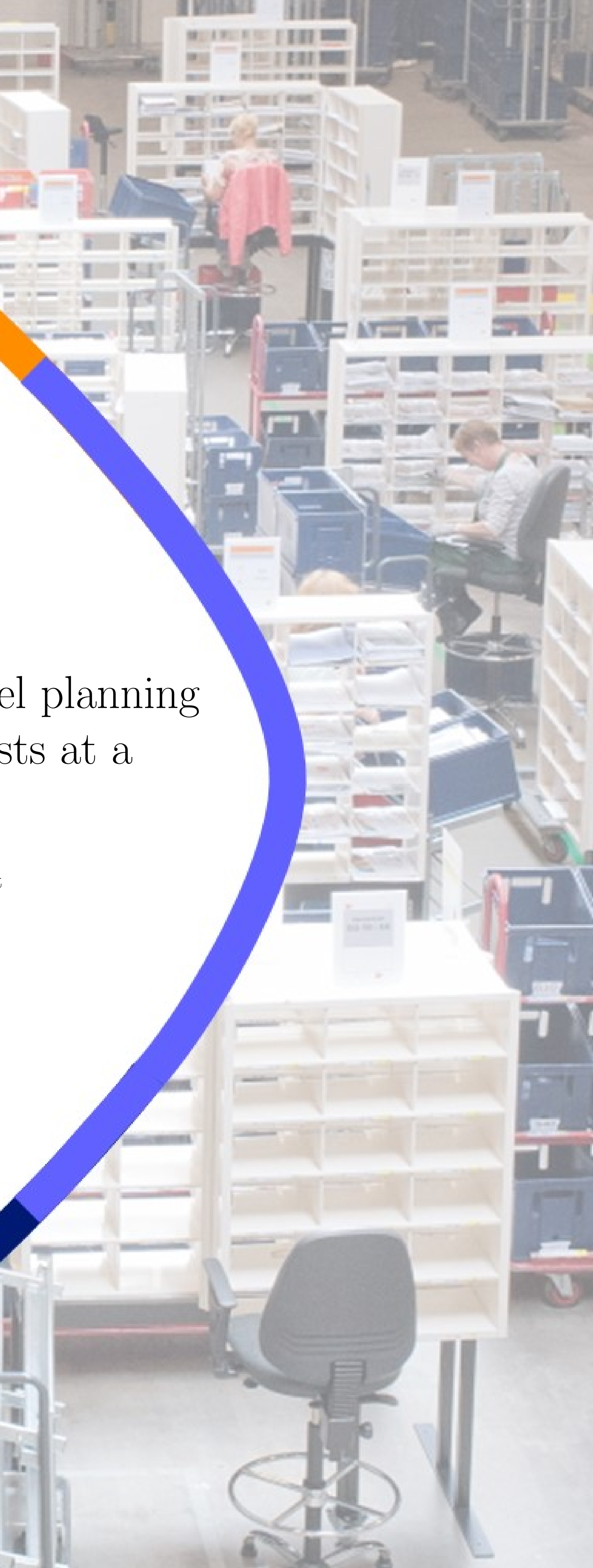

Optimising employee level planning to minimise employee costs at a postal company

Master Industrial Engineering and Management

Hanna Sturm
December 2024

Master thesis Industrial Engineering and Management

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Preface

Dear reader,

In front of you lies my master thesis 'Optimising employee level planning to minimise employee costs'. This thesis marks the end of my student life and studies Industrial Engineering and Management at the University of Twente. Despite a big part of my studies happening during Corona, I am very grateful for the amazing time I had in Enschede. I had the opportunity to develop myself professionally and personally.

First, I would like to thank my first supervisor Wouter van Heeswijk. Thank you for always providing me with valuable feedback and future steps to tackle my problems. I would also like to thank my second supervisor, Engin Topan, for taking the time to read my report and providing useful feedback.

Secondly, I want to thank my supervisors and colleagues from PostNL, Milou Pulles and Arjen Leenheer. We had interesting discussions about the company and the research. They showed me many interesting logistical processes and invited me to interesting meetings. There was always a possibility to explore my interests within the company.

Lastly, I want to thank my friends and family for always supporting me through my studies. Special thanks to my boyfriend for helping me through the hard times during my thesis. A big thank you to my study friends that I made along the way, and especially to the girls who were there with me from the beginning. Lastly, I want to thank everyone from Xoxotywka for always making me laugh.

I hope you enjoy reading this thesis.

Hanna Sturm
Enschede, December 2024

Management summary

This research is conducted at MailNL, the mail processing department of PostNL. At MailNL, multiple logistics processes are performed daily to process the mail and postal packages: collecting, sorting and preparation, and delivery. The focus of this thesis is on the preparation process, where the sorted mail is manually prepared for delivery by employees. There is a mismatch between the scheduled employee hours, where manual labour is performed during the preparation process, and the daily mail demand. Because the scheduled hours do not correspond to the demand, there are high employee costs because employees differ from their contract hours by overworking and leaving work earlier than planned. The employee costs consist of minus hour costs if an employee works fewer hours than their assigned contract per week and plus hour costs if an employee works more hours than their assigned contract per week. The mismatch is mainly caused by fluctuating demand throughout the week and year and the lack of fitting planning for this changing demand. This research aims to answer the following main research question:

"How to improve PostNL's employee level planning for the preparation process to include weekly and yearly demand volume fluctuations in the current and future situation to minimise the excess employee costs?"

A literature review was performed on workforce problems and the postal services industry. From the literature, we distinguished four phases in workforce management: workload prediction, staffing, shift generation and employee rostering. We approached the problem from a tactical level, and thus, we focused on the first two phases of workforce management: workload prediction and staffing. We chose Winter's forecasting model to incorporate the yearly and weekly seasonality pattern and the decreasing trend shown from historical data. Next, to perform the staffing phase, we developed a mathematical model based on the models from Villarreal et al., 2015 and Bard et al., 2003. Villarreal et al. includes elements to deal with flexible demand and focuses on minimising overall costs for scheduling employees and processing demand, while Bard et al. focuses on minimising the total number of employees in a postal environment. These models are combined and extended with different employee contract types to develop our mathematical model. The objective of the mathematical model is to minimise the employee costs in relation to their contracts, the costs for the total number of employees, and the demand costs for moving demand to another day. The objective is restricted by planning constraints, which ensure that employees are planned according to the labour and operational rules. The solution is also restricted to always attaining the minimum assigned service level of demand.

