned time (specific to the hour between 0 and 23). This rate indicates the extent to which transports scheduled at the same time were manually or automatically assigned.

Afterwards, rows without information and the date column are excluded from the training of the MLP model, as the model’s focus is solely on day of the week and hour of the day. The third table of Figure 7.1 presents the remaining and final preprocessed data (total of 25,662 rows with hourly information) including the schematic input and label data used for training and evaluating the MLP model (see subsection 7.1.2) through supervised learning (see subsection 3.2.2.1). The relevance and influence of the derived information on the IHPT capacity planning is also validated by the hospital managers.

Figures A.12 to A.17 (histograms) in appendix A.2 show more detailed information on the attribute categories from the final preprocessed data. After preprocessing in this way, an average of approximately 153 samples are available for each hour on each day of the week (25,662 samples divided by the product of seven days of the week times 24 hours). To avoid the risk of not having enough training data available, more granular predictions are not pursued for days of the week in specific months or calendar weeks. This would require a larger dataset during MLP model development for similarly accurate predictions. Attempts to make predictions on an individual transport case basis have also been conducted but have not been successful. The reasons for this may lie in the heterogeneity of the cases, some of which arrived delayed and some of which did not arrive delayed under similar conditions. By aggregating information, for example per hour, the data becomes less heterogeneous and patterns can be better identified. However, the predictions that can be made out of aggregated data are coarser.

Subsection 6.2.3 already indicated that whether transports are automatically or manually dispatched can have an influence on the transport delays. Figure 7.2 shows the proportion of all days of the week and hours on which the delay rate per hour was greater than 0.0 (i.e. fully manually dispatched transport

Proportion [%] of days of the week and hours, when 0.0 < hourly automatic rate < 1.0

as-planned hour

as-planned day of the week	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	0.0	0.0	0.0	0.0	0.0	6.0	33.1	18.1	13.4	10.4	12.6	13.2	14.3	12.1	42.3	39.4	6.1	0.0	0.0	0.0	0.6	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	26.7	15.8	12.6	15.3	18.6	20.2	19.1	14.8	45.9	36.1	3.8	0.0	0.6	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	2.6	28.7	20.8	11.5	12.6	16.4	15.3	13.7	18.7	48.9	35.0	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	1.4	29.7	18.6	11.7	13.1	12.6	12.0	12.6	17.6	45.3	33.5	3.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	4.4	35.1	17.5	11.6	13.7	13.1	16.9	13.1	15.3	51.6	31.5	3.3	0.6	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.1	0.0	0.6	0.6	0.6	0.0	0.6	0.0	0.6	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Figure 7.2: Proportion [%] of days of the week and hours in the preprocessed dataset (total of 25,662 rows with hourly information) when the transport dispatching is in a mixed operation and thus the hourly automatic rate is greater than "0.0" and smaller than "1.0". In the figure "0.0" means, that 100% of the transports on specific days of the week and hours were either dispatched fully manually (automatic rate of "0.0") or fully automatically (automatic rate of "1.0"), i.e. the transport dispatching is not in mixed operation (own visualisation).

cases) and smaller than 1.0 (i.e. fully automatically dispatched transport cases) in the preprocessed dataset (total of 25,662 rows with hourly information). This means that the IHPT dispatching is in a mixed operation. From Monday to Friday in the main operation hours (between 06:00 and 16:59) the transport dispatching is mainly in a mixed operation. This timeframe is when most of the daily transports take place (see Figure 6.1 from subsection 6.1). Therefore, the hourly automatic rate is used and trained as an MLP input.

In addition to the four derived information per day of the week and hour (see third table of Figure 7.1), further organisational attribute categories from the raw data could be included to make more specific statements. However, the aim of this work is to show that the use of MLP in combination with a GA can theoretically achieve optimisations in the planning of transport capacities, i.e. support the redesign in the IHPT process context. Therefore, a coarse level of predictions, i.e. for days of the week, is considered sufficient for this purpose.

7.1.2 MLP Model Development

The MLP model (see subsection 3.2.2.2) development through supervised learning (see subsection 3.2.2.1) is done using the python libraries "PyTorch" (*Paszke* et al. 2019), "NumPy" (*Harris* et al. 2020), "pandas" (*McKinney* 2010; *The pandas development team* 2023) and "scikit-learn" (*Pedregosa* et al. 2011). Data visualisations are conducted using the python library "Matplotlib" (*Hunter* 2007). During the development of the MLP model *ChatGPT* (versions 3.5 and 4) was used to search for and explain certain methods of the used libraries or python functionalities.

To enable predictions for capacity planning in the context of IHPT an MLP model is used to conduct a regression (see subsection 3.2.2.1). The aim of this model is to predict the resulting delayed cases per hour by specific given input data (see Figure 7.1 from subsection 7.1.1).

7.1.2.1 MLP Model Specifications

The procedure of the MLP (see subsection 3.2.2.2) model development is shown in Figure 7.3. First, the entire preprocessed dataset (see subsection

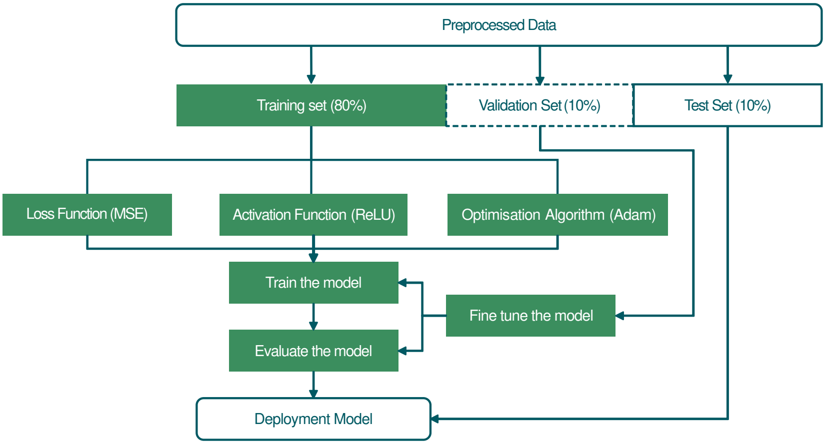


Figure 7.3: MLP development steps in the approach (*Kropp* et al. 2024b).

7.1.1) is divided into training set, validation set and test set, with proportions of 80%, 10%, 10%.

The mean squared error (*MSE*) (see "Squared-error loss" in subsection 3.2.2.1) is selected to be the loss function. The *MSE* is a commonly used metric for the performance evaluation of regression models, calculated according to equation 7.1 (*Goodfellow* et al. 2016; *Russell & Norvig* 2021).

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 \tag{7.1}$$

where m is the number of samples, y_i are the actual values and $\hat{y}_i$ are the predicted values.

For the MLP model, one input layer, three hidden layers and one output layer are chosen. A schematic visualisation of the MLP model is shown in Figure 7.4. There are 5 neurons in the input layer, then 64, 256 and 64 neurons in the hidden layers as well as one neuron in the output layer. The hidden layers with their neurons are derived through trial-and-error procedures where this setup showed improved (i.e. lower) *MSE* values compared to other attempted setups. ReLU (see subsection 3.2.2.2) is chosen as activation

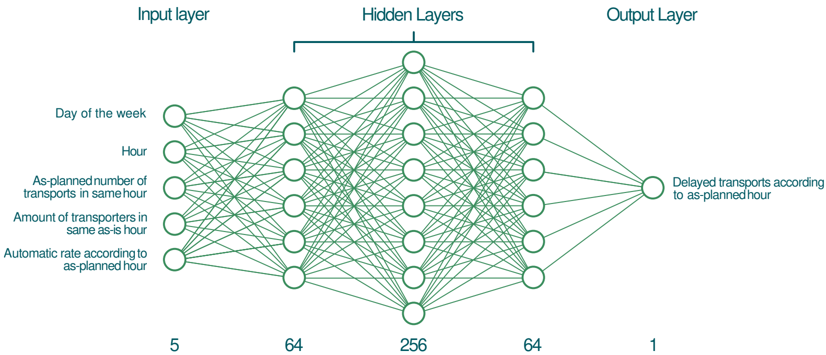
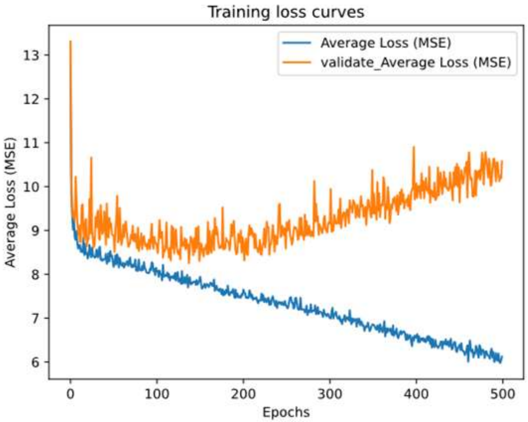


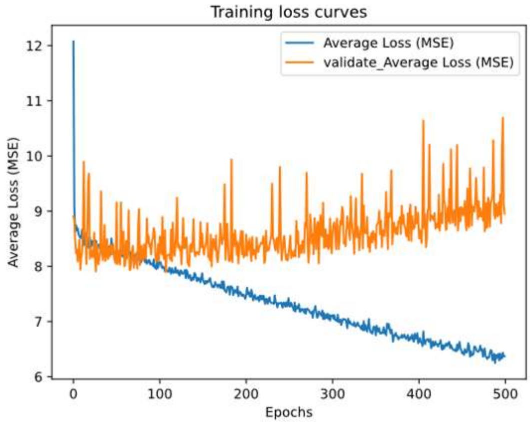
Figure 7.4: Structure of the developed MLP with one input layer, three hidden layers and one output layer. The number of neurons per layer is indicated. The input data per input neuron and the output data for the output neuron is shown (*Kropp* et al. 2024b).

function (in the hidden layers). Attempts with other activation functions such as Sigmoid, Tanh or Softplus showed no considerable differences. Adam (see also subsection 3.2.2.2) is chosen as the optimisation algorithm within the MLP training because it was recommended in *Nas & Koyuncu* (2019) for hourly patient arrival data that is characterised by a lot of variation. Adam is well-suited for first-order gradient-based optimisation of stochastic objective functions based on adaptive estimates of lower-order moments (*Kingma & Ba* 2017). During the training process the parameters of the model are updated in 500 epochs. After the parameters are updated in each epoch, the validation loss is monitored along with the training loss. To avoid overfitting, an early stopping method is applied when the validation loss stops falling. Figure 7.5 shows, for different dataset sizes, how the model training and validation losses evolve.

In comparison with a preprocessed dataset of only 2019, a preprocessed dataset of 2019 to 2020 and a preprocessed dataset of 2019 to 2021, the complete preprocessed dataset from 2019 to June 2022 (derived from subsection 7.1.1) shows, as expected, the best results. Through early stopping, the MLP model at epoch 172 is the best fitting model, as training and validation loss are both relatively and similarly low. Both are at an *MSE* of around 6.4. The test dataset, that showed similar loss results as the validation set, is used to



Trained with dataset from
2019 (0.8 * 7,588 samples)



Trained with dataset from
2019 - 2020 (0.8 * 14,911 samples)

Figure 7.5 part 1/2 - continuation on following page

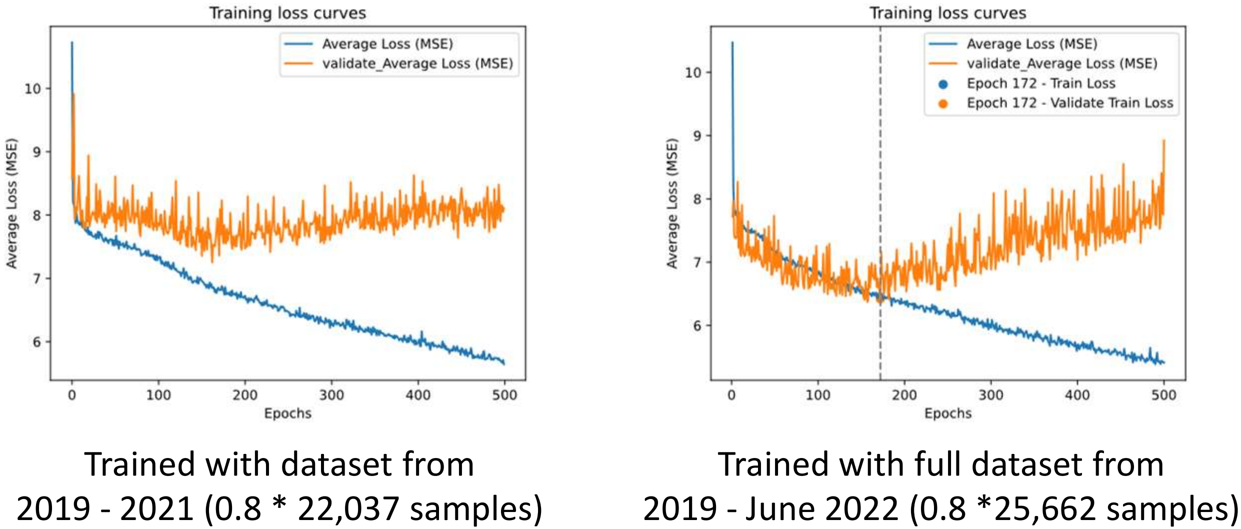


Figure 7.5 part 2/2

Figure 7.5: Training and validation loss per training epoch for different dataset sizes. The full preprocessed dataset showed over the whole training the best results. Early stopping indicates that the MLP model trained with the most data is best performing at epoch 172 because the training and validation loss are both relatively low. Adopted from *Kropp* et al. (2024b).

verify the generalisation ability of the model. The mean absolute error (*MAE*) (see 'Absolute-value loss" in subsection 3.2.2.1) can be calculated according to equation 7.2 (*Goodfellow* et al. 2016; *Russell & Norvig* 2021). For the training, validation and test set, the *MAE* is around 1.5, which means that the MLP model is on average 1.5 delayed transports off for each prediction.

$$MAE = \frac{1}{m} \sum_{i=1}^{m} |y_i - \hat{y}_i| \tag{7.2}$$

where m is the number of samples, y_i are the actual values and $\hat{y}_i$ are the predicted values.

From Figure 7.5 it can be interpreted that the inclusion of additional data in the training would further improve the model, as the *MSE* achieved for the training and validation data with more data is in lower ranges. Even though the complete dataset of 25,662 samples contains only discrete values as delayed transport cases in every single sample, the MLP predicts continuous values. However, the fact that the MLP model can handle continuous values both as output and as input information is intentional, so that it can also deal with, for example, average scenarios. Figure A.18 in appendix A.2 gives an overview on the weights and biases (see also subsection 3.2.2.2) between the different layers of the MLP model. Although not intended from a practical point of view, the MLP model can also predict negative values, i.e. negative delayed transport cases (see also Figure 7.6 in subsection 7.1.2.2). In subsection 7.2, specific constraints are applied to prevent this behaviour of the MLP model during use. In future investigations, predicting negative values can already be avoided by a different ANN configuration (e.g. by using ReLU activation function in the output layer).

7.1.2.2 Further MLP Validation

Figure 7.6 shows the Confusion Matrix of the MLP Model over the complete dataset (25,662 samples) from which R^2 and $adjusted\ R^2$ (see subsection 3.2.2.2) can be derived. Evaluating real and predicted delayed cases (continuous values are not rounded for this calculation) over the complete dataset results in both a R^2 and a $adjusted\ R^2$ of 0.79 ($adjusted\ R^2$ is slightly lower from the fourth decimal onwards). The performance of the MLP model in

Predicted delayed cases

Real delayed cases

	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	Sum
0	3	**5,106**	3,967	370	64	35	6	10	7	4	3	2	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9,579
1	0	1,937	**2,987**	520	122	60	32	31	23	12	7	5	5	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5,745
2	0	188	1,284	**457**	169	74	72	36	36	26	19	8	9	4	1	4	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,391
3	0	0	418	302	**152**	93	86	69	46	44	21	14	10	7	5	3	2	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1,275
4	1	0	100	181	132	**84**	73	78	64	40	40	27	18	11	8	10	3	3	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	876
5	0	0	18	69	63	90	**74**	63	54	46	35	26	22	22	10	9	4	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	608
6	0	0	6	39	39	43	48	**70**	62	59	46	44	18	18	16	9	6	3	4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	531
7	0	0	1	7	21	35	46	49	**64**	63	39	53	29	26	14	9	10	5	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	475
8	0	0	0	3	12	24	38	47	50	**55**	48	42	36	28	21	15	7	4	3	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	435
9	0	0	0	1	1	6	25	38	51	53	**44**	34	53	31	31	21	10	5	4	3	4	0	1	0	0	0	0	0	0	0	0	0	0	0	416
10	0	0	0	0	6	7	23	29	31	45	45	**37**	40	42	23	16	15	4	2	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	369
11	0	0	0	1	1	6	13	10	31	50	50	47	**31**	31	28	18	15	9	5	6	2	1	2	1	1	0	0	0	0	0	0	0	0	0	359
12	0	0	0	0	1	0	6	14	24	27	40	47	47	**46**	20	26	16	15	5	6	3	2	0	0	2	0	0	0	0	0	0	0	0	0	347
13	0	0	0	0	0	2	6	6	21	19	31	19	29	40	**29**	21	9	16	8	6	1	1	2	0	0	0	0	0	0	0	0	0	0	0	266
14	0	0	0	0	0	0	4	8	11	15	21	21	26	36	35	**29**	27	15	9	5	7	2	3	1	1	2	0	0	0	0	0	0	0	0	278
15	0	0	0	0	0	0	0	0	14	10	19	20	30	33	29	23	**16**	18	10	8	4	2	1	2	0	0	0	0	0	0	0	0	0	0	239
16	0	0	0	0	0	0	1	1	6	10	13	17	22	31	17	30	16	**16**	9	11	6	2	8	1	2	1	1	0	0	0	0	0	0	0	221
17	0	0	0	0	0	0	0	1	5	4	12	12	20	28	26	19	24	15	**11**	7	5	5	2	3	1	2	0	0	0	0	0	0	0	0	202
18	0	0	0	0	0	0	0	1	1	1	4	15	12	22	19	25	21	18	9	**5**	6	8	1	2	0	0	1	0	0	0	0	0	0	0	171
19	0	0	0	0	0	0	0	0	0	4	3	7	12	15	18	19	15	12	10	11	**4**	4	5	5	1	0	0	0	0	0	0	0	0	0	145
20	0	0	0	0	0	0	0	0	0	1	2	5	8	9	17	15	9	18	6	5	9	**9**	4	2	1	0	0	0	0	0	0	0	0	0	120
21	0	0	0	0	0	0	0	0	1	2	3	9	4	7	13	12	8	11	18	9	6	3	**5**	2	3	1	0	0	0	0	0	0	0	0	117
22	0	0	0	0	0	0	0	0	1	0	1	4	4	3	9	12	8	12	11	9	4	10	6	**4**	2	1	2	0	0	0	0	0	0	0	103
23	0	0	0	0	0	0	1	0	0	0	1	4	4	5	4	5	9	7	8	8	18	2	5	3	**0**	1	0	0	0	0	0	0	0	0	85
24	0	0	0	0	0	0	0	0	1	0	1	0	0	3	1	6	4	5	7	4	8	6	8	3	4	**3**	0	0	0	0	0	0	0	0	64
25	0	0	0	0	0	0	0	1	1	1	0	3	3	1	4	4	4	3	8	5	7	9	5	1	0	0	**2**	1	0	0	0	1	0	0	64
26	0	0	0	0	0	0	0	0	0	0	0	1	1	0	3	0	6	6	5	7	3	4	2	3	1	2	0	**0**	0	0	0	0	0	0	44
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	3	2	4	3	0	1	1	4	1	0	0	**0**	0	0	0	0	0	22
28	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	2	3	2	1	2	1	6	6	6	1	1	0	0	1	**0**	1	0	0	0	35
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	1	1	2	1	2	3	2	1	2	0	1	0	**1**	0	1	0	21
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	1	3	0	1	1	0	1	2	1	1	1	1	**0**	0	0	17
31	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	**0**	0	6
32	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	3	0	1	1	1	0	0	0	0	1	0	0	0	**0**	9
33	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	0	0	1	0	0	0	0	6
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	0	5
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	2
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	1	0	0	0	0	0	0	0	0	4
37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	3
38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	2
39	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
40	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	2
43	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Sum	4	7,231	8,781	1,950	783	559	554	564	606	592	549	527	493	504	404	368	271	230	164	133	113	79	75	48	32	21	12	2	3	3	4	1	1	1	25,662

Figure 7.6: Confusion Matrix of the MLP model. Predicted delayed cases, as the MLP model outputs continuous values, are rounded to the nearest integer value for simplified visualisation (values exactly halfway between integer values are rounded to the nearest even value) (*Kropp* et al. 2024b).

terms of variance explanation ability is thus in a good range, according to the acceptable bounds as per *Ozili* (2022) (see subsection 3.2.2.2).

Furthermore, a metric called mean error bias (*MEB*), can be calculated, according to *Hernández-Orallo* (2013), in equation 7.3. It indicates whether a model tends to over- or underestimate with its predictions (*Hernández-Orallo* 2013). For the developed MLP model the *MEB* is around -0.056. This indicates that the MLP model predictions $\hat{y}_i$ only slightly underestimate the actual values y_i in the complete dataset. In contrast, a positive *MEB* would indicate, that a model tends to overestimate with its predictions (*Hernández-Orallo* 2013). Furthermore, Figure 7.6 and also *MEB* calculations for dataset subpartitions show that the MLP model tends to underestimate more with its predictions when the values of real delayed cases are greater. This may be due to the higher frequency of low values of real delayed cases (i.e. a high frequency of actual values y_i with a low value) in the dataset that can lead to a biased model. For real delayed cases of e.g. zero (see the first row of Figure 7.6), the MLP model overestimates slightly with its predictions.

$$MEB = \frac{\sum_{i=1}^{m} (\hat{y}_i - y_i)}{m} \tag{7.3}$$

where m is the number of samples, $\hat{y}_i$ are the predicted values and y_i are the actual values.

As a redesign of the capacity planning on a day of the week level is intended, the performance of the MLP model for average day of the week delayed cases predictions is evaluated. Table 7.1 compares the average delayed cases per day of the week, that occurred in reality, with the delayed cases that are predicted by the MLP model using average day of the week input tensors (i.e. samples of preprocessed MLP model input, see also Figure 7.1 from subsection 7.1.1). With an average relative deviation of around 3.9% per day of the week, the predictions of the MLP model are within a satisfactory range. Furthermore, the hourly curves of the predicted delayed cases over the individual days of the week come close to the original curves. In subsection 7.2, the example of Monday and the hourly curves of the delayed cases (see Figure 7.9 in subsection 7.2) will be shown in more detail along with the optimisation process of capacity planning. Figures A.19 to A.24 from appendix A.2 show the hourly curves of the delayed cases over the other individual days of the week.

Table 7.1: Real vs. predicted delayed cases for average days of the week. Adapted from *Kropp et al.* (2024b).

Day of the week	Avg. real delayed cases	Avg. predicted delayed cases	Relative deviation
Monday	106.14	107.60	1.38%
Tuesday	84.42	81.95	2.93%
Wednesday	92.38	86.42	6.45%
Thursday	77.77	82.51	6.09%
Friday	91.63	87.84	4.14%
Saturday	15.20	15.27	0.46%
Sunday	12.28	12.99	5.78%
			Avg. 3.89%

To provide further validation, the method from *Torgo & Ribeiro* (2009) is adopted, who introduce the generalisation of precision, recall and F-score for regression problems. These performance metrics are commonly used in ML classification problems but can also be transferred to regression problems (*Davis & Goadrich* 2006; *Torgo & Ribeiro* 2009). This method has been applied by the authors of (*Torgo & Ribeiro* 2009) to evaluate the performance of different ML models in a regression problem in the economic domain. The core idea is to divide the data into two categories, "target events" (the samples which are considered relevant) and "non-events" (the samples which are considered not or less relevant) (*Torgo & Ribeiro* 2009). This makes it possible to align performance metrics on the ability of the model to make predictions in the relevant ranges (*Torgo & Ribeiro* 2009). Subsequently, the precision, recall and F-score can be calculated (*Torgo & Ribeiro* 2009).

The standard event-driven classification has a positive class, here representing the previously defined "target events" and a negative class, here representing the previously defined "non-events" (*Torgo & Ribeiro* 2009). Table 7.2 is a general confusion matrix of a classification problem, where the precision and recall of a model can be calculated according to equations 7.4 and 7.5 (*Flach* 2003; *Torgo & Ribeiro* 2009).

$$Precision = \frac{TP}{PPOS} \tag{7.4}$$

$$Recall = \frac{TP}{POS} \tag{7.5}$$

where TP stands for True Positive, $PPOS$ stands for Predicted Positive, POS stands for Actual Positive (*Flach* 2003).

Table 7.2: Standard confusion matrix of a classification problem. Adopted from *Flach* (2003) and *Torgo & Ribeiro* (2009).

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

TP = True Positive, FN = False Negative, FP = False Positive, TN = True Negative

The goal was to develop a model that allows accurate predictions of delayed cases in the day-to-day operation of the hospital under investigation. Therefore, the data is divided into two categories according to the "Delayed transports according to as-planned hour": The first category represents the majority of the data, and is designated as the positive class, thus representing the usual operational behaviour in the hospital. The remaining data is considered as negative class (outliers, that occurred rarely in the historical data), which are not relevant for the transport capacity planning. A relevance function $\phi()$ is needed to divide the dataset into these two classes (*Torgo & Ribeiro* 2009). The choice of this relevance function $\phi()$ is domain-dependent and not always easy to set (*Torgo & Ribeiro* 2009). In *Torgo & Ribeiro* (2009), the relevance function $\phi()$ is defined dependent on the ML model label and prediction. In this use case, the relevance function is thus dependent on the real (MLP label, see Figure 7.1 from subsection 7.1.1) and predicted "Delayed transports according to as-planned hour". The mathematical expression of the chosen relevance function $\phi()$ that weights the positive class with 1 (relevant) and the negative class with 0 (not relevant) is presented in equation 7.6 (adapted from *Torgo & Ribeiro* (2009)).

$$\phi(Y) = \begin{cases} 0 & \text{if} \quad Y \geq t_E \\ 1 & \text{if} \quad Y < t_E \end{cases} \tag{7.6}$$

where t_E is the relevance threshold, dependent on the real "Delayed transports according to as-planned hour" and Y can be either the real or predicted "Delayed transports according to as-planned hour" (*Torgo & Ribeiro* 2009). By introducing this idea of relevance, the regression problem is transformed into a binary classification problem (*Torgo & Ribeiro* 2009).

With equation 7.6, the definition of precision and recall for a regression problem are as shown in equations 7.7 and 7.8 (*Torgo & Ribeiro* 2009).

$$Precision = \frac{\sum_{\phi(\hat{y}_i) \leq t_E} \alpha(\hat{y}_i, y_i) \cdot \phi(\hat{y}_i)}{\sum_{\phi(\hat{y}_i) \leq t_E} \phi(\hat{y}_i)} \tag{7.7}$$

$$Recall = \frac{\sum_{\phi(y_i) \leq t_E} \alpha(\hat{y}_i, y_i) \cdot \phi(y_i)}{\sum_{\phi(y_i) \leq t_E} \phi(y_i)} \tag{7.8}$$

where $\phi(\hat{y}_i)$ is the relevance function dependent on the predicted "Delayed transports according to as-planned hour" and $\phi(y_i)$ is the relevance function dependent on the real "Delayed transports according to as-planned hour" (see equation 7.6) and $\alpha(\hat{y}_i, y_i)$ is the accuracy of prediction (i.e. loss between $\hat{y}$ and y) defined according to equation 7.9 (*Torgo & Ribeiro* 2009).

$$\alpha(\hat{y}, y) = I(L(\hat{y}, y) \leq t_L) \tag{7.9}$$

where $I()$ is a indicator function given a value of 1 if its argument is true and 0 otherwise. It is dependent on a tolerance threshold t_L that is to be defined and reflects an admissible error within a loss function $L()$ (e.g. the absolute or squared deviation). Following *Torgo & Ribeiro* (2009) the loss function $L()$ is chosen to reflect the absolute deviation between $\hat{y}$ and y. The definition of the F-score is shown in equation 7.10 (*Torgo & Ribeiro* 2009).

$$F = \frac{(\beta^2 + 1) \cdot Precision \cdot Recall}{\beta^2 \cdot Precision + Recall} \tag{7.10}$$

where $0 \leq \beta \leq 1$, determines the relative importance of recall to precision (*Torgo & Ribeiro* 2009). For an equal weighting of precision and recall, β is chosen to be one. For this setup, the F-score is also known as F1-score (*Ruiz-Sepúlveda* et al. 2009; *Russell & Norvig* 2010).

Now everything except the relevance threshold t_E and the tolerance threshold t_L are defined. To choose t_E, Figure 7.7 that visualises the cumulative frequency of the real "Delayed transports according to as-planned hour", can be viewed.

The top 4.88% of the data are considered as outliers and mapped to the negative class, when t_E is set to 17. For this t_E, the precision with different tolerance

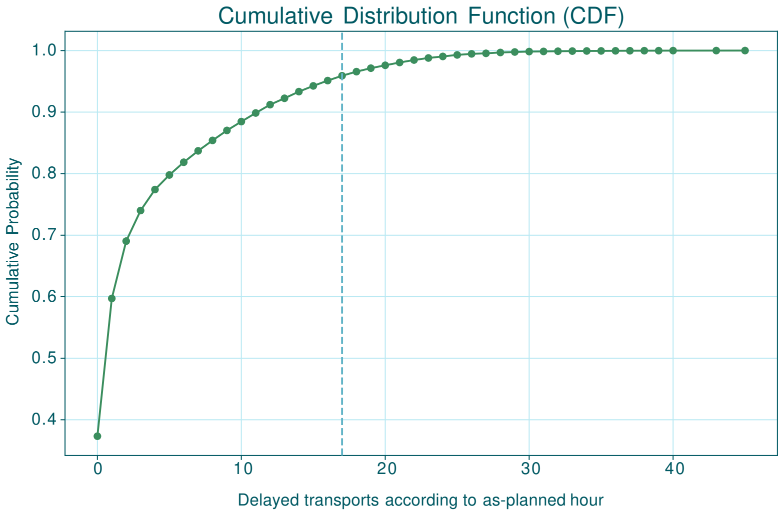


Figure 7.7: Cumulative distribution of real "Delayed transports according to as-planned hour" in complete dataset (25,662 hourly information) (*Kropp* et al. 2024b).

thresholds t_L is calculated. Figure 7.8 shows the results. With increasing tolerance the positive gradient of the precision decreases. A similar behaviour is observed for recall and F1-score.

For example, a tolerance t_L of 2 leads to a precision of around 0.81. This means that the MLP model predicts with 81% probability the correct "Delayed transports according to as-planned hour" with a tolerance of two delayed transports when outliers of 17 and more delayed transports are not considered. The recall with a tolerance t_L of two is around 0.83 and F1-score is around 0.82. The achieved precision, recall and F1-score (and thus indirectly the *MSE* from subsection 7.1.2.1) of the MLP model are rated not yet good enough for practical implementation by the hospital process managers. They propose a minimum precision, recall and F1-score of 0.9 with a tolerance t_L of 1. A tolerance t_L of 1 is argued by the hospital managers because it equals a range of two delayed cases (i.e. up to overestimating and underestimating the real delayed cases by one delayed case). Previous investigations revealed that on average a transporter can more or less conduct three transports per hour (it takes a transporter on average 19-20 minutes from the acceptance of a transport assignment to transport completion, see subsection 6.2.1). With this

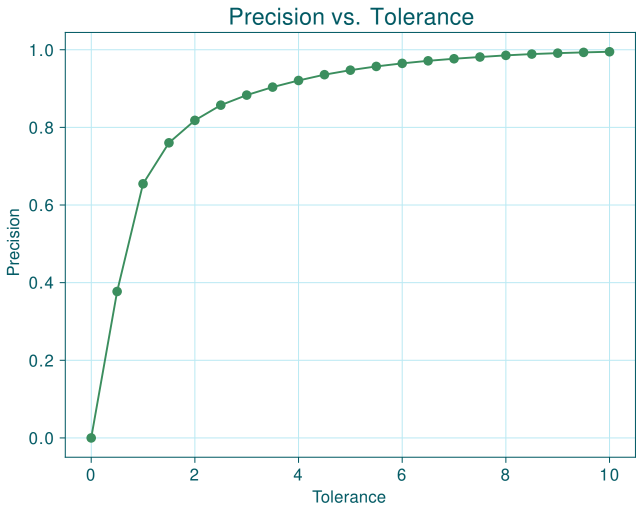


Figure 7.8: Relationship of the precision of the MLP model and tolerance threshold t_L (*Kropp* et al. 2024b).

in mind, a tolerance t_L of 1 around the real amount of delayed transports and thus an allowed range of two delayed transports reflects less than what could possibly be conducted on time by an additional FTE. From a purely economic point of view, a misprediction of the number of delayed transports that leads to a range of over- and understaffing of more than one FTE (e.g. a tolerance t_L of 2 leads to an allowed range of four delayed cases of the predictions, within a maximum of two over and two under the real delayed cases, which is more than what an average FTE can handle) is seen as not precise enough for practical implementation by the hospital process managers. The current MLP model reaches only a precision of 0.64, a recall of 0.66 and an F1-score of 0.65 when the tolerance t_L is set to 1. Therefore, the MLP model still needs to be improved before it can be used in practice. Nevertheless, in the following additional theoretical capacity planning evaluations using the MLP model will be conducted.

The results show, in general, that it is feasible to use precision, recall and F1-score to evaluate the performance of regression models. Furthermore, by setting different relevance thresholds t_E and evaluating the respective performance metrics, it is possible to gain a deeper insight into the performance of the model within specific regions of interest.

7.2 Optimising the Resource Planning

In this subsection, the resource planning will be optimised theoretically by adapting an input tensor so the output of the MLP model (which reflects the delayed cases) will be minimised. As an example for this redesign approach, the input tensor (i.e. samples of preprocessed MLP model input, see also Figure 7.1 from subsection 7.1.1) of an average Monday will be used as original tensor (see Figure 7.9 left part) that is to be altered to find an optimisation of the delayed cases, predicted to occur. Figure 7.9 (right part) shows the real delayed cases per hour on an average Monday and also the amount of delayed cases per hour that the MLP model predicts based on the original tensor. Figures A.19 to A.24 in appendix A.2 show the same for the other days of a week. In reality, there were an average of about 106 delayed cases on Mondays, whereas the MLP predicts a total of around 108 cases (see also Table 7.1 from subsection 7.1.2). As the total predicted delayed cases differs less than 2% from the real delayed cases and as the curve (i.e. the trend) of the predictions through time corresponds well to reality, the reliability of the model to reflect an average Monday is considered good, and an optimisation of the input tensor will be carried out in the following to decrease the predicted delayed cases.

For the optimisation, a GA (see also subsection 3.3.2) is used, because it anneals optimal solutions in complex problems. The GA explores the MLP with numerous solution attempts involving multiple new combinations of discrete variables in the input tensor. The GA aims to achieve an optimised adaptation of the original input tensor (see Figure 7.9 left part) that leads to an optimisation of the overall predicted delayed cases compared to the historical Monday average (see Figure 7.9 right part). For this purpose, the package "geneticalgorithm" (*Solgi* 2020) in python was used. Further used python libraries are "PyTorch" (*Paszke* et al. 2019) and "NumPy" (*Harris* et al. 2020). Data visualisations are conducted using the python library "Matplotlib" (*Hunter* 2007). During the development of the optimisation procedure involving the GA, *ChatGPT* (versions 3.5 and 4) was used to search for and explain certain methods of the used libraries or python functionalities.

	Day of the week	Hour	As-planned number of transports in same hour	Amount of trans-porters in same as-is hour	Automatic rate according to as-planned hour
tensor([[	1.0000,	0.0000,	1.5165,	0.8242,	1.0000],
[	1.0000,	1.0000,	1.2527,	0.6813,	1.0000],
[	1.0000,	2.0000,	0.8846,	0.5989,	1.0000],
[	1.0000,	3.0000,	0.8022,	0.5714,	1.0000],
[	1.0000,	4.0000,	0.6264,	0.4121,	1.0000],
[	1.0000,	5.0000,	0.6154,	0.4835,	0.9578],
[	1.0000,	6.0000,	3.3626,	1.1209,	0.2268],
[	1.0000,	7.0000,	27.5714,	6.5549,	0.1566],
[	1.0000,	8.0000,	28.3242,	6.6374,	0.1405],
[	1.0000,	9.0000,	30.6978,	6.7363,	0.1538],
[	1.0000,	10.0000,	32.4011,	6.8956,	0.1475],
[	1.0000,	11.0000,	29.2253,	6.9780,	0.1511],
[	1.0000,	12.0000,	31.0385,	6.8846,	0.1556],
[	1.0000,	13.0000,	26.9890,	7.6538,	0.1695],
[	1.0000,	14.0000,	18.5549,	7.2747,	0.2985],
[	1.0000,	15.0000,	9.6538,	2.3791,	0.7746],
[	1.0000,	16.0000,	5.9341,	1.9396,	0.9728],
[	1.0000,	17.0000,	4.0879,	1.6978,	1.0000],
[	1.0000,	18.0000,	3.4451,	1.5330,	1.0000],
[	1.0000,	19.0000,	3.0220,	1.5714,	1.0000],
[	1.0000,	20.0000,	2.7198,	1.3846,	0.9994],
[	1.0000,	21.0000,	2.5275,	0.9231,	1.0000],
[	1.0000,	22.0000,	2.5055,	1.0000,	0.9940],
[	1.0000,	23.0000,	2.1264,	0.8407,	1.0000]])

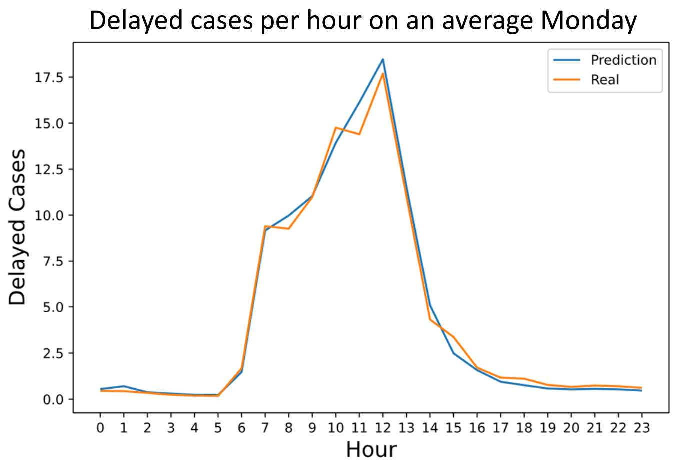


Figure 7.9: Left: Original input tensor with mean values for an average Monday. Right: Real and predicted (through MLP model) delayed cases per hour on an average Monday (*Kropp* et al. 2024b).

7.2.1 Optimising the Number of Transporters per Hour

Initially, the goal is to optimise the number of delayed cases, i.e. minimise them, by simply adjusting the number of transporters per hour. To run the GA, an objective function is defined. This function takes an adapted input tensor and calculates the objective value according to equation 7.11. The objective value consists of two components: The first part in equation 7.11 is defined by the sum of the MLP predictions (these reflect the sum of the delayed cases per day of the week, here Monday). Secondly, there is a constraint part in the objective function, wherein there are constraint penalty terms defined according to other desired goals that are to be reached in addition to minimising the delayed cases.

To optimise the number of transporters per hour, two constraint penalties are defined. The first constraint penalty (see equation 7.12) is determined by computing the difference between the sum of the values in the fourth column (i.e. "Amount of transporters in same as-is hour") of the adapted tensor and the sum of the values in the fourth column of the original tensor. This ensures that the sum of the number of transporters per hour (i.e. the FTE hours per day: transporters of each hour cumulated over the whole day), which are adjusted during the optimisation process, does not deviate greatly upwards from the original tensor. If the difference is negative (sum of the FTE hours after optimisation is less than before), the penalty is set to zero. If fewer transporters are in operation in total and the delayed cases are still minimised, this is considered good, but the constraint penalty should not decrease the objective value as minimising the delayed transports is the main goal. Second, there is a constraint penalty if negative delayed cases are predicted (see also subsection 7.1.2.1) by the model (see equation 7.13).

The meaning of the other variables within the objective function and the constraint penalties are defined according to equations 7.14 - 7.20.

$$\text{objective1} = \sum_{i=1}^{m} MLP(x_i) + w_1 \cdot CP_1 + w_2 \cdot CP_2 \tag{7.11}$$

where,

$$CP_1 = \text{ConstraintPenalty1} = max((\sum_{i=1}^{m}(y_i^4) - \sum_{i=1}^{m}(z_i^4)), 0.0) \tag{7.12}$$

$$CP_2 = \text{ConstraintPenalty2} = -(\sum_{i=1}^{m}(min(MLP(x_i), 0.0))) \tag{7.13}$$

with

$$m = \text{overall no. of rows in the adapted and original tensor} \tag{7.14}$$

$$MLP = \text{Multilayer Perceptron (predicts delayed cases)} \tag{7.15}$$

$$x_i = \text{row i of the adapted tensor} \tag{7.16}$$

$$w_1 = \text{weighting factor of } CP_1 \tag{7.17}$$

$$w_2 = \text{weighting factor of } CP_2 \tag{7.18}$$

$$y_i^4 = \text{element i of column 4 of the adapted tensor} \tag{7.19}$$

$$z_i^4 = \text{element i of column 4 of the original tensor} \tag{7.20}$$

where m is 24, since there is one row for all hours from 0 to 23 in both the adapted input tensor and the original tensor. w_1 is set to 3.5 and w_2 is set to 150. These weighting factors are chosen subjectively to reflect the authors' (*Kropp* et al. 2024b) view of the importance of the constraint penalties. The event log showed that, on average, it took a transporter 20 minutes from the acceptance of a transport assignment to transport completion. Thus, around three transports per hour can be fulfilled on average per transporter. A weighting factor w_1 of 3.5 expresses that one more transporter can be added in the capacity planning if this leads to at least 3.5 fewer delayed transports. This is more than what would be possible by conservatively assuming that all three average feasible transports would be completed on time by one more transporter in that hour. Thus, in terms of the objective function, the GA will only be able to identify a better solution if an additional transporter in one hour reduces more than 3.5 delayed transports (see CP_1 in equation 7.12). With a value of 150, w_2 is set large enough to ensure that no negative delayed cases are predicted by the model (see CP_2 in equation 7.13). Higher values for w_2 are possible, too.

After the objective function is set, the 24 elements in the fourth column of the Monday tensor (see Figure 7.9 from before) will be considered as integer variables that are to be optimised by the GA. Possible integer values are set to be between one and 12. On average, the active transporters per hour on Mondays were historically in all hours under eight transporters (see Figure 7.9 from before) and with the predefined setting the GA does not search for solutions that are far above the historical average values. Furthermore, it is assumed that in every hour there should be at least one active transporter after optimisation. The parameters of the GA are set through trial-and-error to the following and the procedure of the GA is presented in Algorithm 1:

- 'max_num_iteration': 2,000,
- 'population_size': 10,000,
- 'mutation_probability': 0.1,
- 'elit_ratio': 0.01,
- 'crossover_probability': 0.5,
- 'parents_portion': 0.3,
- 'crossover_type': 'uniform',
- 'max_iteration_without_improv': None.

Algorithm 1: GA to minimise the objective value. Adopted from *Kropp* et al. (2024b).

Initialize population with 10,000 random individuals
while iteration ≤ 2,000 **do**
    Evaluate objective value of each individual
    Sort individuals by objective value in ascending order
    Select the top 1% of individuals as elites
    Select 30% of the population as parents
    Perform uniform crossover on selected parents to produce offspring, see documentation of python package "geneticalgorithm" (*Solgi* 2020)
    Apply mutation to offspring with a probability of 10%
    Combine elites, parents, and offspring into new population
    Increment iteration counter
end while

At each iteration, the objective value is evaluated based on the best identified input tensor. Overall, the GA aims to optimise the objective function, which includes both the MLP model predictions and constraint penalties. The optimisation process iteratively updates the input tensor to minimise the objective value by adjusting the tensor values within the specified constraints.

Figure 7.10 (left part) shows the final derived input tensor that leads to an optimisation. The MLP model predicts with the new tensor a sum of delayed cases for a Monday of around 79 delayed cases. Before optimisation, an

	Day of the week	Hour	As-planned number of transports in same hour	Amount of trans-porters in same as-is hour	Automatic rate according to as-planned hour
tensor([[	1.0000,	0.0000,	1.5165,	1.0000,	1.0000],
[	1.0000,	1.0000,	1.2527,	1.0000,	1.0000],
[	1.0000,	2.0000,	0.8846,	1.0000,	1.0000],
[	1.0000,	3.0000,	0.8022,	1.0000,	1.0000],
[	1.0000,	4.0000,	0.6264,	1.0000,	1.0000],
[	1.0000,	5.0000,	0.6154,	1.0000,	0.9578],
[	1.0000,	6.0000,	3.3626,	2.0000,	0.2268],
[	1.0000,	7.0000,	27.5714,	2.0000,	0.1566],
[	1.0000,	8.0000,	28.3242,	2.0000,	0.1405],
[	1.0000,	9.0000,	30.6978,	2.0000,	0.1538],
[	1.0000,	10.0000,	32.4011,	2.0000,	0.1475],
[	1.0000,	11.0000,	29.2253,	12.0000,	0.1511],
[	1.0000,	12.0000,	31.0385,	12.0000,	0.1556],
[	1.0000,	13.0000,	26.9890,	11.0000,	0.1695],
[	1.0000,	14.0000,	18.5549,	8.0000,	0.2985],
[	1.0000,	15.0000,	9.6538,	3.0000,	0.7746],
[	1.0000,	16.0000,	5.9341,	4.0000,	0.9728],
[	1.0000,	17.0000,	4.0879,	1.0000,	1.0000],
[	1.0000,	18.0000,	3.4451,	1.0000,	1.0000],
[	1.0000,	19.0000,	3.0220,	1.0000,	1.0000],
[	1.0000,	20.0000,	2.7198,	1.0000,	0.9994],
[	1.0000,	21.0000,	2.5275,	1.0000,	1.0000],
[	1.0000,	22.0000,	2.5055,	1.0000,	0.9940],
[	1.0000,	23.0000,	2.1264,	1.0000,	1.0000]])

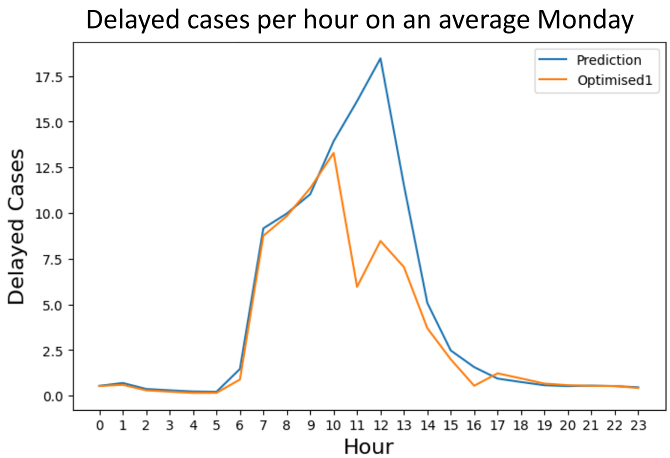


Figure 7.10: Left: Best achieved solution for the input tensor with adjusted number of transporters per hour (see Figure 7.9 from before for comparison to the original tensor for an average Monday) leading to fewer delayed cases. Right: Predicted (through MLP model) delayed cases per hour on an average Monday before and after input tensor optimisation (see left) through the GA (*Kropp* et al. 2024b).

average Monday was predicted to have around 108 delayed cases. At the same time, the 73.6 transporter FTE hours were merely redistributed so that the optimised tensor now contains a total of 73 FTE hours (due to the requirement to use only integer transporter numbers per hour). Figure 7.10 (right part) shows the predicted (through MLP model) delayed cases per hour on an average Monday before and after input tensor optimisation through the GA. While the sum of FTE hours stays quite the same, as intended, the sum of delayed transports as well as the objective function value are minimised. In summary, it is theoretically possible to achieve around 27% fewer delayed transports by simply reallocating transport capacities. This procedure can be used, for example, on a daily basis for capacity planning regarding personnel resources for the following day, but also as a basis for deriving a coarser capacity planning for periods or, for example, the entire year. The approach thus enables decision support at the tactical or strategic level (see also subsection 2.3). Suitable input tensors need to be derived accordingly.

7.2.2 Further Resource Optimisations

In addition to the transporters per hour, other parameters can also be optimised. Therefore, another attempt is made to adjust the input tensor to minimise delayed cases.