We executed multiple experiments on the mathematical model to investigate scenarios, and we researched how the model performed. The scenarios were set up according to the interests of the company and to investigate the performance of the model. The scenarios showed that the runtime performance of the model depends highly on the variation of demand every week. A small problem instance was used as input for a stochastic version, and it was shown that stochasticity could be included for smaller problem instances within a reasonable time. Results from the mathematical model indicate a significant potential for cost savings. For an average demand scenario, 425 employees with 20-hour contracts are optimal, which would reduce current costs by approximately 44.9%, amounting to a saving of 380,250 euros for 4 weeks. These consist of 1000 fixed hiring costs per employee, and the rest are variable plus and minus hour costs. The cost savings occur because more employees are hired, which causes drastically fewer plus hours, and the minus hours are also reduced. In the current situation, the scheduling on the operational level still needs improvement, and therefore, there is a significant difference in the minus hours in comparison with the proposed solution. In reality, there will be extra costs made on the operational level because of planning errors and hiring to accommodate different levels of employees, and thus, the actual cost savings will be lower. We also conclude from demand scenario analysis that the number of employees increased or decreased at almost the

same rate as the demand changed. Because of this relation, the planners can adjust the number of employees that are needed on the operational level easily to accommodate for last-minute changes in demand volumes instead of having to run the model again.

To account for different demand levels during a year, we divided the demand during a year into periods of low, average and high demand. We identified that in high-demand periods, staffing should ideally include 645 employees on 20-hour contracts and 51 on 5-hour contracts, while low-demand periods require only 266 employees on 20-hour contracts to accommodate the demand. The combination of these periods should be used as an employee-level plan to guide the employee levels throughout the year. The findings provide actionable insights into seasonal hiring practices, guiding MailNL on workforce adjustments throughout the year. [redacted]

Implementing this model will enable MailNL to reduce excess costs and optimise workforce planning based on demand forecasts. To conclude, MailNL can improve its employee-level planning by adjusting the total number of employees and their contracts to the advised numbers during the different demand levels throughout the year. During the year, the hiring of MailNL and flex employees can be guided by the advice for the number of employees for high and low demand during the summer and Christmas holiday periods which causes the employee costs to be almost halved.

Contents

1 Introduction

This research is conducted at PostNL and focuses on reducing employee costs. The research aims to improve personnel planning by providing a workforce planning model. This chapter introduces the company and the problem. Section 1.1 describes the company of this research. Section 1.2 describes the research motivation for the research problem described in Section 1.3. Finally, Section 1.4 elaborates on the research design.

1.1 Company description

This section will introduce the company and the different departments working together. This research was performed at PostNL. Since 1799, PostNL has been delivering the national post in the Netherlands and later also packages. More than 40,000 employees work there, and the company delivers to more than 190 different countries. The company's key activity is delivering and sending mail and packages throughout the Benelux. Their goal is to do this simple, smart and together (Koninklijke PostNL, 2024b). Nowadays, the company is doing more than only delivering and sending items. The focus is on providing the best experience for the customer by performing extra services. Figure 1.1 shows the different types of services that PostNL offers aside from parcel and mail delivery.

The company PostNL comprises multiple departments that are all part of this organisation. The different departments are also shown in Figure 1.1. PostNL is separated into mail delivery (MailNL) and parcel delivery (Packages and Logistics). Both of these departments are in contact with Customer Excellence. Lastly, a separate department, Cross Border Solutions, also oversees the company's international position. In this research, we will focus only on the department MailNL. This department takes care of receiving, sorting and delivering about 6.9 million letters and small packages per day on average (Koninklijke PostNL, 2024a).

Figure 1.1: The services that PostNL offers and our focus lies on the mail delivery (Koninklijke PostNL, 2024a).

At MailNL, all the different mail and small postal packages are handled. This is done in three different processes: collection, sorting and preparation and lastly delivery. First, the mail is collected and brought to a sorting centre. There are 5 sorting centres and 11 preparation locations which make a total of 16 locations. These locations are grouped per region. At the sorting and preparation locations the mail and small packages are sorted and have to be bundled for delivery. This bundling is called the preparation process, which happens to prepare the mail and small packages for delivery at the sorting and preparation locations. After the mail is sorted and prepared at the sorting centre, it leaves the centres to be delivered to customers' homes.

1.2 Research motivation

This section explains the motivation behind this research. Earlier this year, there was a reorganisation within a department of the company, MailNL. The result was that responsibilities shifted between employees at the managerial level. Before the reorganisation, a team manager was responsible for the production line within one location. This manager ensured the line was running smoothly and was concerned with recruiting, planning and retaining their personnel for that line. So, the team manager took care of both the logistics and the people side of running the line. The reorganisation resulted in a division between logistics and people management, and the responsibilities were also divided accordingly. People managers are now responsible for recruitment, development and handling of absences of personnel. In comparison, logistics managers focus only on the operational processes of the production line. With the employees that are scheduled for that preparation shift, the logistics managers ensure that all tasks are completed and especially on time. The responsibility of scheduling employees has been handed over to another department within MailNL, the Service Center Operations (SCO). Because of this significant shift in responsibilities, specific and unaddressed problems that had not been discovered before have now risen to the surface. Figure 1.2 shows a simplified representation of the connections between departments to compare the old and new situation.

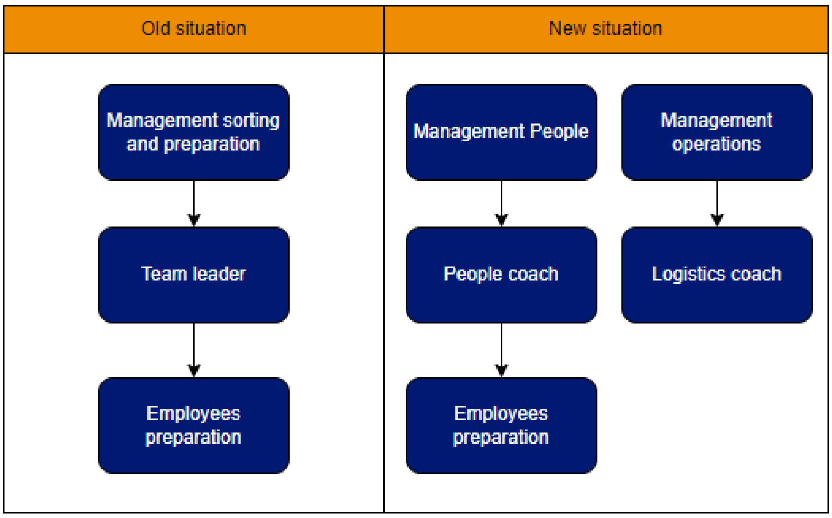


Figure 1.2: A simplified overview of the connections between departments in the old and new situation. The new situation shows the division between the people and logistics responsibilities.

1.3 Problem identification

This section contains the research problem and provides a better understanding of the problem context. It consists of first the action problem, described in Section 1.3.1. The core problem with the corresponding problem cluster is explained in Section 1.3.2.