Next to the number of transporters per hour, the automation rate may be adjusted every hour, as well as the number of planned transports per hour. Regarding automation, the rate should generally always be either exactly 1 or exactly 0 after being adapted. This is based on the findings from preliminary analysis (see subsection 6.2.3) that showed a mixed operation is inefficient.

The total number of transports to be planned on an average Monday should not be lower than the number without tensor adjustment. During the observation period, approximately 270 transports were planned on an average Monday. This boundary is incorporated in a third constraint penalty enhancing the two mentioned constraint penalties of subsection 7.2.1. The new objective function, where the GA aims to optimise three columns of the original tensor (i.e. “As-planned number of transports in same hour”, “Amount of transporters in same as-is hour” and “Automatic rate according to as-planned hour”), is now given in equation 7.21. The third constraint penalty CP_3 is defined according to equation 7.22. The meaning of the other variables within the objective function and the constraint penalties are defined in equations 7.23 - 7.25. If the sum of the number of planned transports per hour after optimisation is higher than before, the penalty is set to zero (see equation 7.22). If more transports are planned in total and the delayed cases are still minimised, this is considered good, but the constraint penalty CP_3 should not decrease the objective value as minimising the delayed transports is the main goal.

$$\text{objective3} = \sum_{i=1}^{m} MLP(x_i) + w_1 \cdot CP_1 + w_2 \cdot CP_2 + w_3 \cdot CP_3 \tag{7.21}$$

where in addition to equations 7.12 - 7.20 from subsection 7.2.1,

$$CP_3 = \text{ConstraintPenalty3} = max((\sum_{i=1}^{m}(z_i^3) - \sum_{i=1}^{m}(y_i^3)), 0.0) \tag{7.22}$$

with

$$w_3 = \text{weighting factor of } CP_3 \tag{7.23}$$

$$z_i^3 = \text{element i of column 3 of the original tensor} \tag{7.24}$$

$$y_i^3 = \text{element i of column 3 of the adapted tensor} \tag{7.25}$$

where the weighting w_3 of the third constraint penalty is subjectively set to 3.5 according to the authors' (*Kropp* et al. 2024b) view on the importance of the constraint penalty. This means that if one less transport was to be planned per day, this must result in at least 3.5 fewer delayed cases. This is about ten times higher than the average delayed case decrease of almost 0.35 (due to an average delay rate of almost 35% over all transport cases, see subsection 5.1) that would result from one less conducted transport. Thus, the GA can understand that fewer transports to be planned through tensor adjustment are only valid if this results in a considerable (tenfold) reduction of delayed cases and decrease in the objective value. The other variables to be set stay as in subsection 7.2.1.

Furthermore, only adjustments in the number of planned transports by the GA will be allowed between the core operating hours of the hospital (between hours 7 and 17). Due to the low expected number of transport assignments outside the core operating hours, adjustments have been excluded in these periods and the values just stay as the historical average Monday values. The possible range for the adjusted number of planned transports in the core operating hours is defined to include all integers from zero to 50. Up to approximately 32 transports per hour were planned for Mondays on average (see Figure 7.9 from before at hour 10). Furthermore, in the historical (i.e. preprocessed) dataset, just a few samples were found that included over 50 planned transports (the maximum was 59 planned transports) in a respective hour. So, the range between zero and 50 is considered meaningful to provide the GA with a sufficient degree of freedom for optimisation.

The parameters of the GA stay the same as in subsection 7.2.1. Figure 7.11 (left part) shows the derived input tensor by the GA that leads to an optimisation with adaptations in columns three to five compared to the original tensor. Figure 7.11 (right part) shows the predicted (through MLP model) delayed cases per hour on an average Monday before and after input tensor optimisation through the GA. While the number of planned transports stays at approximately 270 and the number of transporter FTE hours are at 73, the MLP predicts with the new tensor the sum of delayed Monday cases to be approximately 63 delayed cases. This reflects a reduction of about 42% in delayed cases compared to 108 predicted delayed cases on the historical average Monday (see Figure 7.9 from before) by reallocating the number of transporters per hour, the number of planned transports per hour and the delay rate per hour. In contrast to subsection 7.2.1, that focused on personnel resource allocation, now additionally the number of planned transports and the automation rate were adjustable. However, the procedure can again be used, for example, on a daily basis for capacity planning for the following day, but also as a basis for deriving a coarser capacity planning for periods or, for example, the entire year. The approach thus also enables decision support at the tactical or strategic level (see also subsection 2.3). Suitable input tensors need to be derived accordingly.

In principle, it is also possible to develop an MLP with additional input data (next to the data preprocessed in subsection 7.1.1) and to derive optimisations using the GA. Information on critical routes (see subsection 6.2.2) could also be processed in order to carry out a process optimisation using the combination of the MLP prediction model and GA. However, a meaningful KPI (e.g. ratio of emergency department or endoscopy related transports per hour) must first be derived and the availability of sufficient samples for different conditions must be ensured during MLP development to allow for pattern recognition. This generally applies when preparing data (see also subsection 7.1.1) for MLP (and other ANN) prediction models.

	Day of the week	Hour	As-planned number of transports in same hour	Amount of trans-porters in same as-is hour	Automatic rate according to as-planned hour
tensor([[	1.0000,	0.0000,	1.5165,	2.0000,	1.0000],
[	1.0000,	1.0000,	1.2527,	2.0000,	1.0000],
[	1.0000,	2.0000,	0.8846,	1.0000,	1.0000],
[	1.0000,	3.0000,	0.8022,	1.0000,	1.0000],
[	1.0000,	4.0000,	0.6264,	1.0000,	1.0000],
[	1.0000,	5.0000,	0.6154,	1.0000,	1.0000],
[	1.0000,	6.0000,	3.3626,	3.0000,	0.0000],
[	1.0000,	7.0000,	12.0000,	7.0000,	1.0000],
[	1.0000,	8.0000,	49.0000,	12.0000,	1.0000],
[	1.0000,	9.0000,	42.0000,	3.0000,	0.0000],
[	1.0000,	10.0000,	44.0000,	3.0000,	0.0000],
[	1.0000,	11.0000,	8.0000,	2.0000,	1.0000],
[	1.0000,	12.0000,	7.0000,	3.0000,	1.0000],
[	1.0000,	13.0000,	50.0000,	3.0000,	0.0000],
[	1.0000,	14.0000,	6.0000,	5.0000,	0.0000],
[	1.0000,	15.0000,	14.0000,	7.0000,	0.0000],
[	1.0000,	16.0000,	9.0000,	4.0000,	0.0000],
[	1.0000,	17.0000,	4.0000,	3.0000,	1.0000],
[	1.0000,	18.0000,	3.4451,	2.0000,	0.0000],
[	1.0000,	19.0000,	3.0220,	2.0000,	1.0000],
[	1.0000,	20.0000,	2.7198,	1.0000,	1.0000],
[	1.0000,	21.0000,	2.5275,	2.0000,	1.0000],
[	1.0000,	22.0000,	2.5055,	2.0000,	1.0000],
[	1.0000,	23.0000,	2.1264,	1.0000,	1.0000]])

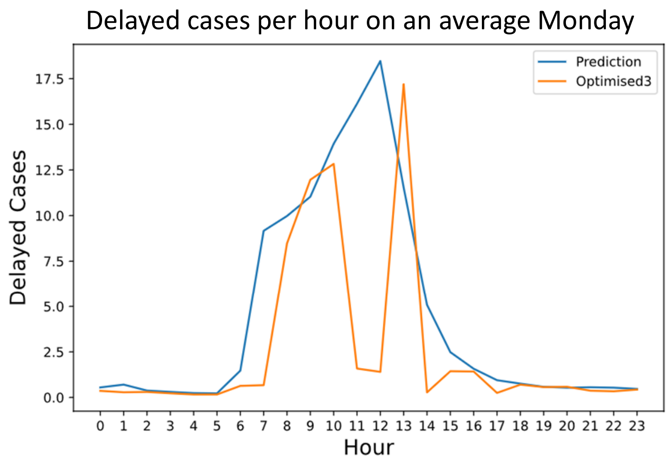


Figure 7.11: Left: Best achieved solution for the input tensor with adjusted number of transporters per hour, number of planned transports per hour and delay rate per hour (see Figure 7.9 from before for comparison to the original tensor for an average Monday) leading to fewer delayed cases. Right: Predicted (through MLP model) delayed cases per hour on an average Monday before and after input tensor optimisation (see left) through the GA (*Kropp* et al. 2024b).

7.2.3 GA Validation

A limited solution space is created to validate the functionality of the GA. The more degrees of freedom the GA has, the more exponentially increasing solutions there will be in general. Thus, the aim is to evaluate the performance of the GA with a problem where there is a limited, comprehensible number of solutions. In total, 100 final solutions will be generated by the GA (following the complete procedure from Algorithm 1, see subsection 7.2.1). Then, it is analysed how these compare to all possible solutions in the limited solution space.

The assumption is that, on an average Monday, it is only possible to adjust the transporters between the full hours of seven and 16 o'clock (i.e. a total of ten hourly slots). A maximum of 60 transporter FTE hours (73.6 FTE hours on an average Monday minus 13.7 FTE hours from the non-adjustable hour slots of an average Monday equals 59.9 FTE hours) should then be distributed across ten specific chosen slots out of the 24 hours on a day. Each slot should have at least one transporter and a maximum of 12 transporters (i.e. possible integer values in the GA are set to be between one and 12, like in subsection 7.2.1). In addition, the number of transporters from one of these ten slots to the next slot should not differ by more than two transporters, for example:

- A slot that starts with one transporter can have one, two or three transporters in the next slot.
- A slot that starts with five transporters can have three, four, five, six or seven transporters in the next slot, and so on.

An objective function that penalises not meeting these requirements is shown in equation 7.26. In contrast to the objective function from equation 7.11, see subsection 7.2.1, a new penalty CP_4 (or "ConstraintPenalty4", see equation 7.26 and equation 7.27) is added. Figure 7.12 visualises the problem and main conditions that the GA is facing.

$$\text{objective\_limited} = \sum_{i=1}^{m} MLP(x_i) + w_1 \cdot CP_1 + w_2 \cdot CP_2 + w_4 \cdot CP_4 \tag{7.26}$$

where in addition to equations 7.12 - 7.20 from subsection 7.2.1,

$$CP_4 = \text{ConstraintPenalty4} = \sum_{i=8}^{16} \begin{cases} \left|y_i^4 - y_{i+1}^4\right|, & \text{if } \left|y_i^4 - y_{i+1}^4\right| > 2 \\ 0, & \text{otherwise} \end{cases} \tag{7.27}$$

with

$$w_4 = \text{weighting factor of } CP_4 \tag{7.28}$$

where the weighting w_4 of the new constraint penalty CP_4 is subjectively (*Kropp* et al. 2024b) set to 150 to ensure that the GA does not develop solutions that allow the next hourly time slots to differ by more than two transporters, which would lie outside the selected limited solution space. The weightings w_1 and w_2 stay as defined in subsection 7.2.1.

	Day of the week	Hour	As-planned number of transports in same hour	Amount of trans-porters in same as-is hour	Automatic rate according to as-planned hour
tensor([[	1.0000,	0.0000,	1.5165,	0.8242,	1.0000],
[	1.0000,	1.0000,	1.2527,	0.6813,	1.0000],
[	1.0000,	2.0000,	0.8846,	0.5989,	1.0000],
[	1.0000,	3.0000,	0.8022,	0.5714,	1.0000],
[	1.0000,	4.0000,	0.6264,	0.4121,	1.0000],
[	1.0000,	5.0000,	0.6154,	0.4835,	0.9578],
[	1.0000,	6.0000,	3.3626,	1.1209,	0.2268],
[	1.0000,	7.0000,	27.5714,	...? ,	0.1566],
[	1.0000,	8.0000,	28.3242,	...? ,	0.1405],
[	1.0000,	9.0000,	30.6978,	...? ,	0.1538],
[	1.0000,	10.0000,	32.4011,	...? ,	0.1475],
[	1.0000,	11.0000,	29.2253,	...? ,	0.1511],
[	1.0000,	12.0000,	31.0385,	...? ,	0.1556],
[	1.0000,	13.0000,	26.9890,	...? ,	0.1695],
[	1.0000,	14.0000,	18.5549,	...? ,	0.2985],
[	1.0000,	15.0000,	9.6538,	...? ,	0.7746],
[	1.0000,	16.0000,	5.9341,	...? ,	0.9728],
[	1.0000,	17.0000,	4.0879,	1.6978,	1.0000],
[	1.0000,	18.0000,	3.4451,	1.5330,	1.0000],
[	1.0000,	19.0000,	3.0220,	1.5714,	1.0000],
[	1.0000,	20.0000,	2.7198,	1.3846,	0.9994],
[	1.0000,	21.0000,	2.5275,	0.9231,	1.0000],
[	1.0000,	22.0000,	2.5055,	1.0000,	0.9940],
[	1.0000,	23.0000,	2.1264,	0.8407,	1.0000]])

Main Conditions of the GA for ...?:

1. Integer Numbers from 1 to 12 can be inserted in ...?
2. ConstraintPenalty1
3. ConstraintPenalty2
4. ConstraintPenalty4: when difference between ...? and a sequential ...? is >2

Figure 7.12: Problem with limited solutions, that the GA aims to solve. The goal is to minimise the objective function (*Kropp* et al. 2024b).

First, a specially created recursive algorithm is used to try all possible numbers of transporters that fulfill the conditions for each slot. The final result, how many solutions there are to distribute a maximum of 60 transporters to ten slots, whereby the distribution fulfils the specified conditions, is 5,589,997 solutions. If these 5,589,997 solutions are assessed with the objective function (see equation 7.26), the following values of the objective function are obtained:

- min 105.05,
- max 396.60,
- average 180.87,
- median 143.23.

For the solutions in which the total FTE hours are 60, which is also the maximum possible, the objective function is always slightly higher than the number of delayed transport cases. This is because, according to equation 7.26, more than the original 59.9 FTE hours are penalised (see CP_1 in equation 7.12 from subsection 7.2.1) in a solution that is evaluated through the objective function. In these instances, the objective function is greater than the number of predicted delayed cases by 0.23 (this rounded value results from the exact calculation of CP_1 in equation 7.12 and the subsequent weighting by w_1, see subsection 7.2.1).

It should be noted that only 69 of these 5,589,997 solutions lead to equal or better objective function values than the average Monday with an objective function value of 107.60. The fact that there are so few solutions that lead to any improvement is partly because only integer numbers are allowed, and partly because, in two consecutive hours, the transporter numbers must not differ by more than two. This severely limits the possible improving solutions. The best solution with an objective value of 105.05 is visualised in Figure 7.13.

Next the GA is used to find an optimised solution for the problem. To evaluate the GA performance, the complete GA procedure (see Algorithm 1 from subsection 7.2.1) is repeated 100 times. Then, all generated optimised solutions are compared to the 5,589,997 possible solutions. In contrast to the prior parameters of the GA (see subsection 7.2.1 and 7.2.2), the parameter "population_size" is decreased from 10,000 to ten to accelerate the 100 independent GA runs, each of which goes through 2,000 iterations. All 100 solutions that the GA presents are listed and evaluated in Table A.2 in appendix A.2. A total

Day of the week	Hour	As-planned number of transports in same hour	Amount of trans-porters in same as-is hour	Automatic rate according to as-planned hour
tensor([[1.0000,	0.0000,	1.5165,	0.8242,	1.0000],
[1.0000,	1.0000,	1.2527,	0.6813,	1.0000],
[1.0000,	2.0000,	0.8846,	0.5989,	1.0000],
[1.0000,	3.0000,	0.8022,	0.5714,	1.0000],
[1.0000,	4.0000,	0.6264,	0.4121,	1.0000],
[1.0000,	5.0000,	0.6154,	0.4835,	0.9578],
[1.0000,	6.0000,	3.3626,	1.1209,	0.2268],
[1.0000,	7.0000,	27.5714,	2.0000,	0.1566],
[1.0000,	8.0000,	28.3242,	2.0000,	0.1405],
[1.0000,	9.0000,	30.6978,	4.0000,	0.1538],
[1.0000,	10.0000,	32.4011,	6.0000,	0.1475],
[1.0000,	11.0000,	29.2253,	8.0000,	0.1511],
[1.0000,	12.0000,	31.0385,	10.0000,	0.1556],
[1.0000,	13.0000,	26.9890,	10.0000,	0.1695],
[1.0000,	14.0000,	18.5549,	8.0000,	0.2985],
[1.0000,	15.0000,	9.6538,	6.0000,	0.7746],
[1.0000,	16.0000,	5.9341,	4.0000,	0.9728],
[1.0000,	17.0000,	4.0879,	1.6978,	1.0000],
[1.0000,	18.0000,	3.4451,	1.5330,	1.0000],
[1.0000,	19.0000,	3.0220,	1.5714,	1.0000],
[1.0000,	20.0000,	2.7198,	1.3846,	0.9994],
[1.0000,	21.0000,	2.5275,	0.9231,	1.0000],
[1.0000,	22.0000,	2.5055,	1.0000,	0.9940],
[1.0000,	23.0000,	2.1264,	0.8407,	1.0000]])

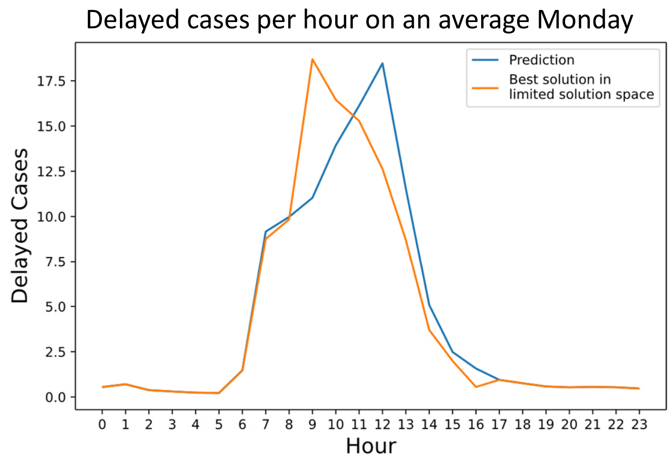


Figure 7.13: Left: Input tensor with mean values for an average Monday with adapted no. of transporters in ten hours (best solution in limited solution space). Right: Predicted (through MLP model) delayed cases per hour on an average Monday before and after inserting the best input tensor (best solution in limited solution space, see left) (*Kropp* et al. 2024b).

of 66 unique final solutions were generated by the GA within the 100 final solutions.

Below, the aggregated results of the objective function value of the 100 final GA solutions are presented:

- min 106.50,
- max 117.34,
- average 109.20,
- median 108.14.

In 33 out of the 100 runs, the GA led to improvements in the objective function. In the other 67 runs the GA did not lead to an improvement in the objective function. As mentioned before, there are rarely improvement solutions in the chosen limited solution space. However, due to the following reasons the GA is considered to perform well: With a minimum objective function value of 106.50 in the 100 runs, the GA was better than 99.99% of all possible solutions. With an average objective function value of 109.2 in the 100 runs, the GA was better than 99.96% of all possible solutions. Even with a maximum objective function value of 117.34 in the 100 runs, the GA was better than 96.94% of all possible solutions. This illustrates the effective functionality of the GA for the limited solution space. At this point, the functionality of the GA is considered validated, although the performance may deteriorate with a different and, importantly, larger solution space. However, with a vast number of solutions, which is possible depending on the considered problem, the validation is extremely complex and time-consuming, which will not be pursued in greater depth at this point.

It can also be seen in Table A.2 in appendix A.2 that the GA produces certain solutions that are likely to differ from reality. For example, solution no. 35 and no. 36 deliver what seems to be a good objective function value, and thus a good result for the sum of delayed cases. The derived solution is visualised in Figure A.25 in appendix A.2. Despite occasionally high numbers of transports in certain hours and a low number of transporters in the same hours, the MLP model does not predict an increased amount of delayed cases. The same applies in particular to solution no. 94, in Table A.2 in appendix A.2, which is the solution the GA produces with the least amount of necessary transporters within the produced 100 solutions. The visualisation of solution no. 94 can be seen in A.26 from appendix A.2. The observation of limited credibility in parts of the solutions also needs to be transferred to other predictions of subsection 7.2. Solutions produced by the GA with the MLP model predictions that deviate considerably from the behaviour discovered in the historical process data need to be investigated further before they are accepted. Generally, such solutions can also be prevented by incorporating appropriate penalty terms in the objective functions that align the possible solutions with the historical process behaviour.

With the investigations of this section, in summary, the functionality of the combination of MLP model and GA for optimised IHPT capacity planning, can be considered as confirmed.

Part IV

Findings

8 Discussions

This section builds on *Kropp* et al. (2023), *Kropp* et al. (2024a), and *Kropp* et al. (2024b).

In this section, discussions related to the results from the IHPT process analysis from section 6 are presented in subsection 8.1. The results of the novel process redesign approach from section 7 are discussed in subsection 8.2.

8.1 Discussions - Process Analysis

This subsection builds on *Kropp* et al. (2023) and *Kropp* et al. (2024a).

Subsection 6.3 provided multiple findings and implications through the conducted process mining analysis of the IHPT process. Here, more general limitations concerning the process analysis will be presented. At the investigated case study hospital, as shown in section 6, evaluations of delays for transport activities can already be conducted well, but an implication for real waiting times of patients or staff (e.g. at examination departments, OR, or nursing stations) cannot be easily determined (see also subsection 6.2.5). This is because the relationship between the IHPT process analysed in the case study and previous or subsequent processes, with the events and people involved, is unknown. To include the interrelationships of different processes in the analysis and derive a more holistic understanding of the processes and their impacts, all the processes involved and their supporting software systems must be combined. However, a link between the IHPT and other related processes should not only consider the requested transport or the patient as a case, but also the transporter or other hospital staff. The linkage should connect these different perspectives. A research domain adressing this more complex analysis of multiple co-evolved and interrelated processes with a greater network of involved resources (or objects) is called object-centric process mining (*Fahland* 2022; *van der Aalst & Carmona* 2022). The interested reader is referred to *Fahland* (2022) and *van der Aalst & Carmona* (2022) for more information on object-centric process mining.

In the case study hospital of this thesis, a simple integration and comparison of data from the HIS providing medical information and the logistics software supporting the IHPT is currently not implemented due to the lack of interfaces. In addition, a patient can be ordered to different places at the same time, because initiating transports is currently possible through both systems. A proper planning and control of patient flows seems impossible under these conditions. To enable consistent planning and execution of the IHPT, interfaces with unified linking keys, such as case IDs, need to be adopted across multiple systems. This allows for a holistic understanding of the IHPT process and related processes, and allows for monitoring of the impact on patients' and employees' satisfaction.

Subsection 6.2.1 already highlighted that the event-specific timestamps in the IHPT process of the case study hospital depend partly on manual transporter confirmations via their mobile devices. This leads to uncertainties in the recorded timestamps of activities, and therefore in the overall process. To make the data more reliable, it might thus be useful in the future to implement radio frequency identification (RFID) or quick response code (QR code) scanning at all the relevant locations (pick-up and target locations) in the hospital to record exactly when the transporters carry out process steps.

In addition, data sets need to be consistently enriched with more detailed information in certain fields to make evaluations more comprehensible and relationships apparent. In the case study dataset, many case-specific attribute categories could not be used for analysis because the corresponding information was not recorded consistently for all cases in the software system (see also subsection 5.1). Attribute categories that lacked information and should have been completed to allow for more detailed analysis are, for example, pick-up room, pick-up room number, arrival room and arrival room number.

As an extension to the analysis carried out in this thesis, an examination of the number of orders open at any given time may be of interest for wider interpretation. Currently, this is not explicitly reflected in the data, but it could be derived by comparing the number of transports requested to the number of transports completed at any time in the time period observed. Through the investigation of open transports at every day of the week and every hour of the day, even more specific capacity analysis can be performed compared to subsection 6.2.4).

Currently, transporters can receive up to three transport assignments per device (see subsection 5.1). However, information on the number of transport assignments from transporters' mobile devices at the respective times when individual transports are carried out is not yet present in the case study raw data provided. As a result, the historical data does not yet allow for an analysis of the adjustment to the maximum number of receivable open transport assignments per transporter. Data recording and management must be improved accordingly. The limitations mentioned and the necessary measures to overcome them are transferable to other hospitals, too.

There are still open questions in data analysis concerning the variety of possible process flows (i.e. 1,977 discovered process variants), which lead to an unstructured process model when all transport cases are taken into account (see subsection 6.2.1). Root causes for the variety of deviations from the as-planned process control flow can only be addressed through an in-depth analysis and interactive collaboration with the relevant stakeholders, including analysts, process managers, staff involved in the process, patients and, importantly, the software system vendor.

However, the main limitation of a pure process analysis and the process knowledge derived is the large number of possible improvement ideas and the uncertainty of the expected effects. In addition to process mining, other methods are needed to quantitatively evaluate improvement ideas and thus to support process redesign, as mentioned already in subsection 3.1.4. To adress this challenge, in section 7, a novel approach to the redesign of IHPT capacity planning was developed and applied, which is discussed in subsection 8.2.

8.2 Discussions - Process Prediction and Redesign

This subsection builds on *Kropp* et al. (2024b).

Table 8.1 summarises the results of the optimisation procedure that was conducted in section 7. The aim was to develop a data-driven forecasting and optimisation method combining an MLP and a GA to achieve theoretically optimal capacity planning to support the process redesign prior to practical implementation. In the pre-processing of the data, case-specific information was aggregated to hourly information for each date of the investigated 3.5 years and new inter-case information was derived. A contribution is thus made to current research trends, that attempt to take inter-case information for process predictions into account (see subsection 3.2.2.3). The approach was tested using an average Monday as an example. In addition to the mean real delayed cases on an average Monday, the predictions of the MLP for an average Monday are shown in Table 8.1 (see also subsection 7.2.1). Furthermore, the improvements in the number of delayed cases are presented for just the adjustment of transporters (see also subsection 7.2.1) as well as for an adjustment involving transporters, planned transports, and automation rates in specific hours (see also subsection 7.2.2).

The GA reallocates the variables (number of transporters, number of planned transports and automation rate per hour) in such a way that many delayed cases occur in a few hours of the day and few delays occur in the remaining hours (see the last two columns of Table 8.1). Furthermore, there are larger jumps in hourly variables, which could be difficult to implement in practice. For example, Figure 7.11 (left part) from subsection 7.2.2 shows that at hour 12 there should be seven transports planned, at hour 13 there should be 50 transports planned, at hour 14 there should be six transports planned and at hour 15 there should be 14 transports planned. In addition, the number of active transporters in the hours seven, eight and nine is reallocated to seven, then 12 and then three transporters in Figure 7.11 (left part) from subsection 7.2.2. When there are these considerable variations in the needed hourly capacity of transporters, they may, however, be available for other tasks within the hospital during times when they are not engaged in IHPT. Whether the transport dispatching from automatic (“1”) to manual (“0”) and vise versa can be switched on an hourly basis (see left part of Figure 7.11 from subsection 7.2.2) is questionable, too. In general, the GA can produce solutions

Table 8.1: Comparison of delayed cases depending on input data. Adapted from *Kropp* et al. (2024b).

Time		Delayed Cases			
Day of the week	Hour	Mean real delayed cases	Predicted delayed cases with mean input data	Optimised delayed cases with adaptation of transporters	Optimised delayed cases with adaptation of transporters, planned cases and automation rate
1	0	0.45	0.55	0.54	0.36
1	1	0.43	0.70	0.60	0.28
1	2	0.34	0.38	0.30	0.30
1	3	0.24	0.30	0.23	0.23
1	4	0.19	0.24	0.16	0.16
1	5	0.18	0.22	0.16	0.16
1	6	1.67	1.47	0.89	0.63
1	7	9.40	9.16	8.76	0.67
1	8	9.26	9.98	9.84	8.47
1	9	10.98	11.03	11.37	11.96
1	10	14.75	13.93	13.29	12.83
1	11	14.39	16.13	5.96	1.58
1	12	17.69	18.47	8.48	1.40
1	13	11.03	11.53	7.05	17.20
1	14	4.31	5.08	3.70	0.28
1	15	3.36	2.48	2.00	1.44
1	16	1.71	1.57	0.55	1.42
1	17	1.16	0.94	1.23	0.25
1	18	1.11	0.76	0.95	0.70
1	19	0.77	0.58	0.67	0.57
1	20	0.66	0.53	0.58	0.58
1	21	0.74	0.56	0.55	0.37
1	22	0.70	0.53	0.53	0.34
1	23	0.62	0.47	0.43	0.43
Delayed cases per day		106.14	107.60	78.83	62.60
Planned cases per day		269.88	269.88	269.88	270.42
Transporter FTE hours per day		73.58	73.58	73	73

in certain hours that are widely different from the behaviour that the MLP model could have encountered during model development with the historical IHPT data, and which may therefore lead to questionable predictions. From a practical view, further investigations on these scenarios need to be conducted. Nonetheless, the aforementioned peaks and discrepancies can be minimised by the implementation of further constraints in the objective functions that the GA aims to optimise. However, this does require practical knowledge and would compromise the optimisation potential.

The chosen example from subsection 7.2 can be critically viewed, too. Data from an average Monday in a data frame of 3.5 years were used for the original input tensor that is to be optimised. Instead, it is also possible to use an average Monday or other day of the week from more recent weeks. For current planning, an average day of the week that is to be optimised from a recent period may be more suitable than an average day of the week calculated from the past 3.5 years. However, it remains to be investigated which historical periods are more reflective of current and future periods than the average long-term dataset, thus enabling even better optimisation approaches.

The results presented in subsection 7.2 showed variation in the attempts with the GA. The GA identifies improvements, but it is not feasible to ascertain that the optimal solution has been reached because the GA works in a trial-and-error manner and can converge to local optima. In general, the presented use case involves a complex problem with multiple optimisation variables. Nevertheless, the GA has achieved considerable improvements in the complex environment characterised by an objective function containing an MLP model (involves non-linearities) for an IHPT capacity planning problem. Subsection 7.2.3 proved for a smaller problem instance that the GA performed reliably well.

Taking an average Monday as an example, the investigations from subsection 7.2 have demonstrated that, under conditions of consistent or similar quantities of planned transport assignments and transporter FTE hours, resource reallocation through a GA led to a theoretical reduction ranging from 27% to 42% in delayed cases. The capacity planning for other days of the week could also be optimised in the same manner. Comparing these potentials with the IHPT literature included in subsections 2.2.2 and 4.2.1, although different areas in IHPT are investigated in literature, the theoretical improvement potentials of the approach in this thesis are relatively high. In literature, several authors[1] reached average IHPT improvements of up to 20%, others[2] of up to between 21% and 36%. The transferability of the potential of the approach of this thesis to the real world is shown by the performance of the MLP model (see subsection 7.1.2). For average day of the week scenarios and concerning the R^2, the results are in an acceptable region (see subsection 7.1.2.2). Precision, recall and F1-score from subsection 7.1.2.2 (thus indirectly the MSE and MAE from 7.1.2.1, too) are not yet considered acceptable by hospital process managers for a practical implementation of the MLP model. Different approaches to improving the performance of MLP models could be, for example, a model development with more data, further filtering of outliers, or the development of several specialised prediction models. This could involve one model for core hospital working hours (during the day from Monday to Friday) and another model for other hours, which are then trained, validated and tested with different datasets.

The improvement potentials revealed by the GA approach can differ based on the chosen weighting factors of the constraint penalties in the objective functions and the possible variable ranges that the GA can choose from (as defined in subsection 7.2). These parameters need to be further discussed and possibly adapted with domain experts or by performing a detailed quantitative sensitivity analysis, to obtain meaningful improvement ideas for IHPT capacity planning. Furthermore, the effects of a potential implementation in practice should be thoroughly evaluated and compared.

In terms of generalisability and transferability, the preprocessing (see subsection 7.1.1) can be similarly carried out at other hospitals without major effort. In total, more than 370 hospitals in Germany, Austria, Switzerland, Italy and Sweden use the software from which the datasets were extracted within this study (according to the logistics software provider). However, the MLP input and label information (see third table in Figure 7.1 in subsection 7.1.1) used here can certainly also be extracted and aggregated from other software systems, as long as similar information is stored. The MLP training, validation and testing (see subsection 7.1.2) must then be completed on an individual basis to develop an accurately functioning MLP model for other hospital environments. Parameters must be set and evaluated again like conducted in

[1] (*Bärmann* et al. 2024; *Fiegl & Pontow* 2009; *Fröhlich Von Elmbach* et al. 2019; *Haldar* et al. 2019; *Jaroon* 2018; *Kergosien* et al. 2011; *Séguin* et al. 2019)

[2] (*Elmbach* et al. 2015; *Gopal* 2016; *Hanne* et al. 2009; *Meephu* et al. 2023; *Turan* et al. 2011; *Vancroonenburg* et al. 2016)

subsection 7.1.2. The GA (see subsection 7.2) will also be applicable to the newly designed ANN. But its functionality should be confirmed again, similar to subsection 7.2.3. Furthermore, re-calibrating the setup and boundaries of adaptable variables, as well as weighting factors and constraint penalties in the objective functions to be optimised, is needed.

In summary, the approach presented in section 7 can be adopted to different clinical, (more generally) logistical and other environments where capacity planning is required. In addition to capacity planning, the general field of organisational hospital management (see the FM products in Figure 2.3 from subsection 2.2.1) can also be supported by the approach where different scenarios need to be evaluated quantitatively before implementing process redesign measures. Often, only certain parameters need to be adapted. However, the overall concept, namely the combination of data preparation, process prediction by an ANN and subsequent optimisation by a metaheuristic algorithm to find improved solutions for processes, can be widely applied. Preceding process mining analysis, as conducted in section 6, and discussing observations with various hospital stakeholders are strongly recommended to establish the necessary process knowledge.

9 Summary

Section 1 has pointed out that the increasing focus on patient-centred care and the rising demand and costs for healthcare services highlight the need for efficient healthcare processes. There are two main types of hospital processes: medical treatment and organisational, with the latter supporting the former (*Lenz & Reichert* 2007). About one third of hospital costs are related to organisational processes, that can also be seen as facility management (FM) processes (*Lennerts* et al. 2003). Subsection 2.3 mentioned that detailed process analysis can lead to improved interaction between primary and secondary processes and thus maximise hospital efficiency (*Lennerts* 2009). *Abel* (2009) further stated, that optimised organisational processes can each save process-related costs between 3% and 70% within each of the processes. This can in sum lead to savings of approximately 25% of the FM related costs in a hospital (*Abel* 2009; *Lennerts* 2009).

Healthcare processes are generally complex, dynamic, ad hoc, and furthermore have significant impacts on human health (*Munoz-Gama* et al. 2022). Subsection 2.3 showed that here, traditional business process management approaches involving interviews of stakeholders and process modeling efforts are time-consuming and likely not provide an accurate picture of the actual processes (*Mans* et al. 2008; *Rebuge & Ferreira* 2012; *Stefanini* et al. 2017; *van der Aalst* 2011). Software systems that support processes, like the hospital information systems (HIS) or logistics software systems, hold valuable data that can improve decision-making (*Munoz-Gama* et al. 2022). Recent digitisation efforts, such as Germany's Hospital Future Act (KHZG), aim to digitise and optimise healthcare processes, reduce costs, and enhance patient outcomes (see section 1). The extraction of knowledge from process supporting software systems and investigations with process mining (see subsection 3.1.4), reduce the analysis effort and allow for accurate insights into the actual processes (*Mans* et al. 2008; *Rebuge & Ferreira* 2012; *Stefanini* et al. 2017). However, research on redesigning healthcare processes using process mining on real hospital data is limited, particularly in organisational processes (*de Roock & Martin* 2022). This underscores the significance of research in this area.

This thesis aims to comprehensibly examine the benefits of real-world data-based analysis and recommendations for improving the hospital operation, using the intra-hospital patient transport (IHPT) process as an example for organisational processes in healthcare. This exceeds the current scope of reviewed IHPT literature, that mostly does not use real-world data or only broader statistics of real-world data for research approaches (see subsection 4.3). Subsection 2.2.2 described how IHPT, which deals with internal transfer of patients within a hospital such as between different wards and functional areas (*Nakayama* et al. 2012), plays a crucial role in facilitating timely medical treatments (*Beckmann* et al. 2004; *Hendrich & Nelson* 2005; *Ulrich & Zhu* 2007). In particular, capacity planning is important in the context of the IHPT process (see subsection 2.2.2) and process data can show how the allocation of resources meets transport requirements.

To gather the necessary knowledge for the approach, section 3 presents fundamentals of process analysis, process prediction and process redesign techniques, as well as current research trends. The goal of this thesis is to develop a practical approach that combines the methods of process mining (see subsection 3.1.4) to generate process insights and the methods of artificial neural networks (ANN) (see subsection 3.2.2.2) and genetic algorithms (GA) (see subsection 3.3.2) to support the redesign of the capacity planning in the context of IHPT. Real-world IHPT process data from the German hospital "Klinikum Magdeburg gGmbH" with approximately 700 to 800 beds and 75,000 inpatient and outpatient cases per year serves as a case study in this thesis. Subsection 4.3 identified state of the art research gaps based on an extensive literature review from section 4.

Subsection 4.1 reviewed current research on process mining analysis in healthcare with a focus on the state of the art in organisational healthcare processes including IHPT. Subsection 4.2 concentrated on data-based redesign approaches of organisational healthcare processes, especially in the IHPT domain. *Andrews* et al. (2020) emphasised that automating the derivation of improvement opportunities in a data-driven manner is a future necessity (see subsection 4.3). If quantitative process redesign approaches are conducted, they are mainly derived by an evaluation of scenarios through DES models, mathematical models and (meta-)heuristic algorithms. The conformity of such approaches highly depend on modelers and access to domain knowledge.

In contrast, ANN models can capture complex behaviour without having to make certain assumptions in advance (*Gardner & Dorling* 1998; *Mitrea* et al. 2009). According to several authors[1], ANN models offer superior predictive capabilities over traditional statistical or mathematical methods, especially with (non-linear) relationships that are difficult to capture and describe. They furthermore outperform process data-derived simulation models when trained with large logs (*Camargo* et al. 2021).

In general, IHPT literature mostly does not use real-world data or only uses broader statistics of real-world data to feed instances into simulation or mathematical models (see subsection 4.3). Predictive performance is also rarely evaluated in detail in the IHPT literature, and if it is, then it is almost exclusively qualitative (see subsection 4.3). However, unless validated with real-world process data, it is difficult to assess the ability of models to reflect reality. In contrast, the developed prediction model in this thesis is validated with historical IHPT process data by means of various performance metrics and thus able to reflect real-world interdependencies.

This thesis aims to communicate the benefits of redesigning IHPT capacity planning following techniques recommended in the literature by combining an ANN (i.e. multilayer perceptron - MLP) and a metaheuristic algorithm (i.e. GA), based on knowledge derived via process mining from real-world IHPT data. In other domains, like textiles production or building energy optimisation, little research could be identified using similar approaches combining ANN and metaheuristic algorithms (see subsection 4.3). The results of the approach in this thesis serve as an input at a tactical or strategic level (see subsection 2.3) to the IHPT literature addressing routing and scheduling planning (see subsection 4.3).

Section 5 elaborates on the combination and purpose of the methods used, and on the characteristics and challenges associated with the underlying case study dataset, which includes 3.5 years of IHPT process information. The dataset incorporates 256,266 accompanied, completed patient transports involving more than 69,000 patients. In total, there are 2,329,635 events in the dataset, each with an event-specific activity, timestamp and transport ID. The transports were further accompanied by 125 attribute categories that contain transport case-specific information, such as priority, pick-up location,

[1] (*Al-Waeli* et al. 2019; *Dumitru & Maria* 2013; *Izadifar & Abdolahi* 2006; *Neto & Fiorelli* 2008; *Nikzad* et al. 2012; *Salami* et al. 2016; *West* et al. 1997)

target location, pick-up house, target house, type of transport vehicle, patient ID (see subsection 5.1 and Table A.1 in appendix A.1 for more information on the attribute categories). Some process steps (i.e. events) from the IHPT are approved manually by transporters, what leads to under-/overestimation of throughput times. This timewise uncertainty could be ruled out through QR/RFID scanning at locations in the future (see subsection 6.3). Furthermore, information on how many orders are open at any given time, that is currently not explicitly available, would be beneficial for a better process analysis and redesign.

Process mining investigations from section 6 showed that, overall 34.2% of the transports were delayed by ten or more minutes. In addition, the transporter's arrival at the patient's pick-up location was already delayed in approximately 50% of all cases delayed by ten or more minutes. These are unsatisfactory rates according to hospital process managers. In general, process mining analysis enables root cause investigations such as capacity evaluations across times of day and days of the week. The average peak number of requested transports per available transporter per hour needs to be reduced to achieve fewer delayed transport cases (see subsection 6.3). Furthermore, the automatic dispatching system and the manual dispatcher should operate at completely separate times (not in parallel) because a parallel operation led to higher delay rates. Pre-registering transports has a good influence on the delay rate. Transports with high delay probability could be prioritised and planned with an increased throughput time. If certain as-planned throughput times between activity intervals in the IHPT process are exceeded, an alarm system or immediate re-request of the affected transports could potentially be triggered to draw attention to the transports and decrease the probability of delayed transports. Subsection 6.2.1 provides proposals for appropriate timespans derived from the historical data.

There are many possible process adjustments that can be made, making it difficult to commit to specific measures. Section 7 presents a solution for this. Using IHPT capacity planning as an example, the approach allows for the prediction of resulting KPIs after adjusting process parameters to support decision-making by evaluating adaptation variants and proposing the best variant for a future practical implementation (although the practical implementation is outside the scope of this thesis). Other applications for data-driven decision-making using IHPT logistics data could address, for example optimising IHPT transports on identified critical routes or hospital layout optimisation.

To optimise the IHPT capacity planning, transport information is first aggregated to hourly information in subsection 7.1.1. The aggregated information spans the 30,672 hours captured in the 3.5 year IHPT dataset and is further prepared for ANN training. Previous process mining analysis and consultation with experts at the hospital helped to select the necessary data attributes. After filtering out hours with missing information, training, validation and test data could be drawn from a pool of 25,662 hours. An MLP model is developed and evaluated in subsection 7.1.2. With five training variables (i.e. MLP model input), that consist of “Day of the week”, “Hour” “As-planned number of transports in same hour”, “Amount of transporters in same as-is hour” and “Automatic rate according to as-planned hour” the MLP model can predict “Delayed transports according to as-planned hour” (i.e. MLP model output).

Through early stopping, the MLP model at epoch 172 out of 500 epochs is considered as best fitting model (see subsection 7.1.2). At epoch 172, training (80% of the complete dataset) and validation (10% of the complete dataset) loss are both relatively low, with an *MSE* of around 6.4. The test dataset (10% of the complete dataset) showed similar loss results and verifies the generalisation ability of the model. For the training, validation and test set, the *MAE* is around 1.5, which means that the MLP model is on average 1.5 delayed transports off for each prediction. For the complete dataset of 25,662 hours, both R^2 and $adjusted\ R^2$ are around 0.79, which is in a good range in terms of variance explanation ability according to the acceptable bounds of models, where human behaviour has greater influence, as per (*Ozili* 2022) (see subsection 3.2.2.2). The *MEB* of the Model for the complete dataset is around -0.056 (see subsection 7.1.2.2), what shows that the MLP model predictions only slightly underestimate actual values. When the values of real delayed cases are higher, the MLP model tends to underestimate more with its predictions.

To redesign the capacity planning on a day of the week level, the MLP model performance is evaluated for average day of the week scenarios (see subsection 7.1.2.2). The total predicted delayed cases per average day of the week deviate by a mean of 3.9% from the real delayed cases. This is within a satisfactory range. The hourly curves of the predicted delayed cases over the average days of the week are similar to the original curves (see Figure 7.9 from subsection 7.2, as well as Figures A.19 to A.24 from the appendix A.2).

Lastly the MLP model precision, recall and F1-score are evaluated in subsection 7.1.2.2. The top 4.88% of the complete dataset (i.e. samples with 17 and more real delayed cases per hour) are considered as outliers and mapped to the negative class. For example, a prediction tolerance of two leads to a precision of around 0.81 (i.e the MLP model predicts with 81% probability the correct "Delayed transports according to as-planned hour" with a tolerance of two delayed transports when outliers of 17 and more delayed transports are not considered). The recall under the same assumptions is respectively around 0.83 and the F1-score is around 0.82. The hospital process managers see the reached precision, recall and F1-score (and thus indirectly the *MSE* and *MAE*) of the MLP model not yet good enough for practical implementation. According to them, a minimum precision, recall and F1-score of 0.9 with a tolerance of one should be the future goal. Otherwise they consider, even from a purely economic point of view, the possible inaccuracy in the assessment of the number of associated transporters required, derived from a possible inaccuracy in the number of delayed transports, to be too severe (see subsection 7.1.2.2). With the requested tolerance of two, the current MLP model reaches only a precision of 0.64, a recall of 0.66 and an F1-score of 0.65. This shows that the MLP model needs to be improved prior to real-world implementation. More data during MLP model development and further filtering of outliers can lead to improved MLP prediction performance. The development of several prediction models is a promising approach, too. For example, one model for core hospital working hours (during the day from Monday to Friday) and another model for other hours could be trained, validated and tested with different datasets.

Nevertheless, the developed MLP model is used for further investigations on IHPT capacity planning because it provides a good prediction performance for average day of the week scenarios, as mentioned previously. Section 7 conducts optimisation procedures using the example of an average Monday and implementing the developed MLP model within different objective functions. Similar procedures are possible for other days of the week. The general aim is to minimise the number of predicted hourly delayed cases by using a GA with different degrees of freedom, which adjusts certain input variables of the MLP model. By just rearranging the number of transporters per hour (see subsection 7.2.1), the approach achieves a decrease in overall delayed cases on an average Monday of around 27%. By additionally rearranging the number of planned transports in certain hours and adapting the automatic rate per hour throughout the day (see subsection 7.2.2), the approach leads to a decrease in overall delayed cases on average Mondays of around 42%. The procedures from subsections 7.2.1 and 7.2.2 can be used, for example, on a daily basis for capacity planning for the following day, but also as a basis for deriving a coarser capacity planning for periods or, for example, the entire year. This corresponds to decision support at the tactical or strategic level (see also subsection 2.3).

Subsection 7.2.3 proves with a small experiment of 100 runs and a limited solution space of the capacity planning problem, that the GA, on average, finds solutions that are better than 99.96% of all possible solutions. The functionality of the GA is thus considered validated. Indeed, it is possible that the performance of the GA may deteriorate with a different and larger solution space. However, with a vast number of solutions, which is possible depending on the problem considered, validation is extremely complex and time-consuming. GA validations in more expanded solution spaces will not be pursued within this thesis because the main purpose of this work is to demonstrate the use of an MLP model and GA for optimised IHPT capacity planning. The approach followed a process mining analysis to derive the KPIs in the IHPT process. The general functionality of the combined methods could be validated through this thesis.

In general, there were certain limitations uncovered during the IHPT process analysis and process redesign. Considering the results of section 6, process mining analysis enables thorough evaluation of delays and throughput times of process intervals. Nevertheless, the resulting waiting times for patients or staff (e.g. transport services, examination departments or nursing wards) cannot be easily derived. The underlying dataset does not provide information on relationships between the IHPT process analysed in the case study and previous or subsequent events for all involved individuals. To derive a more holistic understanding of the interdependencies, knowledge collected from other related processes and their supporting software systems must be integrated.

In addition to individual transports or patients as cases for process mining analysis, other attributes, such as the transporter or other hospital staff, can also be considered as cases. Different perspectives should be combined to examine and fully understand the IHPT process with its pre and post procedures. To measure the impact on patient satisfaction and enable holistic hospital optimisation, interfaces with consistent linking keys, such as case IDs, must be adopted across multiple systems (see subsection 8.1).

The case study dataset showed that for instance, many attribute categories could not be used for evaluations because the corresponding information was not gathered for all cases in the software system. Attribute categories that should have been filled stringently to enable more detailed evaluations are, for example, pick-up room, pick-up room number, arrival room and arrival room number (see subsection 5.1 and Table A.1 in appendix A.1 for more information on missing data within the attribute categories). Attribute categories with missing data are not suitable as potential input information for the development of further redesign approaches with, for example, ANN and GA.

The process mining analysis results from section 6 showed, that there are both organisational (also regarding personnel resources) and infrastructural elements which influence the throughput times and delays in IHPT (see also subsection 2.2.2). Inappropriate resource planning or poor allocation of transports to transporter are examples for organisational problems. Infrastructural issues are, for example, spatial conditions or the availability of elevators. For most of the identified problems, only presumptive improvement strategies can be derived (see subsection 6.3). For the IHPT capacity planning and in the wider sense for similar logistics planning subjects the redesign approach combining an MLP model with a GA, presented in this thesis in section 7, helps to identify improved strategies in a quantitative manner.