1.3.1 Action problem

This section explains the action problem. There are multiple processes in handling the mail; the mail is sorted, then prepared for delivery, and finally, delivered to the customers' homes. In all of these processes, employees are involved in working at machines or performing manual labour, and mainly fixed employees are involved. Especially in the process of preparing the mail, there is a spike in employee costs. These employee costs are twofold. First, an employee can work more hours in a month than the original contract hours of that employee; these hours are called plus hours. These overtime hours are paid at the regular hour rate. On the other hand, some employees work fewer hours in a month than their fixed contract hours; these are minus hours. However, because of regulations, MailNL is still obliged to pay the fixed contract hours for these employees even when they work fewer hours.

According to Heerkens and Winden, 2017, the definition of an action problem is stated as follows: "An action problem is a discrepancy between the norm and reality as perceived by the problem owner". Therefore, the problem should contain the following three elements: norm, reality and problem owner. In our case, the difference between norm and reality is noticed in the increase in money spent on employee hours. On one hand, an employee is paid for more hours than they have actually worked; on the other hand, an employee is paid for working overtime.

The increase in these costs has been noticed in comparison to the old situation by the management. The problem selected to solve in this research is the following action problem.

"MailNL pays high costs for the minus and plus hours of employees at the preparation process."

1.3.2 Core problem

We set up a problem cluster from the action problem's starting point, and the cluster is discussed in this section. The cluster presents the problems and their corresponding connections. Figure 1.3 shows the problem cluster.

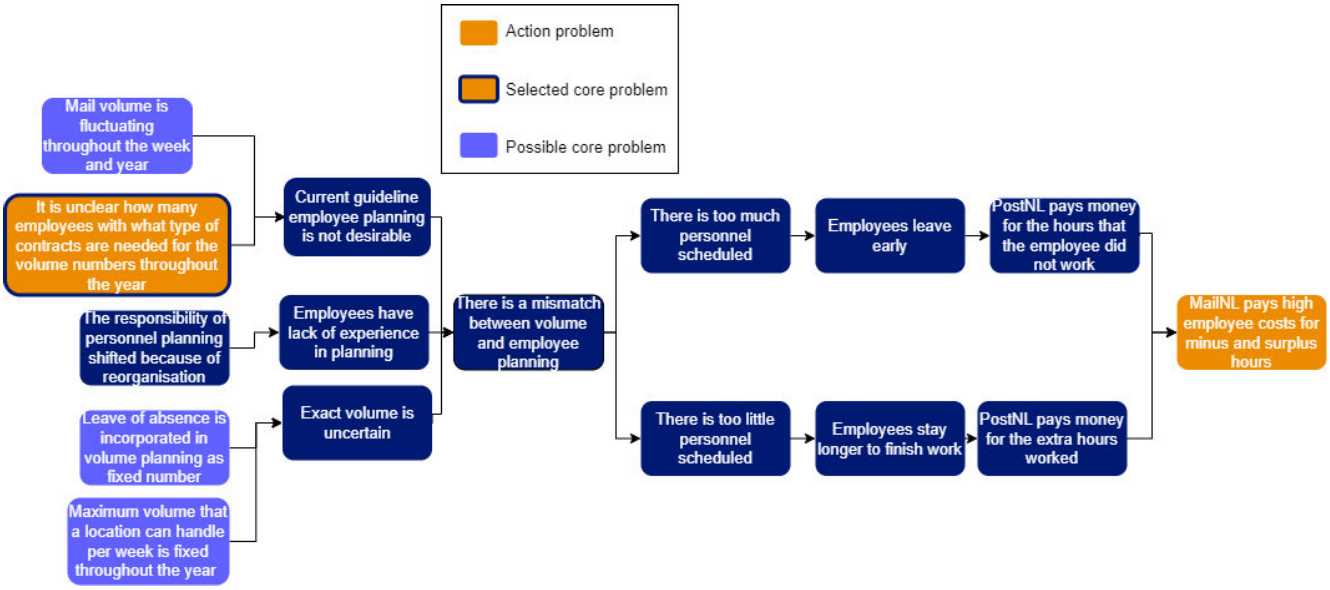


Figure 1.3: Problem cluster which shows the chosen core problem: "It is unclear how many employees with what type of contracts are needed for the demand volume numbers throughout the year".

The action problem, as shown on the right-hand side of Figure 1.3, is caused by two main things. First, by the fact that employees work overtime and second, that employees work fewer hours than their contract. These are rooted in the problem of planning too little or too much personnel. The mismatch between mail volume and employee planning causes the wrong planning. This problem has multiple causes, which can all be considered a possible core problem.

The first potential core problem is that the volume fluctuates heavily throughout the year and week. During the year, there are peak moments around certain periods, such as the Christmas holidays or during government elections. The volume fluctuates during the week, as on Tuesday, the highest volume number decreases slowly during the rest of the week. We cannot influence this problem; therefore, it is not our chosen core problem.

Secondly, we have the possible core problem that it is unclear how many employees are needed to cover the volumes during a year. Currently, MailNL experiences that there is a mismatch between the contract hours of employees and the volumes processed at the annual level. The demand volumes fluctuate throughout the year and thus the level of employees is difficult to match to this fluctuating numbers. It is unclear if the current contract hours and number of employees fit the current volumes. This problem can be influenced and has a potentially large impact.

Another possible core problem, is the responsibilities that shifted. The shift in responsibilities caused that there is knowledge lost and the current employees have a lack of experience in planning. This is something that we cannot influence, as the reorganisation will not be changed back. Therefore this problem is not selected as our core problem.

Lastly, the maximum volume a location can handle per week is a fixed number of volumes throughout the year. The volume planners use this number to indicate how much a location could handle, and this guides their volume planning. This maximum volume is a fixed number and does not fluctuate with the employee's availability or leave of absence. This possible core problem is also shown in the problem cluster, the leave of absence incorporation in the volume planning. These two issues are not addressed as our core problem. The reason for this is that they relate specifically to the accuracy of planning. However, it is important to note that the overall volume planning functions relatively effectively despite these issues.

The problem of an unclear match between volume and employees is chosen as our core problem because it can result in great insights and improvements. Especially with future changes that MailNL will experience in their way of working, this could result in guidance for employee planning.

1.4 Research design

In this section, we explain the approach to solving this problem. First, Section 1.4.1 describes the scope, we state the research questions in Section 1.4.2, followed by the deliverables in Section 1.4.3.

1.4.1 Scope

This research will focus on the preparation process within MailNL. Collection or delivery could have been included, but providing a solution is most beneficial in the preparation process. It was also established before this research that this process has the biggest difference in minus and plus hours measured. Aside from the costs, the preparation process has a crucial role within all the processes, and therefore, there is also a lot to gain in increasing effectiveness.

We approach the problem from a tactical level. This concerns the medium-term company plans. At the tactical level, the most impact can be gained at the moment. The planners are still adjusting their way of working, at the operational level, to their new responsibilities,s, and this situation is not stable yet. The stabilisation is also guided by other employees who are already helping with adjusting the process. Therefore, it is more relevant for this research to look into the tactical level.

This research only focuses on the fixed employees at MailNL. In the preparation process, there are also flexible employees involved, but there is no data available about this, and therefore it is not included in this research.

1.4.2 Research questions

This section introduces the research questions. From our problem cluster and chosen core problem, we define the following main research question:

"How to improve PostNL's employee level planning for the preparation process by incorporating weekly and yearly demand volume fluctuations in the current and future situation to minimise the excess employee costs?"

To answer our main research question and thus solve the core problem, research is conducted by answering sub-questions. The questions structure the research and are formulated as follows:

1. How is employee planning for the preparation process currently organised at MailNL?
   (a) What does the mail preparation process look like, and how is the employee planning organised?
   (b) What does the decision-making process for planning employees look like?
   (c) What role does volume planning play in employee planning at preparation, and what are the volume fluctuations?
   (d) What are the proposed modifications to the preparation process for the future situation at MailNL

   Chapter 2 will answer the first research question and aims to gather insight into MailNL's current processes. It explores the preparation work process itself. Furthermore, it researches the current way of planning employees and the factors that influence the planning.

2. What employee planning methods from literature can be applied to the problem at MailNL?
   (a) What employee planning problems are present in the literature, and how can we classify the planning problem at MailNL?
   (b) What models and methods are available within the literature for constructing employee planning?
   (c) What solution approaches can be used to solve the planning problem at MailNL?

   In Chapter 3, we perform a literature research to answer these questions. First, the problem at hand will be classified according to the literature. The literature will be searched for methods to solve the type of problem and find a fitting method or model to apply to our problem.

3. How can the employee planning of PostNL be modelled as a mathematical model to determine the minimum number of employees needed to satisfy the demand service level while minimising employee and demand costs?
   (a) What input data is required for the mathematical model?
   (b) What modelling assumptions and simplifications do we make?

(c) How can the mathematical model be formulated to determine the minimum number of employees and minimise employee and demand costs?

(d) How can the future changes at MailNL be modelled to determine the minimum number of employees and minimise employee and demand costs?

In Chapter 4, a data analysis is done to gather insights about the available data. The insights are necessary for making choices in the solution design. Chapter 5 combines the knowledge gained in Chapter 3 from the literature and in Chapter 4 from data analysis to construct a mathematical model. It explores the assumptions and required data. The viewpoint of future changes is also considered.

4. What solutions are proposed for different problem scenarios by the mathematical model and how does the model perform?

(a) Which problem scenarios are interesting to be investigated, and what are the corresponding outcomes?

(b) How does the model perform in comparison to reality?

(c) How can the results of the mathematical model be validated?

(d) How sensitive is the performance of the proposed mathematical model to changes in the input parameters?

Chapter 6 tests the model's performance and compares it to reality. The experiments provide insights into employee planning. In addition, the future changes of MailNL are also considered.

5. What conclusions and recommendations can we give to MailNL based on the outcomes of the mathematical model?

(a) How can the model be used by MailNL?

(b) What are the main conclusions of this research?

(c) What are the main recommendations resulting from this research?

(d) What are the limitations of this research, and what are the subjects for further research?

(e) What are the theoretical and practical contributions of the research?

The last chapter 7 elaborates on the implementation, main conclusions of this research and the recommendations. The limitations and future research topics are discussed.

1.4.3 Deliverables

The research questions will be answered at the end of this research, and the following deliverables will be delivered.

- A mathematical model to determine the number and type of contracts necessary for the fluctuating volumes with regard to the service level.
- Guidelines for use for the tactical planning of employees.
- Insights into the necessary number of employees in the future situation for MailNL.
- Guide on how to implement the model.
- Recommendations and conclusions on minimising the employee costs for the preparation process.

2 Context analysis

This chapter provides a context analysis of the current situation at MailNL and answers the first research question posed in Section 1.4:

"How is employee planning for the preparation process currently organised at MailNL?"

This is done by answering the sub-research questions that were constructed. In Section 2.1, the activities of the preparation process are explained. This is followed by the explanation of the planning of employees in Section 2.2. In Section 2.3, the decision-making process surrounding employee planning is explained. This is followed by a description of the future plans of MailNL in Section 2.4. The last Section 2.5 concludes this chapter.

2.1 Preparation process

To understand the preparation process, it is also essential to know how and what type of mail is delivered to the preparation process; therefore, the sorting process is explained globally. During the night, the incoming mail is sorted with different types of machines at the five sorting centres. There are three different levels of sorting. The first sorting process is regional sorting, in which a division is made between the mail for the region of that sorting centre and the mail that belongs to other regions. The mail of that region is already sorted into mail packages and bigger mail items, and standard-sized letters. The second sorting process is in which intermediate sorting products for that region are sorted into end sorting products and intermediate sorting products. The intermediate sorting products then move on to the third and last sorting process. The standard-sized letters are processed in the third sorting based on the delivery people's walking route. After the second and third sorting, all the sorted mail, the big mail from the second sorting and the small mail from the third sorting, moves on to the preparation process. In the sorting process, every piece of mail receives an individual label printed on the mail piece, which is used for the sorting and preparation. This label consists of the route number that this piece is a part of and the sequence of the delivery walking route. The different sorting and types of mail are shown in an overview in Figure 2.1.

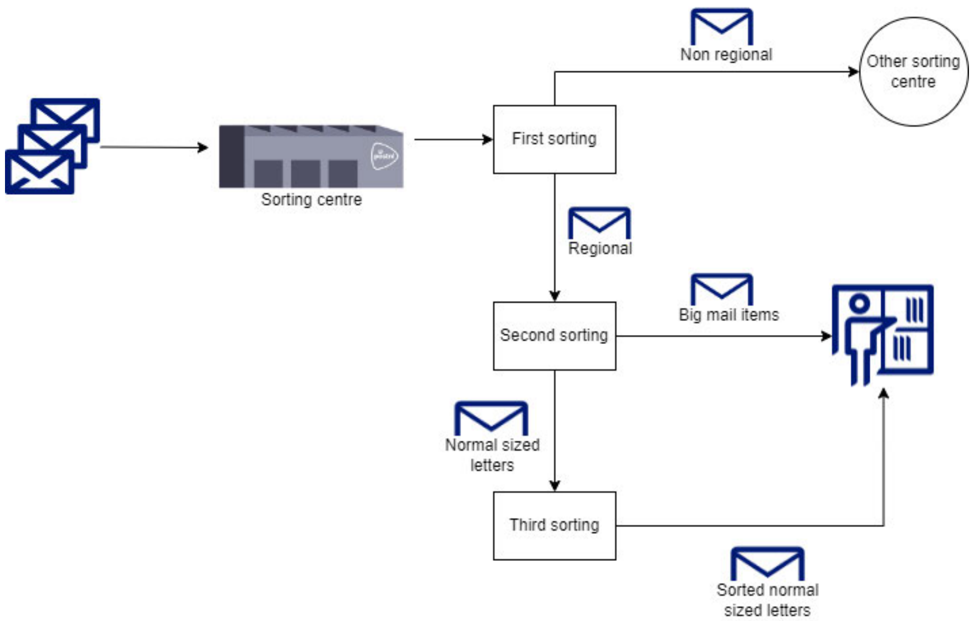


Figure 2.1: The sorting and preparation process which shows the different mail sortings that arrive at preparation