However, the GA reallocates the adjustable variables (number of transporters, number of planned transports and automation rate per hour) in such a way that produced solutions in certain hours differ from the behaviour that the MLP model could have encountered during model development with the historical IHPT data (see subsections 7.2.3 and 8.2). Such solutions can thus lead to questionable predictions. However, this can be resolved by implementing further constraints in the objective functions that the GA is trying to optimise. Implementing these constraints, however, requires practical knowledge and would reduce the optimisation potential. Choosing appropriate weighting factors for the constraints in the objective functions is also a challenging task and affects the optimisation potential. Domain knowledge and quantitative sensitivity analysis are required to determine well-suited weighting factors. From a practical point of view, further research on these observations is needed.

The whole approach from section 7 can be transferred to other hospitals, too, as long as respective IHPT process data is available in software systems.

The preprocessing could be carried out as described in subsection 7.1.1). Afterwards, the MLP training, validation and testing (see subsection 7.1.2) could be performed on an individual basis to develop an accurate MLP model for other hospital environments. Parameters need to be set and assessed similar to subsection 7.1.2. The GA (see subsection 7.2) will also be applicable to the newly designed ANN, but its general functionality should be confirmed again, as conducted in subsection 7.2.3. This would entail a re-calibration of the setup of variables, as well as weighting factors and constraint penalties in the objective functions.

In summary, the approach presented in section 7 can be applied to different clinical, (more generally) logistical and other environments where capacity planning is conducted with just the adaptation of a few specific parameters. This furthermore accounts for the general field organisational hospital management with its sub-domains (see the FM products in Figure 2.3 from subsection 2.2.1) and in addition to capacity planning, various process-specific problems. The overall concept of a data preparation, process prediction by an ANN and subsequent optimisation by a GA to find improved solutions for process redesign, can be widely adopted. The combination of these methods, based on the knowledge previously generated through process mining, has proven to be capable of deriving concrete process redesign measures and further quantifying the expected impact. Like this, real-world data-based decision support for process managers in hospitals is enabled.

Part V

Outlook

10 Conclusions and Future Work

This section builds on *Kropp* et al. (2023), *Kropp* et al. (2024a), and *Kropp* et al. (2024b).

This thesis explores the variable and complex nature of the IHPT process using data processing techniques (i.e. process mining, MLP model and GA) to analyse real-world data and improve the operation of a hospital in Germany. The process analysis including process models using process mining techniques with stakeholder feedback help to obtain a comprehensible view of the process and to set research priorities. First, a global overview from different perspectives of the IHPT process with all digitally captured transport cases within approximately 3.5 years from January 2019 to mid-2022 is obtained. The process mining analysis focused next especially on different process variants, activity intervals, delayed cases and other specific attributes (e.g. if transports were automatically or manually dispatched, different involved departments). In this way, process problems can be identified and solutions derived. The results aimed to address many transport cases in an aggregated way over the whole investigation timespan. No COVID-19-specific investigations were carried out within this thesis. However, an in-depth analysis on the impact of COVID-19 on the IHPT needs to be conducted in the future. This requires particular attention to concept drift and information that goes beyond data captured in software systems.

It should be noted, however, that while the mere application of process mining methods may point to solutions that address process inefficiencies and bottlenecks in IHPT, the explicit effects of redesign measures remain unclear prior to implementation. The large number of potential solutions to specific problems can complicate the decision-making further. In general, there are many possible areas of application in IHPT where decision-making needs to be supported. These can include, for example capacity planning, optimisation of critical routes (i.e. routes that are currently related to high delay rates) in IHPT or optimisation of the hospital layout.

For this reason, this work has, in addition to process analysis, demonstrated the feasibility of a novel process redesign approach in the context of IHPT for more efficient resource allocation in capacity planning by conducting prediction and optimisation procedures. To achieve this, transport-related raw data (information on 256,266 transport cases) is aggregated and preprocessed into hourly data (information on 25,662 hours) within the observation period of approximately 3.5 years (covers actually 30,672 hours, but hours with missing data were filtered out). The number of planned transports, the number of active transporters, and the automation rate of transport dispatching as well as the number of delayed transports for each hour in the observation period are calculated from the raw data to create the new aggregated and preprocessed dataset for an MLP prediction model development. The MLP model predicts the amount of resulting delayed transport cases when day of the week and hour-specific input information is given. Through development and validation with real-world data, the MLP model exceeds the IHPT literature found, which mainly does not validate the manually developed (theoretical) models used to optimise the process (see subsection 4.3). While certain performance metrics of the developed MLP model are within a range that needs to be further improved for practical implementation (primarily by increasing the volume of training data or developing specialised prediction models for different days of the week), predictions for hourly delayed cases are already feasible for individual days of the week. By incorporating data from additional observation periods, it might be possible to achieve predictions that are specific to calendar weeks, months, or even specific days in a year. More specific predictions require a more extensive data availability for sufficient model training.

Using a GA, the IHPT related resources of an average Monday were adjusted in a manner that led to a reduction in daily delayed cases while maintaining a consistent sum of planned transports and aggregated number of transporters per hour (i.e. FTE hours) on a day. To achieve this, transporters per hour were first redistributed throughout the day. In a second attempt, a transporter redistribution is conducted by the GA alongside adjustments to the distribution of planned transports and the automation rate of transport assignment dispatching. This achieved theoretical improvements with 27% - 42% fewer delayed cases in IHPT just by reorganising resources (i.e. without adding additional resources). Here, the combination of an MLP model that can predict delayed cases when given specific IHPT process information and a GA that can adapt the input information to minimise the predicted delayed cases has proven effective. However, there is potential for further improvement both in the performance of the ANN and the application of the metaheuristic algorithm to reliably find the best solution for capacity planning. The practical implementation of the proposed planning is pending.

As mentioned in subsection 4.3, there are no predictive performance metrics of IHPT processes in literature that the MLP model performance could be compared to. Nevertheless, the achieved predictive performance metrics for delayed cases in IHPT will serve as a benchmark for further research. Moreover, other ANN models for the IHPT process should be developed and compared to this study. Filtering the training data when developing the MLP model can help to create models that are more accurate in certain situations (e.g. when the number of as-planned transports per hour is relatively high). Initial approaches using RNN and CNN architectures on the underlying data (beyond the investigations of this work) have also shown slightly improved *MSE* values, but need to be further investigated and compared. Metaheuristic algorithms other than GA, such as swarm-intelligence algorithms (see subsection 3.3.2), could also be used to improve the reorganisation of IHPT capacity planning, and their performance should be evaluated and compared. If additional hourly attributes of the IHPT process, e.g. transport priorities, transport vehicle types, pick-up or arrival locations, are added to the MLP model training, the MLP model could generate more specific predictions and offer more variables for adjustment within optimisation of delayed cases through the GA. Other attributes, that could potentially be used for the training of an MLP and solving resource optimisation problems are described in subsection 5.1 in relation to the raw data presentation. However, more extensive data collection is also a prerequisite, ensuring that specific information is recurrently present throughout the MLP training process to allow for accurate predictions. The overall improvement potential for the processes under investigation will vary from one application to another and should be examined and compared to draw reliable, general conclusions.

It is essential that hospital managers and transport staff are made aware of process errors, that workflows are continuously monitored and that improvement strategies are actively implemented. Concrete improvement measures, which can be derived following the process redesign approach of this thesis, have to be specified by the process managers of the hospital and implemented by the executing personnel. Prediction methods, such as the ANN-based one presented in this thesis, help stakeholders to anticipate situations before the implementation of specific measures and act with foresight. The process redesign approach of this thesis is targeted for the tactical and strategic management levels (see subsections 2.3, 4.3 and 7.2). As mentioned in subsection 4.3, the proposed solutions of this thesis can be followed by routing and scheduling research focusing on specific operational recommendations. The combination of process mining, ANNs and metaheuristic algorithms to optimise processes in a real-world data-driven way can be adopted in general to the area of organisational hospital management and its sub-domains (see the FM products in Figure 2.3 from subsection 2.2.1). Continuous feedback loops at all levels help to monitor impacts and constantly improve processes. Future research will need to engage all the stakeholders involved in a process (extending beyond hospital process managers to administrative and operative staff). The joint analysis and further processing of real-world data will allow for the derivation of integrated, practical and comprehensible solutions. Integrating furthermore the subjective experience of patients and others involved in or affected by the interrelated processes under investigation will be a key factor in optimising the operation of hospitals.

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A Appendix

A.1 Appendix for Section 5

Table A.1: Statistics on attribute categories in master table (own table).

No.	Attribute category	Not related to as-is event-timestamp information	Possible no. of information	No. of of cases without information	Percentage of cases without information [%]	No. of unique information (without NA, "", "-", " ","NULL")
1	Ursprungs_ID	yes	256,266	0	0	256,266
2	Zaehler	yes	256,266	0	0	1
3	Anforderungsdatum	no	256,266	0	0	1,278
4	Anforderung	no	256,266	0	0	255,580
5	Anforderer	yes	256,266	0	0	59
6	Auftragsstelle	yes	256,266	0	0	101
7	kostenstelle	yes	256,266	4,741	1.85	77
8	Orgbereich	yes	256,266	7,010	2.74	33
9	LetzteLeitstelle	yes	256,266	0	0	1
10	ErsteLeitstelle	yes	256,266	0	0	2
11	PlanBeginn	yes	256,266	0	0	206,598
12	Plan_Stunde	yes	256,266	0	0	24
13	Plan_Minute	yes	256,266	0	0	60
14	Planungsdatum	yes	256,266	0	0	206,598
15	IstBeginn	no	256,266	0	0	255,562
16	IstBeginn_Stunde	no	256,266	0	0	24
17	IstBeginn_Minute	no	256,266	0	0	60
18	IstDatum	no	256,266	0	0	255,562
19	Jahr	no	256,266	0	0	4
20	Monat	no	256,266	0	0	12
21	Tag	no	256,266	0	0	31
22	Kalenderwoche	no	256,266	0	0	53
23	Wochentag	no	256,266	0	0	7
24	Voranmeldung	yes	256,266	0	0	1,231
25	Nummer	yes	256,266	0	0	256,266
26	Folge	yes	256,266	0	0	5
27	Transportobjekt	yes	256,266	0	0	1
28	auftragsstatus_id	yes	256,266	0	0	1
29	status	yes	256,266	0	0	1
30	prioritaet	yes	256,266	0	0	4
31	Transportart	yes	256,266	0	0	18
32	Transportartgruppe	yes	256,266	0	0	6
33	Information	yes	256,266	160	0.06	28
34	Abholstelle	yes	256,266	0	0	109
35	Abholstelle_ID	yes	256,266	0	0	109

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Table A.1 – continuation

No.	Attribute category	Not related to as-is event-timestamp information	Possible no. of information	No. of of cases without information	Percentage of cases without information [%]	No. of unique information (without NA, "", "-", " ","NULL")
36	Abholzimmer	yes	256,266	89,917	35.09	350
37	Abholzimmer_ID	yes	256,266	89,917	35.09	350
38	Ankunftsstelle	yes	256,266	0	0	118
39	Ankunftsstelle_ID	yes	256,266	0	0	118
40	Ankunftszimmer	yes	256,266	94,783	36.99	261
41	Ankunftszimmer_ID	yes	256,266	94,783	36.99	261
42	Abholhaus	yes	256,266	10	0	10
43	Abholhaus_ID	yes	256,266	10	0	10
44	Ankunftshaus	yes	256,266	17	0.01	9
45	ASAnkunftshaus_ID	yes	256,266	17	0.01	9
46	Abholebene	yes	256,266	10	0	30
47	Abholebene_ID	yes	256,266	10	0	30
48	Ankunftsebene	yes	256,266	17	0.01	28
49	Ankunftsebene_ID	yes	256,266	17	0.01	28
50	Abholstrasse	yes	256,266	256,266	100	1
51	Abholort	yes	256,266	256,266	100	1
52	Ankunftsstrasse	yes	256,266	256,266	100	1
53	Ankunftsort	yes	256,266	256,266	100	1
54	Abholprioritaet	yes	256,266	0	0	1
55	Ankunftsprioritaet	yes	256,266	0	0	1
56	Abholstellenart	yes	256,266	0	0	3
57	Ankunftsstellenart	yes	256,266	0	0	3
58	transportschein	yes	256,266	256,266	100	2
59	Objektkategorie	yes	256,266	0	0	2
60	anzahl	yes	256,266	0	0	1
61	StreckenID	yes	256,266	0	0	517
62	Streckenbezeichnung	yes	256,266	139,242	54.33	517
63	Entfernung	yes	256,266	0	0	1
64	Bemerkung	yes	256,266	235,264	91.8	4,802
65	Dienstleister	yes	256,266	256,266	100	1
66	transportgrund	yes	256,266	256,266	100	1
67	fahrzeugart	yes	256,266	256,266	100	1
68	Geraet	yes	256,266	111	0.04	24
69	Geraete	yes	256,266	111	0.04	24
70	Fahrer	yes	256,266	0	0	53
71	Tour	yes	256,266	0	0	11,155
72	Fahrzeug	yes	256,266	81	0.03	11
73	Unterschriftvorhanden	yes	256,266	0	0	1
74	Plandauer	yes	256,266	0	0	17
75	Dispo	no	256,266	0	0	253,798
76	Gesendet	no	256,266	0	0	256,250
77	Angenommen	no	256,266	0	0	256,254
78	anAbholort	no	256,266	0	0	256,262
79	Begonnen	no	256,266	0	0	255,562
80	anAnkunftsort	no	256,266	1	0	256,261
81	Beendet	no	256,266	0	0	254,790
82	Beendet_Stunde	no	256,266	0	0	24
83	Planende	yes	256,266	0	0	206,902
84	Planende_Stunde	yes	256,266	0	0	24
85	Automatik	yes	256,266	0	0	2
86	generiert	yes	256,266	0	0	1
87	IstAuftragsDauerV1	no	256,266	0	0	131
88	IstAuftragsDauerV2	no	256,266	0	0	152
89	IstTransportdauerV1	no	256,266	0	0	132
90	IstTransportdauerV2	no	256,266	0	0	132
91	IstAuftragsdauerV3	no	256,266	0	0	1

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Table A.1 – continuation

No.	Attribute category	Not related to as-is event-timestamp information	Possible no. of information	No. of of cases without information	Percentage of cases without information [%]	No. of unique information (without NA, "", "-", " ","NULL")
92	AuftragsdauerV3_Stunden	no	256,266	0	0	1
93	WartezeitAbholstelle	no	256,266	0	0	118
94	WartezeitAnkunftsstelle	no	256,266	0	0	93
95	SummeWartezeiten	no	256,266	0	0	134
96	Abholpuenktlich	no	256,266	0	0	300
97	Ankunftspuenktlich	no	256,266	0	0	310
98	Puenktlich_Zeit	no	256,266	0	0	311
99	Puenktlich	no	256,266	0	0	2
100	Verspaetet	no	256,266	0	0	2
101	Verfrueht	no	256,266	0	0	2
102	Stornogrund	yes	256,266	256,139	99.95	2
103	fallnr	yes	256,266	18,898	7.37	69,802
104	Service	yes	256,266	256,266	100	1
105	Inventar	yes	256,266	256,266	100	1
106	Inventarnummer	yes	256,266	256,266	100	1
107	Inventar_Typkatalog	yes	256,266	256,266	100	1
108	Inventar_Material	yes	256,266	256,266	100	1
109	Client	yes	256,266	5,426	2.12	144
110	AbholraumNummer	yes	256,266	89,917	35.09	350
111	Abholraum	yes	256,266	89,917	35.09	48
112	AnkunftsraumNummer	yes	256,266	94,783	36.99	261
113	Ankunftsraum	yes	256,266	94,783	36.99	56
114	Beschwerde	yes	256,266	0	0	1
115	beschwerdekategorie	yes	256,266	256,266	100	1
116	beschwerdetext	yes	256,266	256,266	100	1
117	beschwerdevermerk	yes	256,266	256,266	100	1
118	AbholEinrichtung	yes	256,266	0	0	1
119	AnkunftsEinrichtung	yes	256,266	0	0	1
120	ErsteAnkunftsstelle	yes	256,266	0	0	118
121	ErsteAnforderung	no	256,266	0	0	255,519
122	einrichtung_id	yes	256,266	0	0	1
123	leitzo_id	yes	256,266	0	0	1
124	beginn	no	256,266	0	0	255,669
125	ende	no	256,266	0	0	255,666

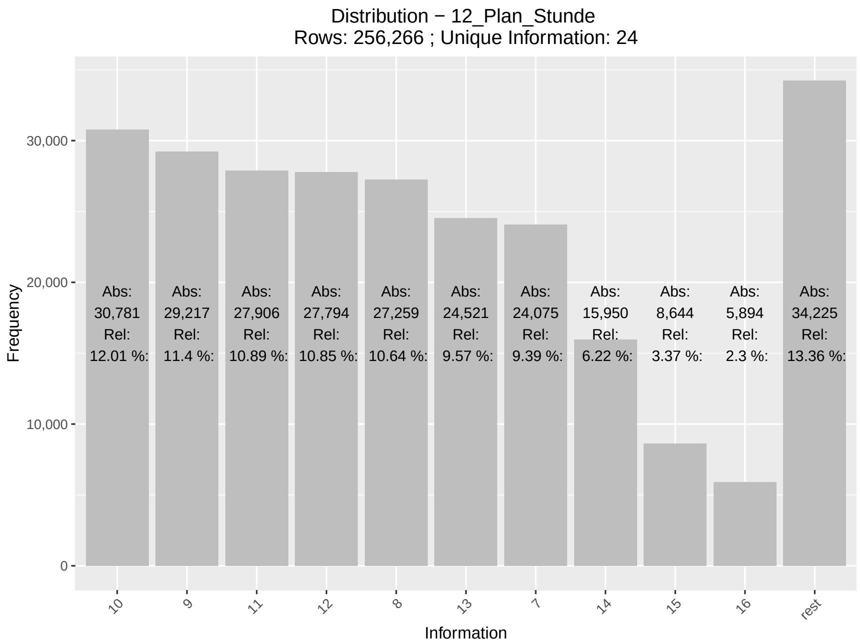

Figure A.1: Histogram of information frequency of attribute category 12 (see Table A.1) - “Plan_Stunde” (here: engl. “as-planned transport start hour”) (own visualisation).

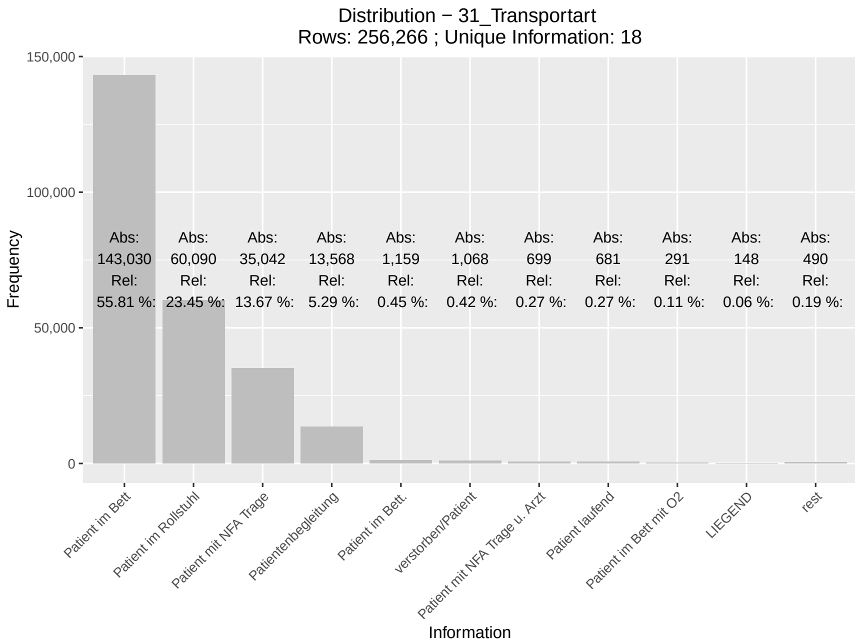

Figure A.2: Histogram of information frequency of attribute category 31 (see Table A.1) - “Transportart” (here: engl. “transport vehicle type”) (own visualisation).

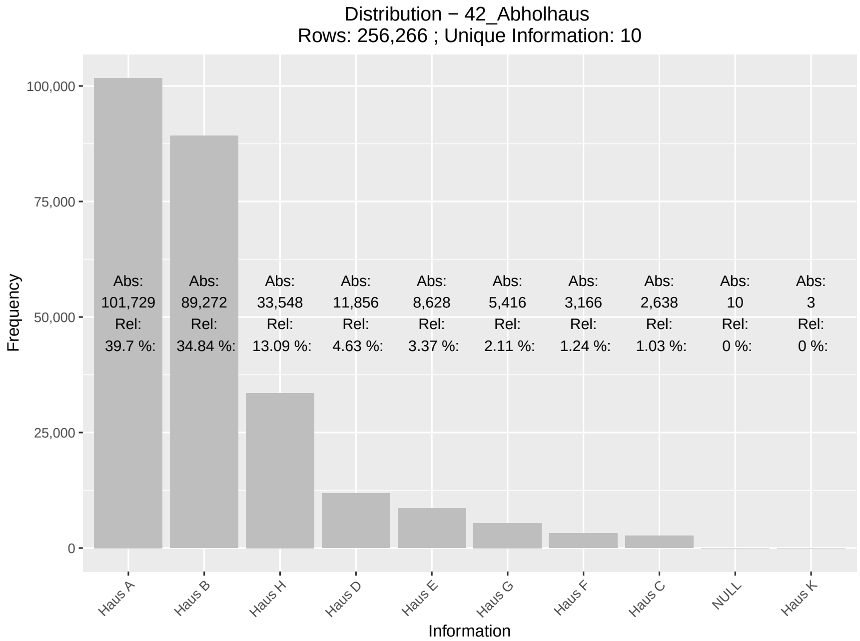

Figure A.3: Histogram of information frequency of attribute category 42 (see Table A.1) - “Abholhaus” (here: engl. “pick-up house”) (own visualisation).

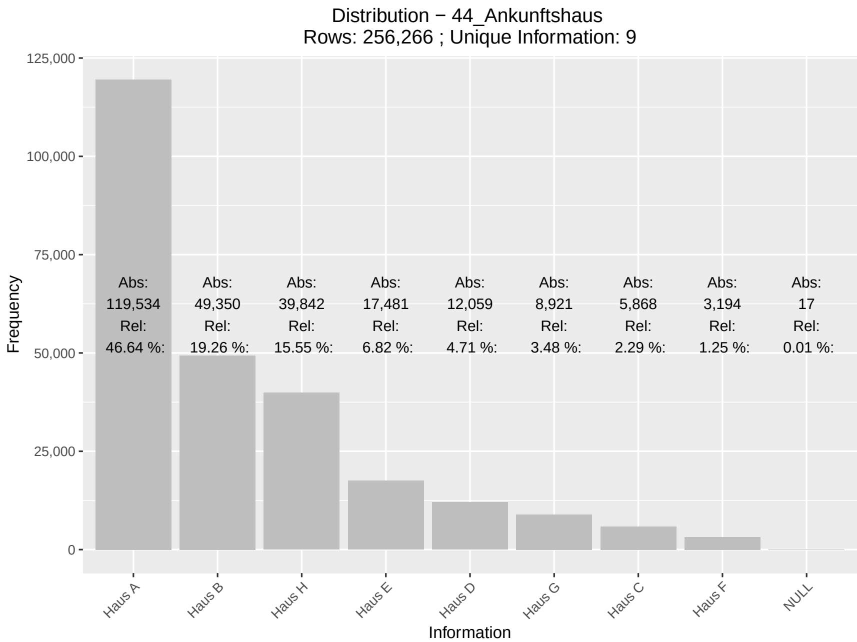

Figure A.4: Histogram of information frequency of attribute category 44 (see Table A.1) - “Ankunftshaus” (here: engl. “target house”) (own visualisation).