During the preparation process, people work in units. There is a total of 174 units at the 16 locations. One unit consists of eight sorting cabinets; four cabinets are placed on the opposite side of the other four. At every sorting cabinet, one person is stationed to work during their shift, and each sorting cabinet consists of 100 shelves. At every unit, a mail handler is also stationed. This employee has the responsibility of dividing the mail between the other employees of that unit and making sure that the processed mail is correctly placed for internal transport. In between dividing and moving the mail, the mail handler also works behind a sorting cabinet. Behind a sorting cabinet, the two types of sorted mail are collated. This is done based on the printed label on the pieces of mail. The shelf number of the cabinet is printed on the mail, followed by the sequence of all the mail on that same shelf. The mail from the shelves is bundled with elastics and put into a delivery bag. The internal transport employees of MailNL then move the delivery bags to the pickup place for transport and then the bags are ready for delivery. This coordinated process ensures that mail is efficiently sorted, bundled, and transported, ensuring that all incoming mail is processed.

The preparation process consists of a morning process, the 24H process, and an afternoon process, the N24H process. In the morning, all the mail that needs to be delivered within 24 hours is processed. Employees work in shifts from 5.00 to 10.00 in the morning and from Tuesday until Saturday. The afternoon process takes care of the mail, which has a longer delivery window than 24 hours, for example, large magazine contracts. Employees work from 10.00 in the morning to 17.00 in the afternoon, and the shifts are from Monday until Thursday. The main difference between these two processes is that in the 24H, there is a strict planning with deadlines to ensure that the mail leaves on time for the different locations. This mail of the morning process is delivered on that same day and should, therefore, leave on time.

2.2 Employee planning

The actual planning of employees is done by the department Service Center Operations (SCO). Every sorting centre has its dedicated human planner of the SCO department that plans employees for that region at the central and decentral locations. The planner schedules the employees at an appointed unit, and usually, every unit also needs a mail handler, which should also be scheduled.

The SCO planner is responsible for the planning of employees, while there is a separate volume planner who schedules the volumes for a location throughout the week. On each Wednesday, a first draft schedule of the weekly volume planning is communicated to the SCO planner. This planner can then start to make a weekly employee schedule for the preparation process. On Thursday and Friday, revised versions of the volume plannings are sent to the SCO planner. The SCO planner makes a schedule per payment period, and every week, this is made in more detail by making a weekly plan.

There are two different schedules: one for the morning process, 24H, and one for the afternoon, N24H. The primary guideline used in the planning is that an employee can process 165 mail pieces per hour in the morning process and 450 pieces per hour in the afternoon. This number can fluctuate greatly depending on the employee's experience and productivity. This working speed is something that employees build up in their first working period.

In the morning schedule, the volume is more fixed because of the strict mail deadlines. There a an stable volume that is processed in the morning, and the hard deadlines are based on these volumes and the corresponding working speed. Therefore, there is little room for assigning extra volume. Thus, the guidelines for the 24H process are based on the fluctuating volumes throughout the week. On Tuesday, the highest volumes are processed because of e-commerce orders made over the weekend, and the volume decreases during the rest of the week. The exact values can be seen in Table 2.1a. For the afternoon process, there are also guidelines which are

Table 2.1: The employee planning guidelines

(a) Employee planning guidelines for the 24H preparation process per unit

	Number of employees per unit
Tuesday	8
Wednesday	7
Thursday	7
Friday	6
Saturday	5

(b) Employee planning guidelines per day for the N24H preparation process per unit

Volume lower and upper bounds (Pieces)	Number of employees
616 - 2665	1
2666 - 4715	2
4716 - 6765	3
6766 - 8815	4
8816 - 10865	5
10866 - 12915	6
12916 - 14965	7
14966 - 17015	8
17016 - 19065	9

linked to the volumes. A SCO planner uses the guidelines and looks at the number of people available per week to schedule people. The exact values for the afternoon guidelines are shown in Table 2.1b.

2.3 Decision-making process

In the planning of employees, there are many different parties involved, and this section enlightens the decision-making and responsibilities between them. A representation of the process is also shown in Figure 2.2.

The volume planner makes the initial weekly volume planning per unit. This planning is communicated to the SCO planner, who makes a personnel plan based on this. Then, the manager chain optimisation receives the personnel and volume planning and is responsible for looking into the match of volume and personnel planning. If needed, the manager asks for adjustments in the flexible volume part of the volume planning. The volume planner has insights into the flexible and fixed volumes and can adjust the schedule.

When the employee schedule for a week is done, the SCO planner takes their hands off the execution of the schedule. The logistics coach of the preparation process receives the employee and volume planning per unit and also oversees if employees are absent on that current day. It is their responsibility that all mail is processed in the preparation process, and thus, they shift employees between units to evenly distribute the employees over all units. Each unit handles its mail volumes with the employees that are working in that unit and when a unit is not meeting the time deadlines, employees from other units help. The shifts of employees between units are fed back to the SCO planner to process in the system.

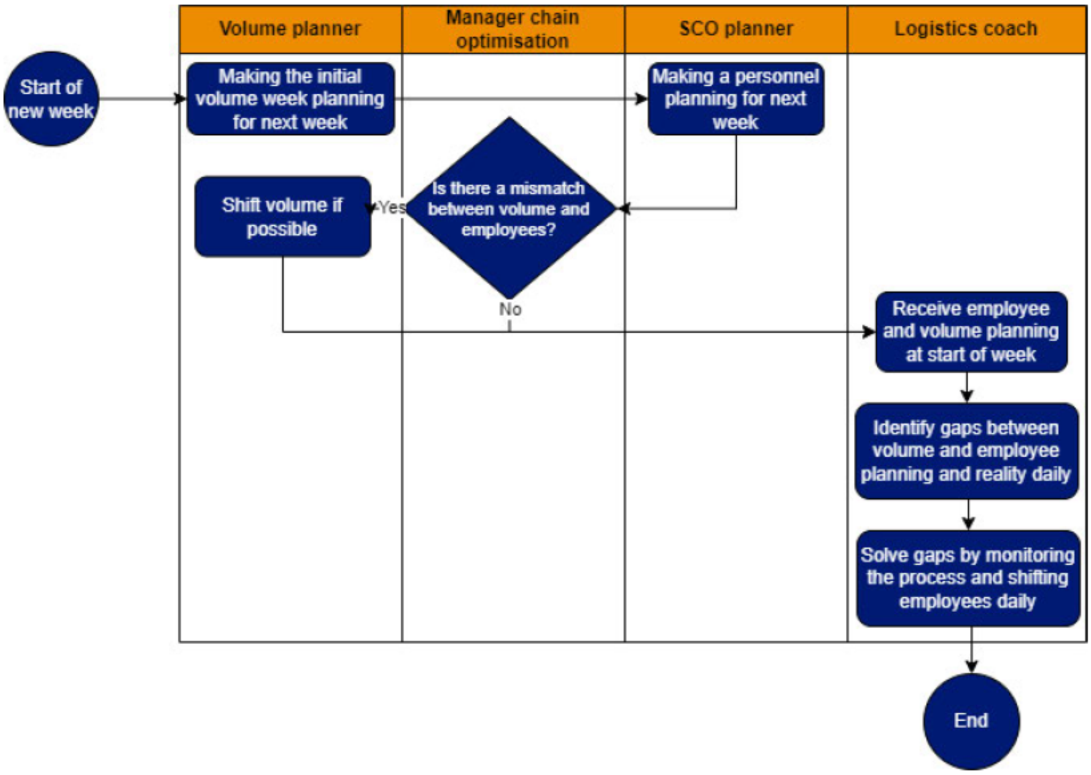


Figure 2.2: Decision-making process around making the employee planning for the preparation process per week. The different interactions between the employees for planning are shown.

2.4 Future plans

[redacted]

2.5 Conclusion

This chapter offers an overview of the current situation at MailNL. This is done by answering the research question: *"How is employee planning for the preparation process currently organised* *at MailNL?"*. In this chapter, a description of the sorting and preparation process is given. The sorting process sorts the mail in different steps and processes. The preparation process consists of bundling the different sorted mail flows together to prepare the mail for delivery. A weekly volume planning is provided by the volume planners and the SCO planners schedule the employees for this demand. The manager chain optimisation makes the match between the planned volumes and employees and makes any last adjustments. The different guidelines for planning were discussed for the morning and afternoon process. A description of the decision-making process regarding the planning and how the logistics coach does the final operational planning was provided. [redacted]

3 Literature review

This chapter dives into the literature to answer our next research question:

"What employee planning methods from literature can be applied to the problem at MailNL?"

In Chapter 1, we determined the core problem is unclarity about the number of employees necessary for the volume numbers throughout the year. The focus lies on the mismatch between the number of employees and the volume of mail during a year. In this chapter, we will look into the literature on how to approach and solve this problem.

First, the different types of employee planning problems are identified, and our research problem is classified. This is done in Section 3.1. This is followed by a literature review of models and methods available for constructing employee planning. Then, Section 3.2 states literature about workforce management solution methods. Section 3.3 describes scheduling and planning research in the postal services context. The literature from Section 3.2 and Section 3.3 is analysed to find models that could be suitable for our situation in Section 3.5. Lastly, Section 3.6 gives the conclusions of this literature review.

3.1 Problem classification

This section will classify the type of problem at hand in this research. This consists first of determining what characteristics the problem has in Section 3.1.1. Secondly, it is important to classify the decision-making level that we are dealing with in Section 3.1.2. Lastly, the type of employee planning problem is determined in Section 3.1.3.

3.1.1 Problem characteristics

To classify the problem, we look at what characteristics the problem contains. The first distinction in the type of problems is made in deterministic or stochastic. A deterministic problem considers input that is known with certainty, while a stochastic problem deals with uncertain input that is represented by a probability distribution (Poler et al., 2014). Our problem contains stochastic elements because of uncertain demand but we choose to approach it deterministically. This is done because the stochastic formulation could become computationally intensive for our large problem size. Aside from this, there is no data available for the future situation, and thus, there would be no input for this stochasticity; because of these reasons, we approach the problem deterministically. The second distinction is between static and dynamic. When a fixed decision is made at a specific time, and the model parameters do not change over time, this is called static (Ziukov, 2015). Within a dynamic context, decisions are made at multiple decision stages because more information is available after each stage (Ojeda Rios et al., 2021). In a scheduling context, this means that jobs arrive after a fixed time interval in a static environment, while in a dynamic context, jobs arrive randomly at a machine Amjad et al., 2018. Our problem concerns a fixed decision which is evaluated over time and therefore it can be classified as static. Lastly, the distinction is made between online and offline decision problems. Online problems concern decisions that are made without knowledge of the future. It is involved with monitoring processes and making decisions while events happen (Kalai & Vempala, 2005). Offline problems concern the planning of operations in advance with prior knowledge (Atoui et al., 2018).

Another characteristic of our problem is how to classify the type of demand that arrives at the company. A part of the demand is from contracts with customers; this demand is known precisely beforehand. The contract exists of the volume that the customer wants to send and within what time frame this volume should be delivered. The other and more significant part of the demand is the mail that is collected throughout the region. The volume of this collected mail is not known with certainty, and therefore, MailNL predicts the volume based on historical data. The customer demand at MailNL is deterministic because it is known beforehand. The collected mail part can be classified as stochastic because it is not entirely known beforehand.

The part of the demand that has a predetermined time frame for delivery is often called the grace period or defined as the demand time-window (Lee et al., 2001). This is a time window during which the mail can be delivered, and there is no penalty received. This part of the demand can be seen as flexible demand, as the day on which it is scheduled can be changed most of the time.

3.1.2 Planning or scheduling

The next step in the problem classification is establishing the decision-making level of the problem. We determine whether we are dealing with a scheduling or planning problem. A strict distinction between these concepts is made by Bopalia, 2023. The focus of planning is on the overall project goals and how to create value. In comparison, scheduling is focused on assigning tasks to available resources for a specific time duration. Planning deals more globally with the what and how of a project, while scheduling looks at the when and who. Badejo and Ierapetritou, 2022 shows that planning is commonly associated with the strategic and tactical level for long- and midterm planning, while scheduling is associated with the operational level, the short-term planning. As we determined in Section 1.4.1, this research is approached from the tactical level and not the operational. Therefore, this research is concerned with planning and not scheduling. Tactical planning addresses the organisation of the execution, and decisions are made on a longer planning horizon than in operational planning. The planning horizon length is somewhere between the strategic and the operational levels. With tactical planning, there is less demand certainty than in operational planning, but because of the planning horizon length, there is more flexibility (Hans et al., 2012).