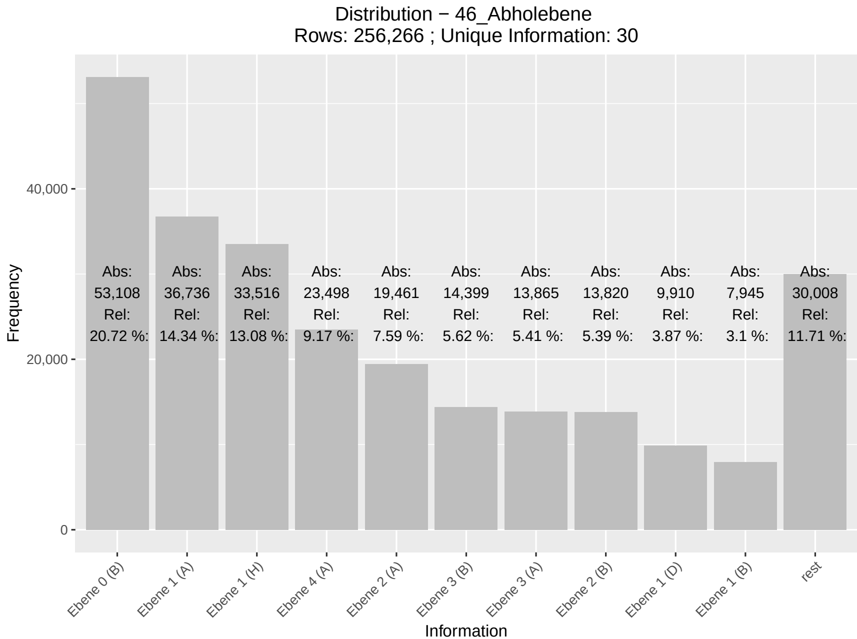

Figure A.5: Histogram of information frequency of attribute category 46 (see Table A.1) - “Abholebene” (here: engl. “pick-up floor”) (own visualisation).

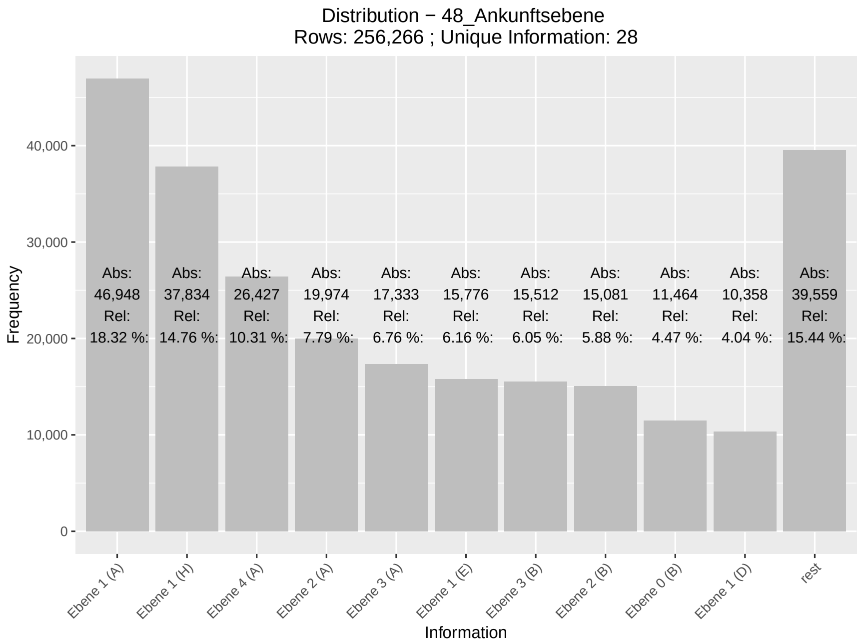

Figure A.6: Histogram of information frequency of attribute category 48 (see Table A.1) - “Ankunftsebene” (here: engl. “target floor”) (own visualisation).

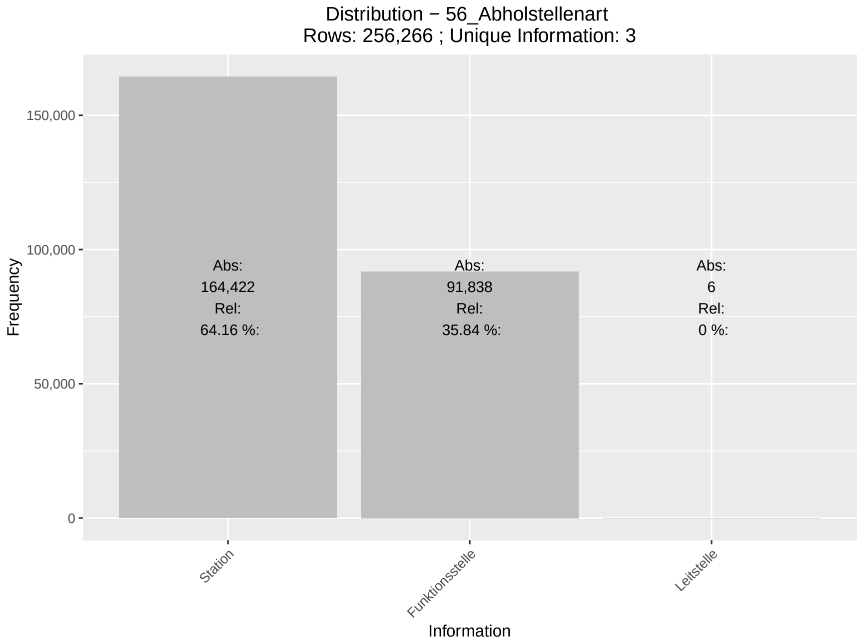

Figure A.7: Histogram of information frequency of attribute category 56 (see Table A.1) - “Abholstellenart” (here: engl. “pick-up location type”) (own visualisation).

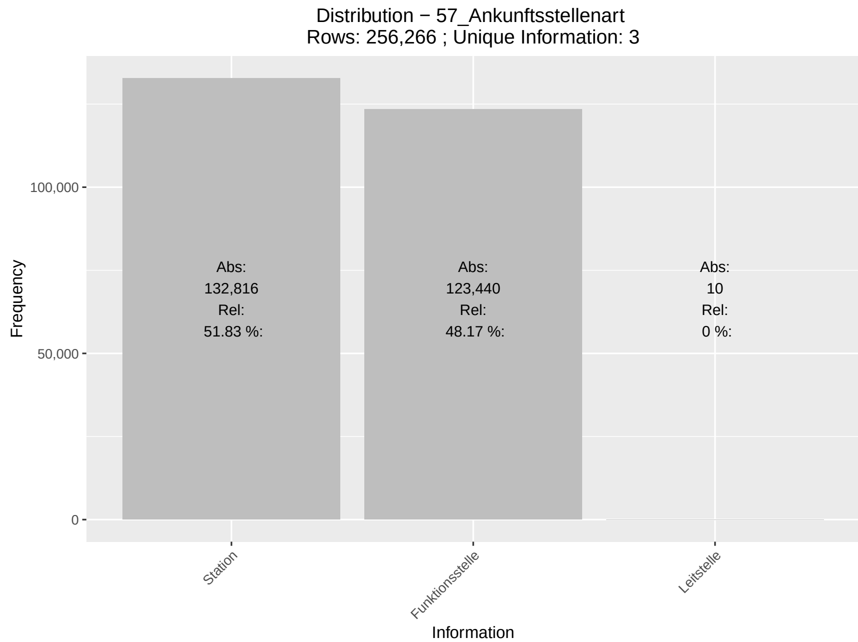

Figure A.8: Histogram of information frequency of attribute category 57 (see Table A.1) - “Ankunftsstellenart” (here: engl. “target location type”) (own visualisation).

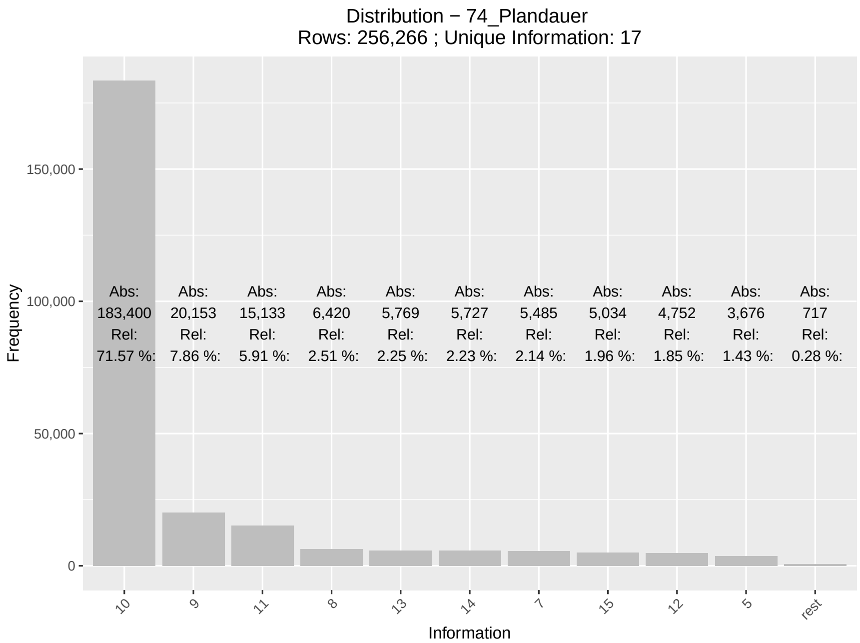

Figure A.9: Histogram of information frequency of attribute category 74 (see Table A.1) - “Plandauer” (here: engl. “as-planned transportation time from pick-up to target location”) (own visualisation).

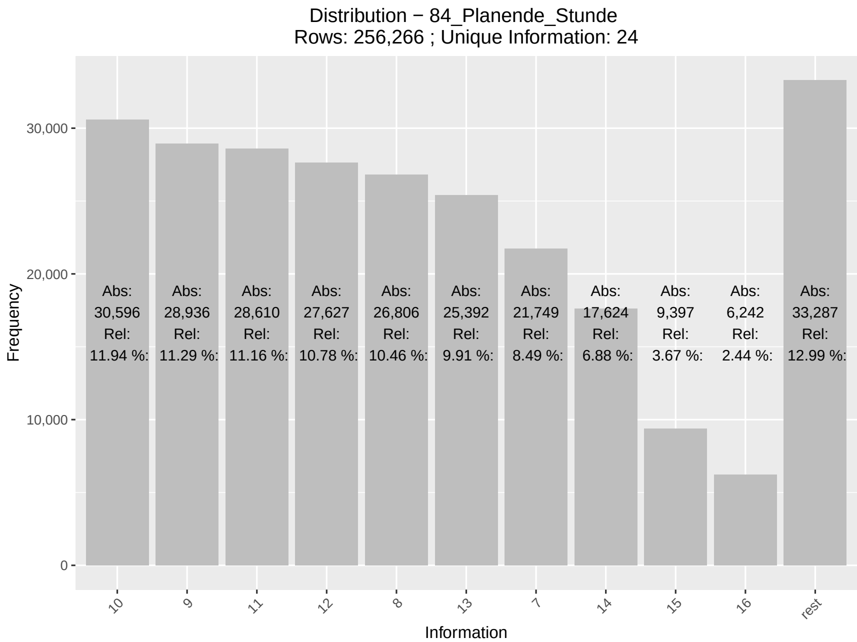

Figure A.10: Histogram of information frequency of attribute category 84 (see Table A.1) - “Planende_Stunde” (here: engl. “as-planned hour of transport completion”) (own visualisation).

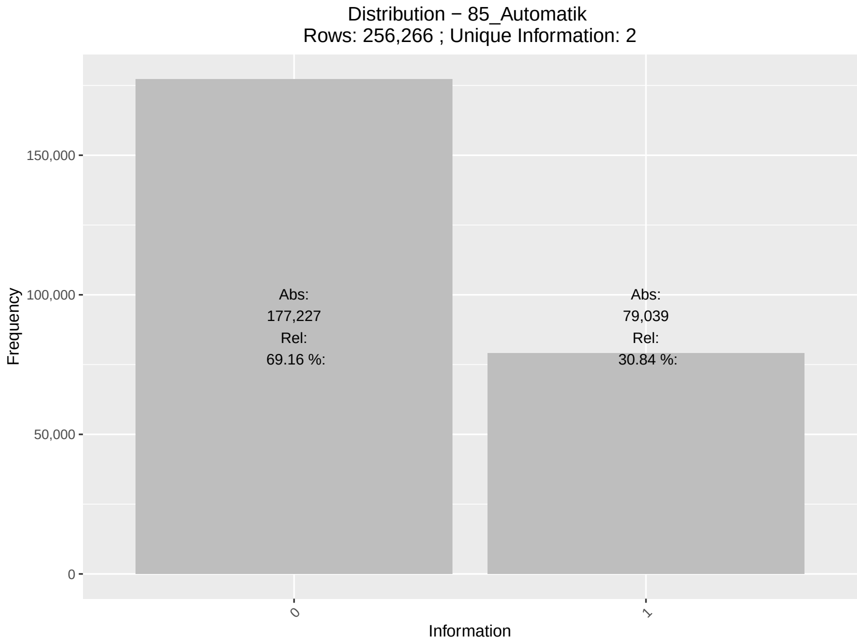

Figure A.11: Histogram of information frequency of attribute category 85 (see Table A.1) - “Automatik” (here: engl. “automatic dispatching”) (own visualisation).

A.2 Appendix for Section 7

A.2.1 Preprocessed Hourly MLP Input and Label Data (covering 26,662 Hours)

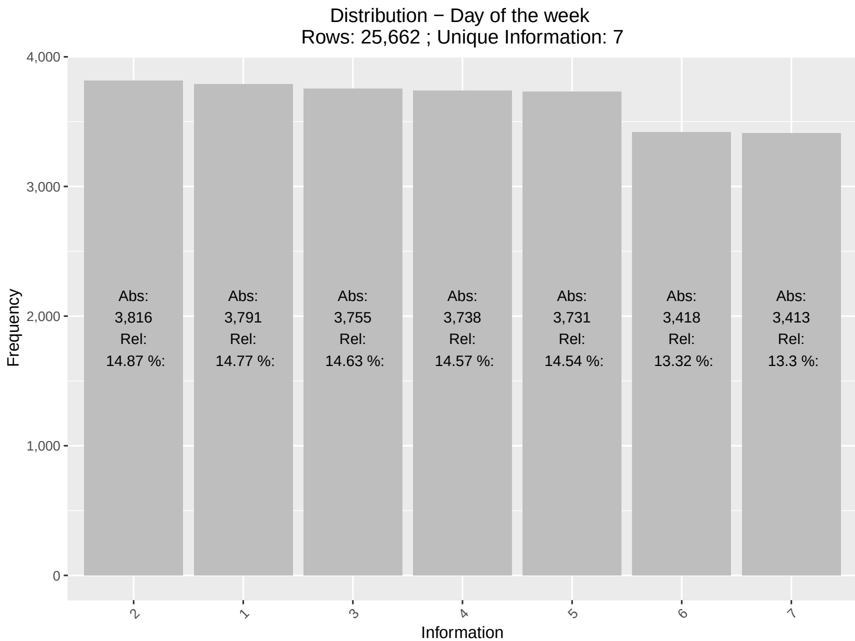

Figure A.12: Histogram of the hourly information frequency of the “days of the week” within the preprocessed MLP input data (own visualisation).

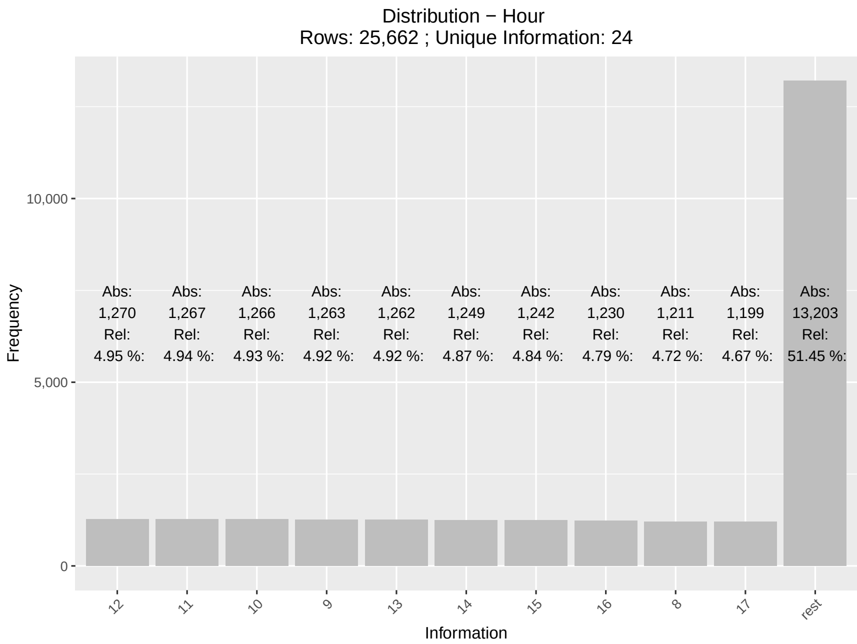

Figure A.13: Histogram of the hourly information frequency of "hours" within the preprocessed MLP input data (own visualisation).

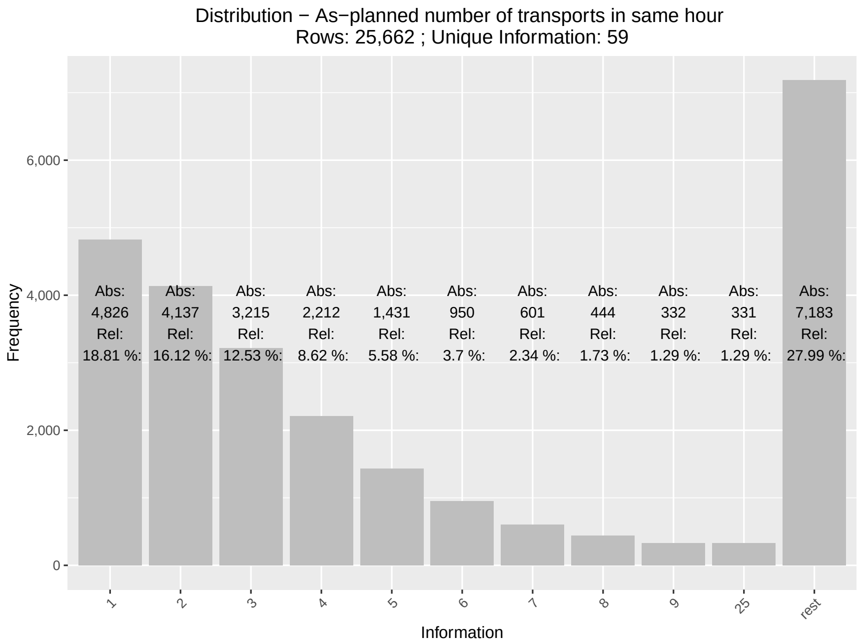

Figure A.14: Histogram of the hourly information frequency of newly created attribute category "As-planned number of transports in same hour" within the preprocessed MLP input data (own visualisation).

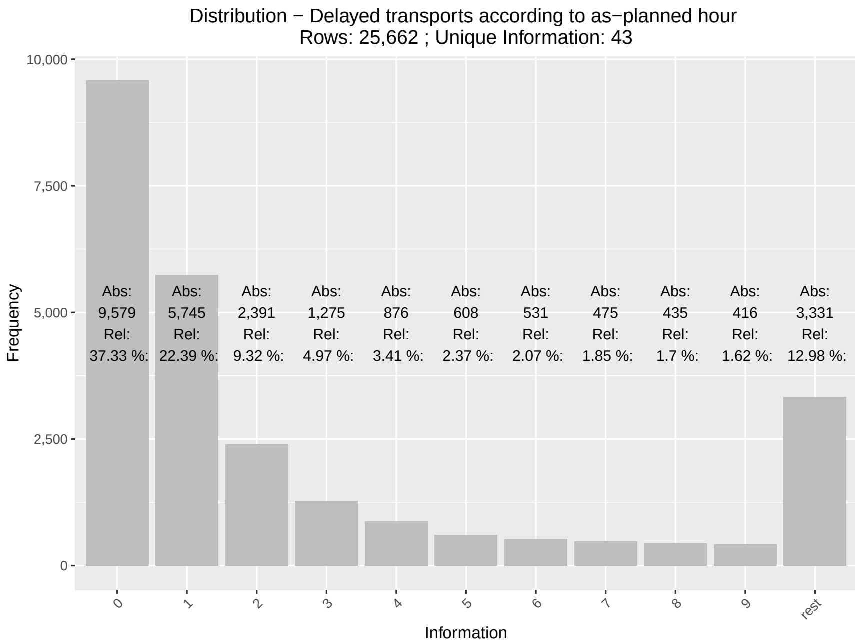

Figure A.15: Histogram of the hourly information frequency of newly created attribute category “Delayed transports according to as-planned hour” within the preprocessed MLP label data (own visualisation).

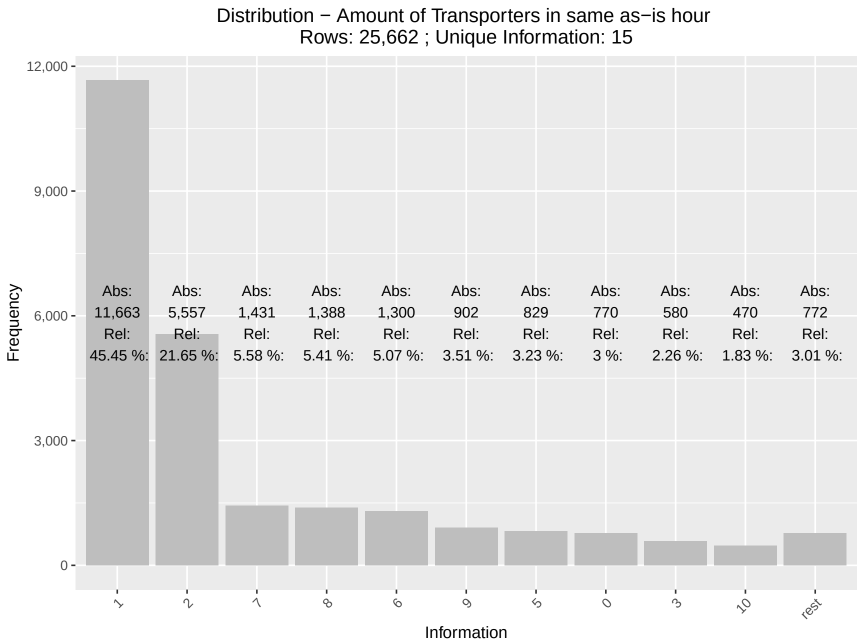

Figure A.16: Histogram of the hourly information frequency of newly created attribute category “Amount of Transporters in same as-is hour” (equals the number of unique device IDs active in the same hour) within the preprocessed MLP input data (own visualisation).

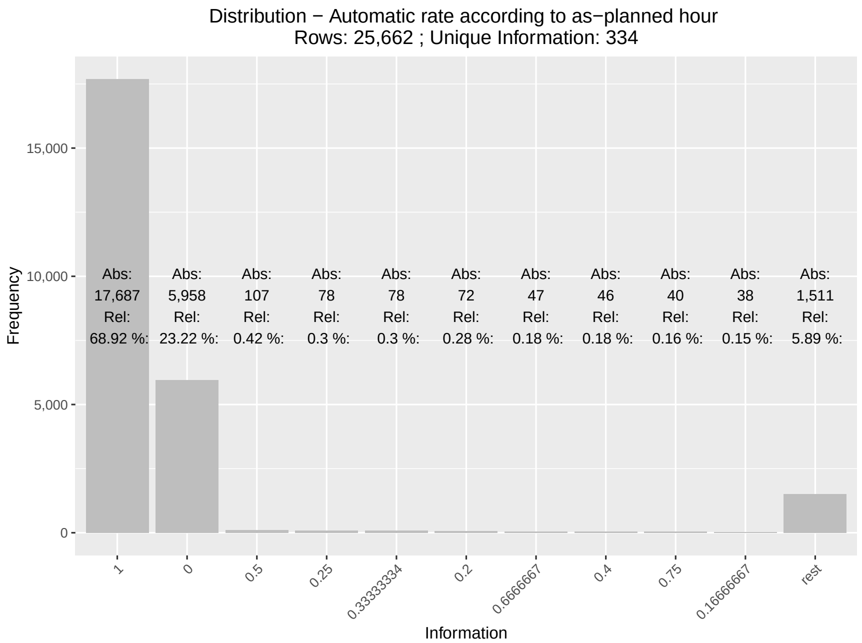

Figure A.17: Histogram of the hourly information frequency of newly created attribute category "Automatic rate according to as-planned hour" within the preprocessed MLP input data (own visualisation).

A.2.2 MLP Model Parameters

```
fc1.weight:
[[ 0.825126 -0.295566  0.017288 -0.108384 -1.263222]
 [-0.205918 -0.083989  0.006353  0.078975 -0.166994]
 [ 0.363117 -0.530517 -0.238769 -0.72846  -0.172361]
 [-0.400298 -0.408559 -0.414359  0.22301  -0.313589]
 [ 0.155269 -0.095033  0.100122 -0.636515 -0.136307]
 [ 0.053006 -0.785937  0.175005  0.118856  0.064699]
 [-0.076107  0.472145 -0.025826 -0.466198  0.771676]
 [ 0.071422  0.264626 -0.731633  0.555117 -0.163539]
 [-0.264669  0.105879  0.180798 -0.643618  0.035415]
 [ 0.12051   0.192604 -1.16858  -0.032323  0.463651]
 [ 0.015149  0.34671  -0.202365  0.071422  0.174317]
 [ 0.056755  0.050462 -0.222287  0.382204  0.876648]
 [-0.452998  0.10288   0.092657 -0.541337 -0.480566]
 [ 0.732789 -0.197544 -0.06089  -0.113986  1.136215]
 [ 0.127026 -0.614476  0.041568  0.040031 -0.145918]
 [ 0.147766  0.153821  0.052984 -0.497819  0.710459]
 [ 0.104575 -0.117284 -0.052115  0.392182  0.79797 ]
 [ 0.262649  0.266572 -0.10321  -1.401369  0.243189]
 [-0.652398 -0.089515  0.188627 -0.574441  0.413723]
 [-0.157886 -0.352102 -0.326762  0.05739  -0.124063]
 [ 0.050897  0.133841  0.277929 -0.645309  0.147035]
 [ 0.378207  0.034646 -0.562929  0.555571  0.686452]
 [-0.340499 -0.377217 -0.433738  0.300239  0.142276]
 [ 0.231021  0.211265  0.008951 -0.109628  0.525718]
 [ 0.251723  0.051902  0.021855  0.043236  1.289189]
 [ 0.116492 -0.096907  0.113756 -0.431123  0.178154]
 [ 0.069572 -0.430608  0.014077  0.703075  0.22574 ]
 [-0.109461  0.072478  0.232943 -0.632029 -0.608666]
 [ 0.380204 -0.685413 -0.430919  0.495109 -0.228486]
 [ 0.157361 -0.486903  0.179776 -0.57039   1.246817]
 [-0.569841 -0.449898  0.052307  0.709238 -1.324762]
 [-0.395778 -0.288186 -0.341824  0.15204   0.2275  ]
 [ 0.035418 -0.469373  0.224139 -0.704544  0.242468]
 [ 0.151578 -0.603252  0.038337 -1.136519 -0.059946]
 [-0.185652  0.063328  0.091943 -0.541337 -0.926787]
 [ 0.033418  0.153129 -0.009939  0.086689 -0.60253 ]
 [ 0.17975  -0.196453 -0.135367  0.360968  0.309296]
 [-0.340015  0.343986  0.055303 -0.552836 -0.179845]
 [-0.267913 -0.460364  0.202901 -0.096738  1.434088]
 [ 0.484365  0.160088 -0.348765  0.349417 -0.0836  ]
 [-0.024253  0.066993  0.088735 -0.677656  0.766967]
 [-0.622883 -0.616947  0.209532  0.246987 -1.488276]
 [ 0.274837 -0.075782 -0.03827   0.018701 -0.228897]
 [-0.16383   0.316376  0.020456 -0.076169 -0.615657]
 [-0.016793  0.448065 -0.203942 -0.26064  -1.163101]
 [-1.889986  0.192607  0.035102  0.067388 -0.132711]
 [ 0.265259 -0.002486  0.065414 -0.562399 -0.466066]
 [-0.032074  0.288544 -0.09594   0.401    -0.449336]
 [ 0.01284   0.002117  0.082524 -1.26987   0.423015]
 [-0.064014  0.156306  0.042474  0.005487 -0.119984]
 [ 0.069875 -0.038137  0.054291 -0.348186 -0.401017]
 [-0.464    -0.523341  0.027989  0.027093  0.224066]
 [ 0.068867  0.46403  -0.33397  -0.612389  0.641592]
```

Figure A.18 part 1/3 - continuation on following page

```
 [-0.340776 -0.337354 -0.11639  -0.025717  0.048798]
 [ 0.03562  -0.35134   0.260614 -0.623569 -0.709929]
 [-0.385879  0.23389  -0.803532  0.425948  0.71459 ]
 [ 0.396806 -0.592716  0.018025  0.574961  0.385048]
 [-0.489685 -0.083952 -0.086624  0.420381  1.940533]
 [-0.089446 -0.383726  0.059411  0.016416 -0.329258]
 [ 0.603864 -0.404015  0.018559 -0.296589 -1.033538]
 [ 0.249316 -1.051695  0.098189 -0.438768  0.196223]
 [-0.147306 -0.069381 -0.133445  0.005507 -0.415715]
 [-0.597354  0.053414 -0.15195   0.517068  0.511191]
 [-0.513436 -0.399457  0.207714 -0.611822 -0.108251]]
fc1.bias:
[ 0.663086 -0.41471  -0.085266 -0.256446  0.017844 -0.181251 -1.259741
  0.248013  0.555771  0.043928 -0.32787  -0.153224 -0.771789 -0.48397
  0.669138 -0.419484  0.905626 -0.148726  0.007077  0.270017 -0.207011
  0.165328 -0.393164 -1.824182 -1.797937 -0.995776  0.005778  0.436811
  0.362219  0.500762  0.334766  0.347628 -0.064462 -0.10817  -0.598939
 -1.82747   1.279216 -0.563786  0.116564  1.011404 -0.195592  0.847386
  1.427406 -1.678284  0.120994 -0.125995  0.597866 -1.501594 -0.199246
 -2.3921   -0.489109  0.559284  0.592696 -0.045891  0.851865  0.113463
  0.447176  0.87899  -0.323751  0.526465 -0.260502 -0.167819 -0.026347
 -0.359975]
fc2.weight:
[[ 0.015443  0.071926  0.042772 ...  0.113283 -0.100753 -0.113309]
 [-0.164101 -0.106385  0.031914 ... -0.10946   0.012008 -0.081923]
 [ 0.099562  0.031958  0.210813 ... -0.036627  0.083465 -0.088022]
 ...
 [-0.271755  0.044765 -0.517706 ... -0.084061  0.464822 -0.09887 ]
 [-0.146512 -0.036106  0.048799 ...  0.106317 -0.175298  0.056397]
 [-0.86109   0.068933  0.162941 ... -0.05883   0.113647  0.011349]]
fc2.bias:
[ 0.038857 -0.124581 -0.006824 -0.000914  0.095637 -0.496949 -0.025232
  0.013793 -0.108247 -0.225713 -0.140031 -0.066815 -0.129748 -0.040469
 -0.028712 -0.113716 -1.428406 -0.649078 -0.12397  -0.217029  0.181487
  0.264225  0.023856  0.391695 -0.016674 -0.058175  0.211243  0.448386
  0.018163 -0.35862   0.071614 -0.472943  0.030132  0.323945  0.034058
 -0.151581 -0.100521  0.130281 -1.243158  0.394325  0.130047 -0.261356
  0.143161 -0.04716  -0.11305  -0.085999  0.063063 -0.217206 -0.071229
 -0.168267 -1.161878 -0.309166  0.086528 -0.135271 -0.080275 -0.010146
 -0.047943 -0.169693 -0.135348 -0.148666 -0.053417  0.089766 -0.11914
 -0.313017  0.108208 -0.308021 -0.050964 -0.553701 -0.027624 -0.004312
 -0.150214 -0.018265 -0.100004 -0.155001 -0.040443 -1.400609  0.064015
  0.026839 -0.015917 -0.013763 -0.104533  0.016024 -0.085921  0.005541
  0.030388 -0.005869 -0.02119   0.067576 -0.341021 -0.098376  0.139101
  0.057361 -0.119414  0.09326  -0.119634  0.242127 -0.067965 -0.174746
  0.375053 -0.069906 -0.409874  0.015126  0.084578  0.440709  0.297321
  0.004416  0.238503 -0.144122 -0.260007 -0.546212 -0.135774  0.040978
 -0.138776 -0.146261 -0.028896 -0.077921  0.318711  0.352416 -0.327405
 -0.025226  0.153607 -0.017514 -0.071288 -0.683243  0.094061  0.024844
 -0.0875   -0.183359 -0.443267 -0.050405 -0.007267 -0.131618 -0.115181
  0.162458  0.291961  0.512034  0.181106 -1.388042  0.895864 -0.066725
  0.095683  0.041    -0.095691  0.139288 -0.031629  0.01737   0.109775
 -0.051923 -0.098093 -0.093427 -0.030285 -0.271611 -0.469025  0.069581
 -0.064302 -0.397066 -0.024122 -1.338081 -0.051793  0.438944 -0.236461
```

Figure A.18 part 2/3 - continuation on following page

```
  0.093077  0.034871  0.070235 -0.14399   0.660701  0.065458 -0.453507
 -0.068117 -0.120062 -1.163262 -0.369406 -0.196386 -0.588145 -0.042229
 -0.004803  0.428466 -0.65711   0.039736 -0.326065  0.204476 -0.085989
 -0.360215 -0.088908  0.268235  0.109529  0.253056 -0.038867 -0.096536
  0.033833  0.023448 -0.025794  0.465811 -0.082046 -0.111727  0.092594
  0.058483 -1.513039 -0.082567  0.215885  0.129423 -0.119724 -0.025907
  0.073035 -0.519578 -1.547892  0.411058  0.070418  0.176197 -0.134656
 -0.364619  0.034543  0.309644 -0.083721 -0.036703  0.119679  0.098654
  0.068833  0.182149 -0.693806 -0.165135 -0.101285 -0.011962 -0.092411
 -0.102651 -0.013966 -0.143179 -0.310939  0.089244  0.034949 -0.275601
 -0.804851 -0.117636 -0.781692 -0.015048  0.035731  0.32056   0.079266
 -0.431184 -0.132302  0.007436  0.28791  -0.065396 -0.107398 -0.119111
  0.134701 -1.324695 -0.041069 -0.147533  0.654829 -0.101755 -0.217212
 -0.078647  0.174297  0.065925  0.017492]
fc3.weight:
[[-0.012426  0.024526  0.049012 ... -0.010819  0.048593  0.004484]
 [ 0.059546 -0.027541  0.026241 ... -0.164406 -0.069171 -0.023266]
 [ 0.055507 -0.007955 -0.038962 ...  0.132605 -0.036034 -0.161356]
 ...
 [ 0.052895  0.033492  0.045628 ... -0.034349 -0.057498  0.047848]
 [-0.034265 -0.031432 -0.007589 ...  0.035326 -0.033975 -0.114999]
 [-0.019746  0.034057  0.048476 ... -0.020839  0.02125   0.005224]]
fc3.bias:
[-0.00072  -0.15752  -0.163641 -0.070878  0.637155 -0.062033  0.006221
 -0.090991 -0.071201 -0.119928  0.445532 -0.097726  0.205186 -0.066238
  0.431658  0.621993  0.669564  0.060829  0.596631 -0.055258  0.411044
 -0.034757 -0.100188 -0.095692 -0.269923 -0.095851 -0.086207  0.248165
 -0.099731 -0.044738 -0.039504 -0.109043 -0.150863 -0.085709 -0.074045
  0.469742 -0.145628 -0.091031 -0.018161  0.483396  0.214948  0.099605
 -0.07439  -0.044633 -0.144997 -0.039609 -0.073438 -0.038797 -0.298371
 -0.133109  0.627896  0.34754   0.5744    0.011267 -0.11339  -0.069377
  0.674746 -0.079234 -0.080851  0.601759 -0.068343 -0.069675 -0.077067
 -0.058211]
fc4.weight:
[[-0.003648  0.011754 -0.09388  -0.005077  0.18818  -0.005853  0.005392
   0.001102 -0.043692  0.0008    0.215503  0.012961 -0.125277 -0.017593
   0.258442  0.085709  0.258302 -0.13092   0.262033 -0.036575  0.215832
  -0.025839  0.010676  0.005955 -0.597303 -0.027353  0.008541  0.168945
   0.023188 -0.032244 -0.097267  0.027573 -0.013156 -0.040792  0.010735
   0.065097 -0.001347  0.044347 -0.005814  0.027834  0.16033  -0.186625
  -0.025654 -0.007199 -0.605523  0.608699  0.000564  0.0157   -0.582
   0.006358  0.149192  0.214446  0.137538 -0.038499 -0.012065 -0.102658
   0.204943 -0.028317  0.025063  0.178228  0.01031  -0.079793 -0.068001
  -0.002023]]
fc4.bias:
[0.701149]
```

Figure A.18 part 3/3

Figure A.18: MLP weights and biases after Training - Overall 33,537 parameters: input layer to 1st hidden layer "fc1" has 320 weights and 64 biases, 1st hidden layer to 2nd hidden layer "fc2" has 16,384 weights (abbreviated) and 256 biases, 2nd hidden layer to 3rd hidden layer "fc3" has 16,384 weights (abbreviated) and 64 biases, 3rd hidden layer to output layer "fc4" has 64 weights and one bias (own visualisation).

A.2.3 Day of the Week MLP Predictions Comparison to Real Data

	Day of the week	Hour	As-planned number of transports in same hour	Amount of trans-porters in same as-is hour	Automatic rate according to as-planned hour
tensor([[	2.0000,	0.0000,	1.7049,	0.8634,	1.0000],
[	2.0000,	1.0000,	1.3716,	0.7377,	1.0000],
[	2.0000,	2.0000,	0.9836,	0.6175,	1.0000],
[	2.0000,	3.0000,	0.8634,	0.5301,	1.0000],
[	2.0000,	4.0000,	0.6831,	0.4918,	1.0000],
[	2.0000,	5.0000,	0.5410,	0.4153,	1.0000],
[	2.0000,	6.0000,	4.2514,	1.2131,	0.1844],
[	2.0000,	7.0000,	24.5847,	6.9781,	0.1232],
[	2.0000,	8.0000,	29.7923,	7.2240,	0.1302],
[	2.0000,	9.0000,	29.5246,	7.2459,	0.1497],
[	2.0000,	10.0000,	32.4426,	7.4098,	0.1542],
[	2.0000,	11.0000,	27.9672,	7.3880,	0.1441],
[	2.0000,	12.0000,	27.8142,	7.3169,	0.1494],
[	2.0000,	13.0000,	25.7104,	8.0546,	0.1417],
[	2.0000,	14.0000,	17.4863,	7.5464,	0.2853],
[	2.0000,	15.0000,	8.6448,	2.4918,	0.7815],
[	2.0000,	16.0000,	5.6776,	1.9727,	0.9775],
[	2.0000,	17.0000,	3.7049,	1.6995,	1.0000],
[	2.0000,	18.0000,	3.2842,	1.5191,	0.9991],
[	2.0000,	19.0000,	2.7923,	1.5246,	1.0000],
[	2.0000,	20.0000,	2.6393,	1.4372,	1.0000],
[	2.0000,	21.0000,	2.4809,	0.9727,	1.0000],
[	2.0000,	22.0000,	2.4208,	0.9945,	1.0000],
[	2.0000,	23.0000,	2.0656,	0.8689,	1.0000]])

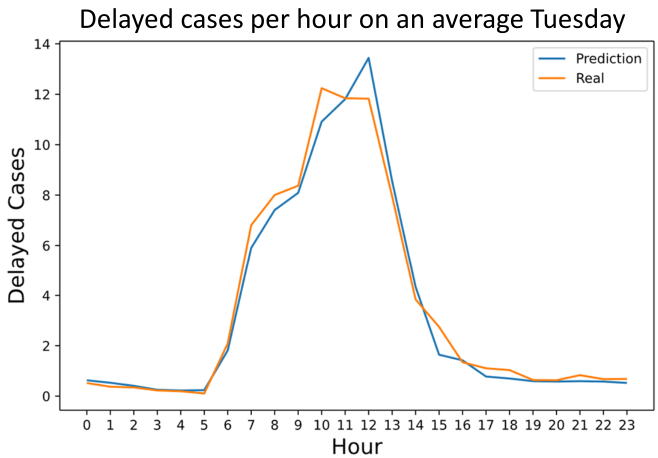

Figure A.19: Left: Original input tensor with mean values for an average Tuesday. Right: Real and predicted (through MLP model) delayed cases per hour on an average Tuesday (own visualisation).

	Day of the week	Hour	As-planned number of transports in same hour	Amount of trans-porters in same as-is hour	Automatic rate according to as-planned hour
tensor([[	3.0000,	0.0000,	1.6011,	0.8087,	1.0000],
[	3.0000,	1.0000,	1.2951,	0.7104,	1.0000],
[	3.0000,	2.0000,	1.0929,	0.6175,	1.0000],
[	3.0000,	3.0000,	0.7705,	0.4699,	1.0000],
[	3.0000,	4.0000,	0.6284,	0.4809,	1.0000],
[	3.0000,	5.0000,	0.6557,	0.4481,	0.9637],
[	3.0000,	6.0000,	4.0109,	1.2514,	0.2014],
[	3.0000,	7.0000,	28.4262,	7.1967,	0.1381],
[	3.0000,	8.0000,	28.2459,	7.3060,	0.1349],
[	3.0000,	9.0000,	30.6175,	7.4153,	0.1463],
[	3.0000,	10.0000,	32.0382,	7.5847,	0.1380],
[	3.0000,	11.0000,	29.3661,	7.6776,	0.1296],
[	3.0000,	12.0000,	30.8470,	7.6120,	0.1233],
[	3.0000,	13.0000,	26.2842,	8.1913,	0.1446],
[	3.0000,	14.0000,	16.4262,	7.2678,	0.3382],
[	3.0000,	15.0000,	8.3934,	2.5574,	0.8052],
[	3.0000,	16.0000,	5.3607,	2.0437,	0.9753],
[	3.0000,	17.0000,	3.9290,	1.6667,	1.0000],
[	3.0000,	18.0000,	2.9672,	1.4262,	1.0000],
[	3.0000,	19.0000,	2.7322,	1.5355,	1.0000],
[	3.0000,	20.0000,	2.4863,	1.4208,	1.0000],
[	3.0000,	21.0000,	2.0328,	0.8525,	1.0000],
[	3.0000,	22.0000,	2.0437,	0.9508,	1.0000],
[	3.0000,	23.0000,	1.9672,	0.8579,	1.0000]])

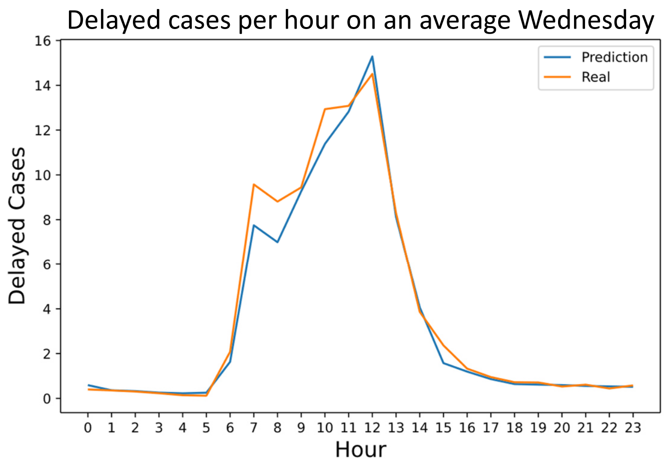

Figure A.20: Left: Original input tensor with mean values for an average Wednesday. Right: Real and predicted (through MLP model) delayed cases per hour on an average Wednesday (own visualisation).

	Day of the week	Hour	As-planned number of transports in same hour	Amount of trans-porters in same as-is hour	Automatic rate according to as-planned hour
tensor([[	4.0000,	0.0000,	1.6831,	0.7923,	1.0000],
[	4.0000,	1.0000,	1.0984,	0.6776,	1.0000],
[	4.0000,	2.0000,	0.8743,	0.5738,	1.0000],
[	4.0000,	3.0000,	0.6995,	0.4536,	1.0000],
[	4.0000,	4.0000,	0.6120,	0.4098,	1.0000],
[	4.0000,	5.0000,	0.5683,	0.4044,	0.9667],
[	4.0000,	6.0000,	4.0109,	1.1366,	0.2224],
[	4.0000,	7.0000,	23.9617,	6.7978,	0.1406],
[	4.0000,	8.0000,	28.8470,	6.9727,	0.1482],
[	4.0000,	9.0000,	28.9508,	7.0984,	0.1632],
[	4.0000,	10.0000,	31.3443,	7.3224,	0.1527],
[	4.0000,	11.0000,	27.2842,	7.3279,	0.1448],
[	4.0000,	12.0000,	25.9672,	7.1858,	0.1527],
[	4.0000,	13.0000,	24.1694,	7.7978,	0.1695],
[	4.0000,	14.0000,	14.9617,	7.0874,	0.3599],
[	4.0000,	15.0000,	8.1202,	2.5027,	0.8083],
[	4.0000,	16.0000,	5.1858,	2.0546,	0.9886],
[	4.0000,	17.0000,	3.6995,	1.6831,	1.0000],
[	4.0000,	18.0000,	3.1475,	1.5464,	1.0000],
[	4.0000,	19.0000,	2.8962,	1.5902,	1.0000],
[	4.0000,	20.0000,	2.5738,	1.4262,	1.0000],
[	4.0000,	21.0000,	2.5191,	0.9126,	1.0000],
[	4.0000,	22.0000,	2.2350,	1.0000,	1.0000],
[	4.0000,	23.0000,	2.1038,	0.8361,	1.0000]])

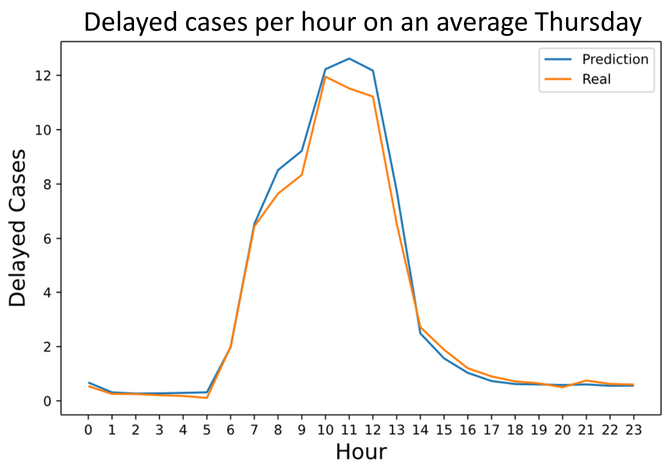

Figure A.21: Left: Original input tensor with mean values for an average Thursday. Right: Real and predicted (through MLP model) delayed cases per hour on an average Thursday (own visualisation).

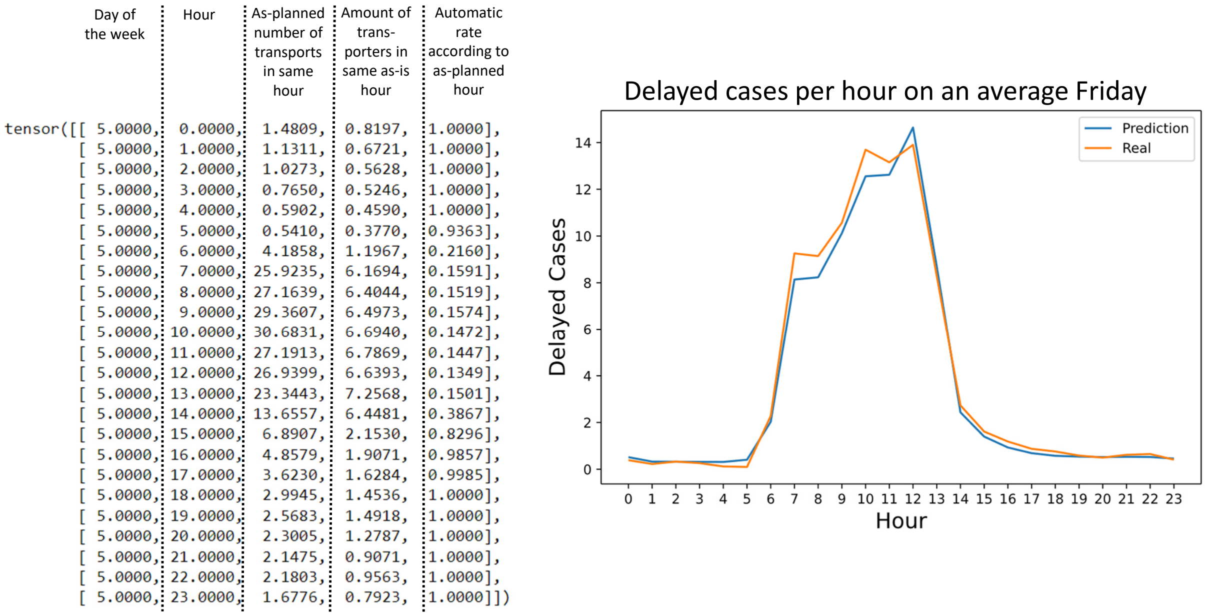

Figure A.22: Left: Original input tensor with mean values for an average Friday. Right: Real and predicted (through MLP model) delayed cases per hour on an average Friday (own visualisation).