3.1.3 Workforce problem

To further specify what type of planning problem we have, we review the literature of Hans et al., 2012. The different managerial levels of planning are considered, and two are shown in Table 3.1. The managerial level of resource capacity planning addresses the dimensioning, planning, scheduling, monitoring and control of renewable resources. Therefore, this is the level that this research is focused on. On a tactical level, the following examples are mentioned: block planning, staffing, and admission planning. The literature of Hans et al., 2012 is mainly focused on the healthcare sector but the examples can also be applied to other research fields.

In the overview in Table 3.1, a distinction is made between Workforce planning on a strategic level and staffing on a tactical level. In comparison to this, De Bruecker et al., 2015 argues that workforce planning defines when and how many employees should be available to work and what shift times the employees should work. Therefore, workforce planning is a combination of staffing and planning decisions. For this research, the focus is on the match between demand values and the number of people necessary to achieve minimum service levels. Therefore, this problem is addressed as a workforce planning problem. “A workforce management problem in service industries is to determine how to allocate engineers to jobs such that the service demand can be satisfied as much as possible at minimum costs.” (Yang, 1996) The problem is focused on the match between service capacity and service demand, and when this is a mismatch, it results in losing customers or wasting resources. According to the classification in Table 3.1, this problem would fit partly with demand planning on a tactical level and with workforce planning on a strategic level. Demand planning is also necessary to be able to determine the workload and, from this, determine the necessary workforce. So, the type of employee planning problem in this research is workforce planning.

Table 3.1: Examples for planning at different managerial areas and hierarchical levels (Hans et al., 2012). Our focus lies on resource capacity planning at the tactical level, which is coloured orange.

	Resource capacity planning	**Materials planning**
Strategic	Workforce planning	Supply chain and warehouse design
Tactical	Demand planning	Supplier selection
Offline operational	Workforce scheduling	Materials purchasing
Online operational	Monitoring	Inventory replenishing

3.2 Solution approach

This section discusses solution approaches for workforce problems by literature. Section 3.2.1 shows what a workforce problem consists of and what all the solution phases are. Section 3.2.2 explains the workload prediction phase, followed by the staffing phase explained in Section 3.2.3. Then, the shift generation phase is explained in Section 3.2.4 and the employee rostering in Section 3.2.5.

3.2.1 Workforce phases

In this section, we look into the different approaches to workforce management. There are different phases determined by literature when approaching a workforce problem. Literature differs on how these phases are defined and how many phases there are. Four sources which use different phases are shown in Figure 3.1. To start with the different literature, De Causmaecker et al., 2004 describes three different phases: staffing, personnel scheduling and allocation. Van Hulst et al., 2017 describes the process of Workforce management (WFM) also in three different phases: workload prediction, shift generation and employee rostering. In contrast, Bhulai et al., 2008 and Nilssen, 2014 add the staffing phase between workload prediction and shift generation. Lastly, Musliu et al., 2004 divided workforce management into four different phases. The first phase is temporal workforce requirements, followed by the total workforce. After this, there are two possible approaches. Shift generation and employee rostering can be considered sequential phases and approached that way. The other approach is to consider these problems together as one single phase and solve them simultaneously. The literature approaches workforce management with different phase distinctions but overall the following phases can be determined: workload prediction, staffing, shift generation and employee rostering. The different phases will be discussed in more detail in the following sections to give insights into how a workforce problem can be approached and how different literature approaches this.

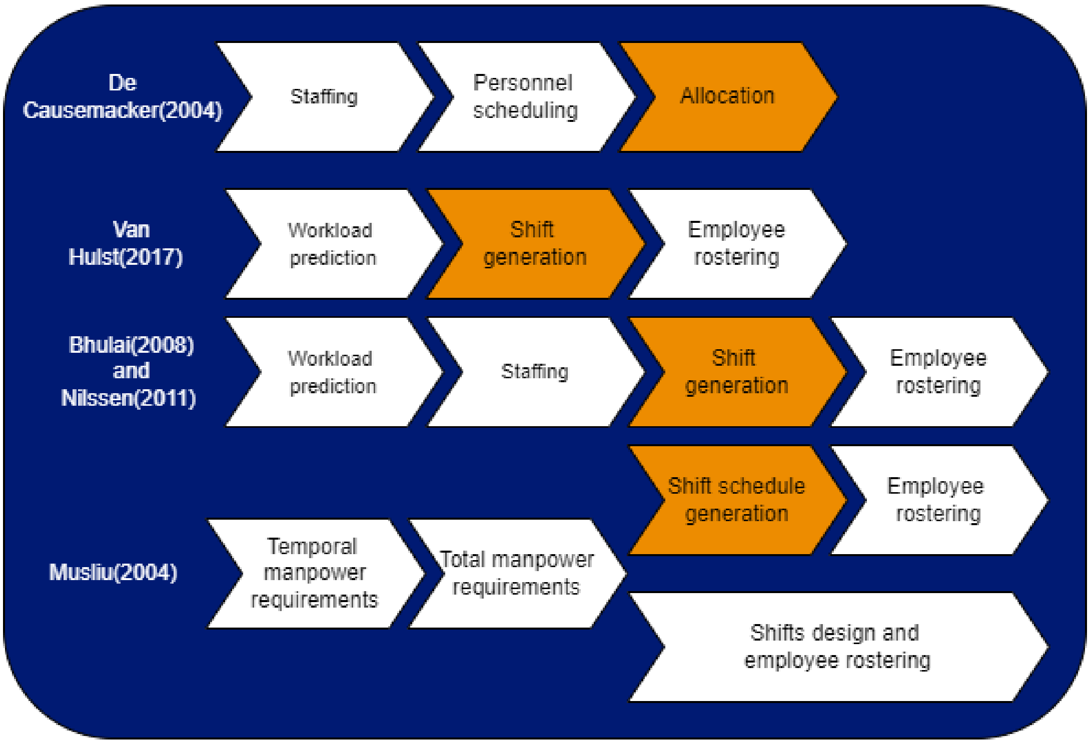


Figure 3.1: The different phases of workforce management (WFM) described by the different papers of Bhulai et al., 2008; Musliu et al., 2004; Nilssen, 2014; Van Hulst et al., 2017. The orange blocks indicate the subject of the papers.