Day of the week | Hour | As-planned number of transports in same hour | Amount of trans-porters in same as-is hour | Automatic rate according to as-planned hour

```
tensor([[ 6.0000,  0.0000,  1.6978,  0.7857,  1.0000],
        [ 6.0000,  1.0000,  1.3956,  0.7363,  1.0000],
        [ 6.0000,  2.0000,  1.0714,  0.6209,  1.0000],
        [ 6.0000,  3.0000,  0.7198,  0.4890,  1.0000],
        [ 6.0000,  4.0000,  0.7308,  0.4725,  1.0000],
        [ 6.0000,  5.0000,  0.5549,  0.4231,  1.0000],
        [ 6.0000,  6.0000,  0.3681,  0.3242,  1.0000],
        [ 6.0000,  7.0000,  0.5604,  0.3626,  1.0000],
        [ 6.0000,  8.0000,  4.1868,  0.9396,  1.0000],
        [ 6.0000,  9.0000,  6.3297,  1.6923,  1.0000],
        [ 6.0000, 10.0000,  5.7033,  1.7308,  0.9926],
        [ 6.0000, 11.0000,  7.1374,  1.7692,  0.9944],
        [ 6.0000, 12.0000,  5.5879,  1.8077,  0.9954],
        [ 6.0000, 13.0000,  4.2527,  1.6703,  0.9984],
        [ 6.0000, 14.0000,  3.1538,  1.6484,  0.9988],
        [ 6.0000, 15.0000,  2.8846,  1.5330,  0.9940],
        [ 6.0000, 16.0000,  2.5934,  1.5330,  0.9970],
        [ 6.0000, 17.0000,  2.3077,  0.9615,  1.0000],
        [ 6.0000, 18.0000,  2.4011,  0.8956,  0.9969],
        [ 6.0000, 19.0000,  2.1538,  0.9396,  1.0000],
        [ 6.0000, 20.0000,  1.9945,  0.9011,  1.0000],
        [ 6.0000, 21.0000,  2.0659,  0.9121,  1.0000],
        [ 6.0000, 22.0000,  2.0659,  0.9121,  1.0000],
        [ 6.0000, 23.0000,  2.0934,  0.8791,  1.0000]])
```

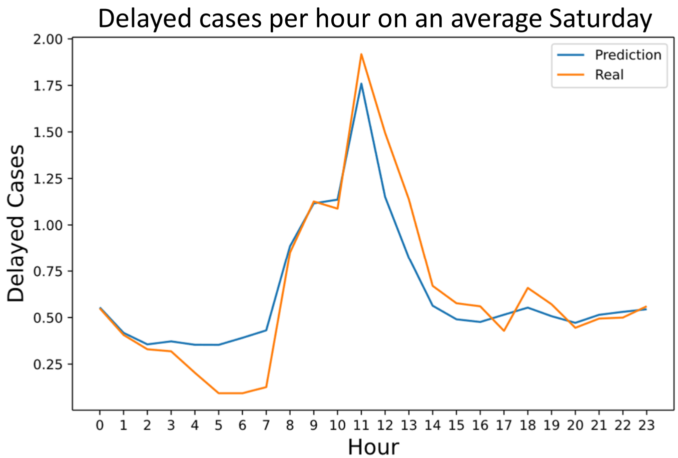

Figure A.23: Left: Original input tensor with mean values for an average Saturday. Right: Real and predicted (through MLP model) delayed cases per hour on an average Saturday (own visualisation).

Day of the week	Hour	As-planned number of transports in same hour	Amount of trans-porters in same as-is hour	Automatic rate according to as-planned hour
tensor([[7.0000,	0.0000,	1.5769,	0.8022,	1.0000],
[7.0000,	1.0000,	1.3407,	0.7747,	1.0000],
[7.0000,	2.0000,	1.1703,	0.6813,	1.0000],
[7.0000,	3.0000,	1.0385,	0.5275,	1.0000],
[7.0000,	4.0000,	0.7692,	0.5055,	1.0000],
[7.0000,	5.0000,	0.5714,	0.4505,	1.0000],
[7.0000,	6.0000,	0.4231,	0.3626,	1.0000],
[7.0000,	7.0000,	0.6868,	0.3956,	1.0000],
[7.0000,	8.0000,	2.5879,	0.7637,	1.0000],
[7.0000,	9.0000,	4.4011,	1.5714,	1.0000],
[7.0000,	10.0000,	3.8187,	1.5385,	1.0000],
[7.0000,	11.0000,	4.5440,	1.6264,	1.0000],
[7.0000,	12.0000,	3.9066,	1.6429,	1.0000],
[7.0000,	13.0000,	3.4341,	1.6044,	1.0000],
[7.0000,	14.0000,	3.0549,	1.5879,	1.0000],
[7.0000,	15.0000,	2.7308,	1.5220,	1.0000],
[7.0000,	16.0000,	2.6593,	1.4341,	1.0000],
[7.0000,	17.0000,	2.4066,	0.9780,	1.0000],
[7.0000,	18.0000,	2.2967,	0.9286,	1.0000],
[7.0000,	19.0000,	2.3132,	0.9890,	1.0000],
[7.0000,	20.0000,	2.1758,	0.9341,	1.0000],
[7.0000,	21.0000,	2.1429,	0.8956,	1.0000],
[7.0000,	22.0000,	2.2582,	0.9835,	1.0000],
[7.0000,	23.0000,	1.8901,	0.8846,	1.0000]])

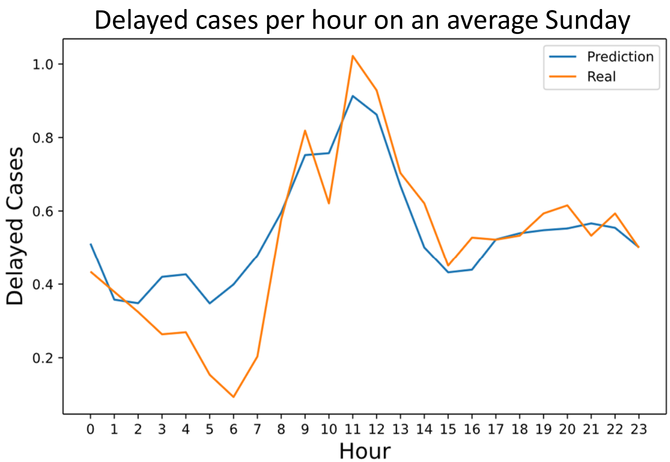

Figure A.24: Left: Original input tensor with mean values for an average Sunday. Right: Real and predicted (through MLP model) delayed cases per hour on an average Sunday (own visualisation).

A.2.4 GA Validation Runs

Table A.2: 100 GA results for limited space of 5,589,997 possible solutions sorted by increasing objective function value (own table).

No.	Optimised No. of Transporters	Sum of Trans- porters	Sum of MLP Output (Predicted Delayed Cases)	Objective Function Value
1	[2. 3. 5. 7. 9. 10. 8. 7. 5. 4.]	60	106.27	106.50
2	[7. 7. 7. 7. 7. 9. 7. 5. 3. 1.]	60	106.30	106.53
3	[7. 8. 8. 7. 7. 7. 7. 5. 3. 1.]	60	106.61	106.84
4	[7. 7. 7. 9. 7. 7. 7. 5. 3. 1.]	60	106.70	106.94
5	[7. 7. 7. 9. 7. 7. 7. 5. 3. 1.]	60	106.70	106.94
6	[7. 7. 7. 9. 7. 7. 7. 5. 3. 1.]	60	106.70	106.94
7	[2. 2. 2. 4. 6. 8. 10. 8. 8. 8.]	58	106.94	106.94
8	[2. 2. 2. 4. 6. 8. 10. 8. 8. 8.]	58	106.94	106.94
9	[2. 2. 2. 4. 6. 8. 10. 8. 8. 8.]	58	106.94	106.94
10	[2. 2. 2. 4. 6. 8. 10. 8. 8. 8.]	58	106.94	106.94
11	[2. 2. 2. 4. 6. 8. 10. 8. 8. 8.]	58	106.94	106.94
12	[2. 2. 2. 3. 5. 7. 9. 8. 8. 8.]	54	107.02	107.02
13	[2. 2. 2. 3. 5. 7. 9. 8. 8. 8.]	54	107.02	107.02
14	[2. 2. 2. 3. 5. 7. 9. 8. 8. 8.]	54	107.02	107.02
15	[2. 2. 2. 3. 5. 7. 9. 8. 8. 8.]	54	107.02	107.02
16	[10. 11. 10. 8. 6. 4. 2. 3. 3. 3.]	60	106.92	107.15
17	[10. 11. 10. 8. 6. 4. 2. 3. 4. 2.]	60	107.02	107.25
18	[8. 8. 8. 7. 6. 7. 7. 5. 3. 1.]	60	107.05	107.28
19	[8. 8. 8. 7. 6. 7. 7. 5. 3. 1.]	60	107.05	107.28
20	[3. 5. 7. 9. 11. 9. 7. 5. 3. 1.]	60	107.10	107.33
21	[7. 8. 8. 7. 6. 7. 7. 5. 3. 2.]	60	107.13	107.36
22	[7. 8. 8. 7. 6. 7. 7. 5. 3. 2.]	60	107.13	107.36
23	[7. 8. 9. 9. 7. 7. 6. 4. 2. 1.]	60	107.20	107.43
24	[7. 8. 9. 9. 7. 7. 6. 4. 2. 1.]	60	107.20	107.43
25	[7. 8. 8. 9. 7. 7. 6. 4. 3. 1.]	60	107.26	107.49
26	[9. 11. 10. 8. 6. 4. 2. 3. 4. 3.]	60	107.26	107.49
27	[11. 11. 9. 7. 5. 3. 2. 3. 4. 4.]	59	107.50	107.50
28	[11. 11. 9. 7. 5. 3. 2. 3. 4. 4.]	59	107.50	107.50
29	[11. 11. 9. 7. 5. 3. 2. 3. 4. 4.]	59	107.50	107.50
30	[11. 11. 9. 7. 5. 3. 2. 3. 4. 4.]	59	107.50	107.50
31	[11. 11. 9. 7. 5. 3. 2. 3. 4. 4.]	59	107.50	107.50
32	[8. 8. 9. 9. 7. 7. 5. 3. 3. 1.]	60	107.35	107.58
33	[8. 8. 9. 9. 7. 7. 5. 3. 3. 1.]	60	107.35	107.58
34	[7. 7. 9. 9. 7. 7. 6. 4. 3. 1.]	60	107.37	107.61
35	[2. 2. 2. 2. 2. 4. 6. 8. 8. 8.]	44	107.61	107.61
36	[2. 2. 2. 2. 2. 4. 6. 8. 8. 8.]	44	107.61	107.61
37	[7. 8. 9. 9. 7. 7. 5. 3. 3. 2.]	60	107.42	107.65
38	[7. 8. 9. 9. 7. 7. 5. 3. 3. 2.]	60	107.42	107.65

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Table A.2 – continuation

No.	Optimised No. of Transporters	Sum of Trans-porters	Sum of MLP Output (Predicted Delayed Cases)	Objective Function Value
39	[8. 8. 9. 9. 7. 7. 5. 3. 2. 2.]	60	107.43	107.66
40	[2. 2. 2. 2. 3. 5. 7. 8. 8. 8.]	47	107.68	107.68
41	[2. 2. 2. 2. 3. 5. 7. 8. 8. 8.]	47	107.68	107.68
42	[7. 7. 7. 9. 7. 6. 7. 5. 3. 2.]	60	107.48	107.71
43	[8. 8. 8. 9. 7. 7. 5. 3. 3. 2.]	60	107.49	107.72
44	[7. 9. 8. 9. 7. 7. 6. 4. 2. 1.]	60	107.52	107.75
45	[8. 7. 8. 9. 9. 7. 5. 3. 3. 1.]	60	107.58	107.81
46	[2. 2. 3. 5. 7. 9. 10. 8. 6. 8.]	60	107.73	107.96
47	[7. 8. 9. 8. 7. 7. 6. 4. 3. 1.]	60	107.79	108.03
48	[7. 8. 7. 9. 7. 7. 6. 5. 3. 1.]	60	107.80	108.03
49	[7. 8. 8. 8. 7. 7. 6. 5. 3. 1.]	60	107.86	108.09
50	[9. 11. 9. 7. 5. 3. 5. 3. 4. 4.]	60	107.87	108.10
51	[8. 8. 10. 8. 6. 4. 6. 5. 3. 2.]	60	107.96	108.19
52	[2. 3. 5. 7. 7. 9. 9. 8. 6. 4.]	60	107.96	108.19
53	[2. 3. 5. 7. 7. 9. 9. 8. 6. 4.]	60	107.96	108.19
54	[8. 7. 7. 9. 7. 7. 6. 5. 3. 1.]	60	107.98	108.21
55	[8. 8. 9. 8. 7. 7. 5. 3. 3. 2.]	60	108.02	108.25
56	[2. 2. 2. 2. 4. 6. 8. 8. 8. 8.]	50	108.31	108.31
57	[2. 2. 2. 2. 4. 6. 8. 8. 8. 8.]	50	108.31	108.31
58	[2. 2. 2. 2. 4. 6. 8. 8. 8. 8.]	50	108.31	108.31
59	[8. 9. 11. 9. 7. 5. 3. 3. 3. 2.]	60	108.15	108.38
60	[2. 2. 3. 5. 7. 9. 9. 8. 7. 8.]	60	108.16	108.39
61	[9. 10. 9. 7. 5. 3. 5. 6. 4. 2.]	60	108.18	108.41
62	[9. 8. 7. 9. 7. 7. 5. 3. 3. 2.]	60	108.19	108.42
63	[2. 2. 3. 5. 7. 9. 8. 8. 8. 8.]	60	108.34	108.58
64	[8. 10. 10. 8. 6. 4. 6. 4. 2. 2.]	60	108.37	108.60
65	[2. 3. 5. 7. 9. 9. 7. 8. 6. 4.]	60	108.49	108.72
66	[7. 8. 9. 9. 7. 5. 6. 4. 3. 2.]	60	108.51	108.74
67	[8. 8. 9. 7. 5. 3. 5. 7. 5. 3.]	60	108.57	108.81
68	[8. 8. 9. 7. 5. 3. 5. 7. 5. 3.]	60	108.57	108.81
69	[8. 8. 9. 7. 5. 3. 5. 7. 5. 3.]	60	108.57	108.81
70	[7. 9. 9. 8. 6. 4. 6. 5. 3. 3.]	60	108.70	108.93
71	[8. 9. 8. 8. 6. 4. 6. 5. 3. 3.]	60	108.77	109.00
72	[7. 9. 9. 7. 5. 3. 5. 7. 5. 3.]	60	108.82	109.05
73	[2. 2. 2. 2. 2. 3. 5. 7. 8. 8.]	41	109.09	109.09
74	[2. 2. 2. 2. 2. 3. 5. 7. 8. 8.]	41	109.09	109.09
75	[2. 2. 2. 2. 2. 3. 5. 7. 8. 8.]	41	109.09	109.09
76	[7. 7. 7. 8. 6. 4. 6. 7. 5. 3.]	60	110.61	110.84
77	[2. 2. 2. 2. 2. 3. 5. 6. 8. 8.]	40	111.11	111.11
78	[11. 9. 7. 5. 3. 3. 5. 7. 5. 4.]	59	111.60	111.60
79	[9. 7. 5. 3. 2. 4. 6. 8. 8. 8.]	60	111.41	111.64
80	[9. 7. 5. 3. 2. 4. 6. 8. 8. 8.]	60	111.41	111.64
81	[11. 10. 8. 6. 4. 2. 2. 3. 5. 4.]	55	112.58	112.58

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Table A.2 – continuation

No.	Optimised No. of Transporters	Sum of Trans- porters	Sum of MLP Output (Predicted Delayed Cases)	Objective Function Value
82	[10. 9. 7. 5. 3. 4. 6. 7. 5. 4.]	60	112.42	112.65
83	[9. 7. 5. 3. 2. 3. 5. 7. 8. 8.]	57	112.88	112.88
84	[9. 7. 5. 3. 2. 3. 5. 7. 8. 8.]	57	112.88	112.88
85	[8. 7. 5. 3. 5. 7. 9. 7. 5. 4.]	60	112.68	112.91
86	[8. 7. 5. 3. 5. 7. 9. 7. 5. 4.]	60	112.68	112.91
87	[9. 8. 6. 4. 2. 3. 5. 7. 8. 8.]	60	112.72	112.95
88	[9. 8. 6. 4. 2. 3. 5. 7. 8. 8.]	60	112.72	112.95
89	[9. 8. 6. 4. 2. 3. 5. 7. 8. 8.]	60	112.72	112.95
90	[10. 8. 6. 4. 2. 3. 5. 7. 7. 8.]	60	113.31	113.54
91	[9. 8. 6. 4. 3. 5. 7. 8. 6. 4.]	60	113.40	113.63
92	[2. 2. 2. 2. 2. 2. 3. 5. 7. 8.]	35	113.71	113.71
93	[2. 2. 2. 2. 2. 2. 3. 5. 7. 8.]	35	113.71	113.71
94	[2. 2. 2. 2. 2. 2. 3. 5. 5. 4.]	29	114.08	114.08
95	[2. 3. 5. 7. 7. 7. 7. 8. 6. 8.]	60	113.88	114.11
96	[11. 9. 7. 5. 3. 2. 3. 5. 7. 8.]	60	114.58	114.81
97	[7. 7. 5. 3. 3. 5. 7. 8. 7. 8.]	60	114.94	115.17
98	[3. 5. 7. 7. 6. 7. 7. 8. 6. 4.]	60	115.37	115.60
99	[8. 6. 4. 2. 4. 6. 8. 8. 6. 8.]	60	117.11	117.34
100	[8. 6. 4. 2. 4. 6. 8. 8. 6. 8.]	60	117.11	117.34

	Day of the week	Hour	As-planned number of transports in same hour	Amount of trans-porters in same as-is hour	Automatic rate according to as-planned hour
tensor([[	1.0000,	0.0000,	1.5165,	0.8242,	1.0000],
[	1.0000,	1.0000,	1.2527,	0.6813,	1.0000],
[	1.0000,	2.0000,	0.8846,	0.5989,	1.0000],
[	1.0000,	3.0000,	0.8022,	0.5714,	1.0000],
[	1.0000,	4.0000,	0.6264,	0.4121,	1.0000],
[	1.0000,	5.0000,	0.6154,	0.4835,	0.9578],
[	1.0000,	6.0000,	3.3626,	1.1209,	0.2268],
[	1.0000,	7.0000,	27.5714,	2.0000,	0.1566],
[	1.0000,	8.0000,	28.3242,	2.0000,	0.1405],
[	1.0000,	9.0000,	30.6978,	2.0000,	0.1538],
[	1.0000,	10.0000,	32.4011,	2.0000,	0.1475],
[	1.0000,	11.0000,	29.2253,	2.0000,	0.1511],
[	1.0000,	12.0000,	31.0385,	4.0000,	0.1556],
[	1.0000,	13.0000,	26.9890,	6.0000,	0.1695],
[	1.0000,	14.0000,	18.5549,	8.0000,	0.2985],
[	1.0000,	15.0000,	9.6538,	8.0000,	0.7746],
[	1.0000,	16.0000,	5.9341,	8.0000,	0.9728],
[	1.0000,	17.0000,	4.0879,	1.6978,	1.0000],
[	1.0000,	18.0000,	3.4451,	1.5330,	1.0000],
[	1.0000,	19.0000,	3.0220,	1.5714,	1.0000],
[	1.0000,	20.0000,	2.7198,	1.3846,	0.9994],
[	1.0000,	21.0000,	2.5275,	0.9231,	1.0000],
[	1.0000,	22.0000,	2.5055,	1.0000,	0.9940],
[	1.0000,	23.0000,	2.1264,	0.8407,	1.0000]])

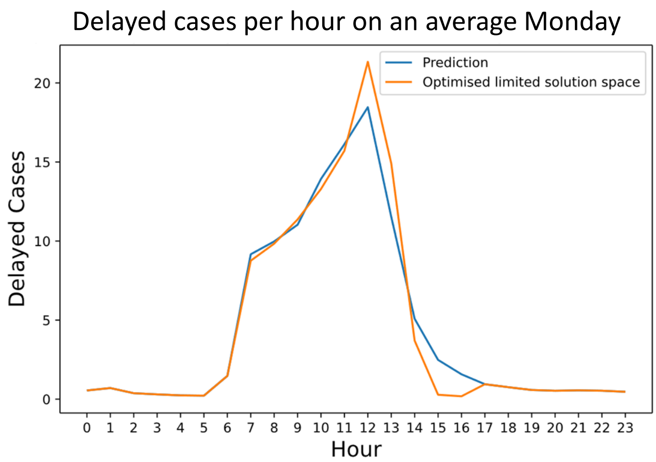

Figure A.25: Left: Original input tensor with mean values for an average Monday with adapted no. of transporters in 10 hours (according to Table A.2 no. 35 and no. 36). Right: Prediction (through MLP model) of delayed cases on an average Monday and and optimised (through GA) predicted delayed cases (own visualisation).

Day of the week	Hour	As-planned number of transports in same hour	Amount of trans-porters in same as-is hour	Automatic rate according to as-planned hour

```
tensor([[ 1.0000,  0.0000,  1.5165,  0.8242,  1.0000],
        [ 1.0000,  1.0000,  1.2527,  0.6813,  1.0000],
        [ 1.0000,  2.0000,  0.8846,  0.5989,  1.0000],
        [ 1.0000,  3.0000,  0.8022,  0.5714,  1.0000],
        [ 1.0000,  4.0000,  0.6264,  0.4121,  1.0000],
        [ 1.0000,  5.0000,  0.6154,  0.4835,  0.9578],
        [ 1.0000,  6.0000,  3.3626,  1.1209,  0.2268],
        [ 1.0000,  7.0000, 27.5714,  2.0000,  0.1566],
        [ 1.0000,  8.0000, 28.3242,  2.0000,  0.1405],
        [ 1.0000,  9.0000, 30.6978,  2.0000,  0.1538],
        [ 1.0000, 10.0000, 32.4011,  2.0000,  0.1475],
        [ 1.0000, 11.0000, 29.2253,  2.0000,  0.1511],
        [ 1.0000, 12.0000, 31.0385,  2.0000,  0.1556],
        [ 1.0000, 13.0000, 26.9890,  3.0000,  0.1695],
        [ 1.0000, 14.0000, 18.5549,  5.0000,  0.2985],
        [ 1.0000, 15.0000,  9.6538,  5.0000,  0.7746],
        [ 1.0000, 16.0000,  5.9341,  4.0000,  0.9728],
        [ 1.0000, 17.0000,  4.0879,  1.6978,  1.0000],
        [ 1.0000, 18.0000,  3.4451,  1.5330,  1.0000],
        [ 1.0000, 19.0000,  3.0220,  1.5714,  1.0000],
        [ 1.0000, 20.0000,  2.7198,  1.3846,  0.9994],
        [ 1.0000, 21.0000,  2.5275,  0.9231,  1.0000],
        [ 1.0000, 22.0000,  2.5055,  1.0000,  0.9940],
        [ 1.0000, 23.0000,  2.1264,  0.8407,  1.0000]])
```

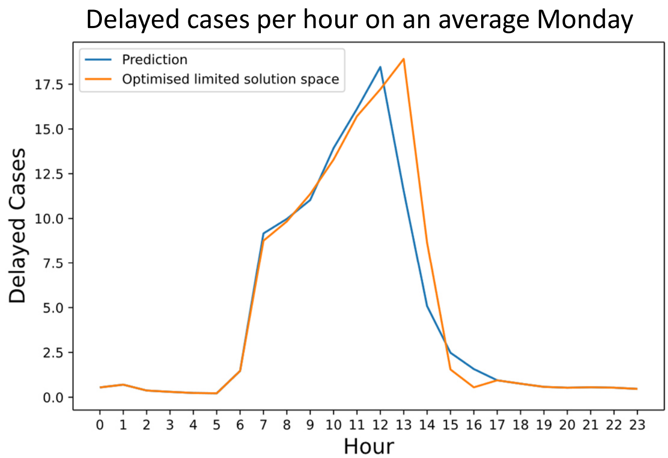

Figure A.26: Left: Input tensor with mean values for an average Monday with adapted no. of transporters in 10 hours (according to Table A.2 no. 94). Right: Prediction (through MLP model) of delayed cases on an average Monday and optimised (through GA) predicted delayed cases (own visualisation).