3.2.2 Workload prediction

Workload prediction is focused on estimating the amount of work that is offered to the company (Bhulai et al., 2008). The phase of Van Hulst et al., 2017 is described differently but aims to achieve the same result. The data of workload information that is transformed into workload curves is used as input for the next phase. This describes the steps of estimating workload and translating this to the number of employees necessary for that amount of work. In Bhulai et al., 2008 and Nilssen, 2014, these steps are split into first the workload prediction and then matching the employee numbers to this with the staffing step. Lastly, Musliu et al., 2004 also describes processes that will result in a workload prediction. The first stage is the determination of the temporal workforce requirements. This is concerned with first finding the number of employees for every time slot of the upcoming planning period. And in the next phase, the total number of employees that are needed is determined. This is a combination of the workload prediction and staffing phases. All these different descriptions can be seen as a workout of a workload prediction, but some methods include both estimating workload and the staffing step to match the number of employees. This phase is included in our research.

3.2.3 Staffing

After the workload prediction, the next phase is staffing. Staffing is described by De Causmaecker et al., 2004 as a "long-term process of determining how many personnel must be employed by the organisation to provide a predetermined level of service". With this definition of staffing, it is assumed that the amount of work is already known and that only the number of employees needs to be matched to it. De Causmaecker et al., 2004 only includes the staffing phase, which indicates that the workload prediction is already known, while Van Hulst et al., 2017 only includes the workload prediction and not the staffing phase. The translation from workload to the number of employees and the other way around must be done so; therefore, it is highly likely that it is included but not mentioned or used as input in the phases. This phase is included in our research.

3.2.4 Shift generation

All mentioned papers contain a phase for shift generation. This is also coloured orange in Figure 3.1 because this is where the focus lies for almost all the different sources. Therefore, this phase is described in detail and the other phases are summarized or the results are only used as input. De Causmaecker et al., 2004 describes personnel scheduling as "the process of converting expected daily workforce requirements into precise scheduling assignment". The expected daily workforce requirements are the output of the previous phase, and thus, personnel scheduling consists of generating a precise scheduling assignment. Here Musliu et al., 2004 makes a distinction between first determining the shift generation and, when this is complete, starting on the employee rostering. As this is an interrelated process, it is also suggested that these phases be treated at the same time. This phase is not included in our research because it is more focused on the operational level.

3.2.5 Employee rostering

The last phase of the WFM phases is employee rostering and allocation at an operational level. De Causmaecker et al., 2004 describes allocation as the "actual assignment of scheduled personnel to work sites". Employee rostering specifically talks about assigning employees to the previously designed shifts, while allocation is broader, talking about work sites. This phase can be seen as the match between the number of employees and the designed shifts. This is a task on an operational level and is done and monitored by planners, and therefore not our focus for this research. It is essential that the output of the previous phases can be used as input for this final phase. This phase is also not included in our research because it is focused on the operational level.

3.3 Postal services literature

The postal service industry is an area that has been researched in different problem contexts, and this section discusses the research that has been done in this area. It describes what problems were researched and how these problems were solved. Not all problems that are described, correspond to our research problem but they are in the field of planning and scheduling. The research is done in the same context, the postal services, and therefore the problems and solution methods are reviewed. This gives insights into how scheduling and planning problems in the same context are solved.

Selma et al., 2019 acknowledge that the postal industry is a particular type of work. The postal industry runs outside the average office hours and experiences significant differences in workload per period. Because of this, a particular need is necessary to determine the planning of employees. In Bard et al., 2007, the United States Postal Service is described and also identified as a service organisation that processes wide fluctuations in demand. The paper addresses a staffing problem, and it is approached with a two-stage stochastic integer program with recourse. The first stage focuses on setting up a permanent workforce without knowing the demand, and in the second stage, the demand is known, and employees are assigned to a specific shift. To approach this problem, first, a deterministic model is developed, and a point forecast of the demand is used. Then, in the stochastic formulation, a demand distribution is used. To solve the two-stage stochastic program, the authors reformulate it into a mixed integer program(MIP) and solve it with a target heuristic.

Another research at the United States Postal Service by Bard et al., 2003 discusses a tour scheduling problem to address the staff scheduling of the company. The focus is on establishing a shift schedule per employee, which is formulated as an integer linear program. The number of workers required for each working period is used as input, and a work schedule per employee is the output of the model. Multiple scenarios are considered in this research: different ratios of full-time and part-time workers, consecutive days off, and variations in start time.

The paper of Brunner and Bard, 2013 considers the same mixed-integer programming formulation for a tour scheduling problem at the United States Postal Service. Because this formulation is complex and cannot be solved in practice situations, the paper proposes a set covering formulation. This formulation solves the linear programming relaxation, and a branch and price algorithm is used to determine the integer results.

Research is also performed at the Portuguese postal service company by Júdice et al., 2005. In this case, the problem is focused on matching the staff to the work requirements. This is combined with determining the correct lot sizes for the mail processing centre because the production and transfer amounts are determined during the day at this centre. This combined problem is solved with an integer programming formulation.

Another research at the US Postal Service Processing and Distribution centres by Bard, 2004. The focus is on a multi-skilled workforce problem where the benefits of planning an employee with high-level skills to a job with lower-level skills are quantified. To solve this problem, a mixed-integer linear programming model is set up as a primary planning model. Then, certain constraints are relaxed to investigate the effect of downgrading employees. All these researches are conducted in the context of a postal environment and each consider their own specific element for research. Some focus only on the staffing level while other sources also have a additional focus on multi-skilled employees or correct lot sizes for example. Our problem focuses first on the workload prediction and then the staffing but also includes a part where demand can be moved to another day and this combination is not researched yet in these sources in the postal environment.

3.4 Workforce management models

As described in Section 3.2, the first phase in approaching a WFM problem is to predict the workload and match the staff to this. In our case, we are dealing with uncertain demand, and therefore, we should forecast the expected workload. This section discusses different workforce models and the solving techniques used in these models. In Section 3.4.1 the different methods for forecasting workload are discussed, followed by Section 3.4.2, that explains the different staffing methods.

3.4.1 Forecasting workload methods

There are different prediction techniques for forecasting demand: statistical approaches, machine learning and deep learning (Ali Kadioglu & Alatas, 2023); these are classified as time series prediction techniques.

Four different forecasting methods are classified by Chopra and Meindl, 2007: qualitative, time series, causal and simulation. Qualitative methods are based on human judgment and are typically used when little historical data is available. In comparison, time series make use of historical demand to construct a forecast. The time series methods are appropriate when the demand pattern is similar every year. Next, the causal forecasting methods assume that the demand pattern is dependent on certain environmental factors. The external factors can be estimated to explain parts of the demand variability (Beutel & Minner, 2012). Lastly, simulation forecasting can be used to model consumer choices that make up the demand pattern. Of all these methods, we look further into the different time series methods because our research handles demand that has the same and a clear pattern every year.

Time series models are fitting for demand that is related to historical demand and follow a clear growth pattern or seasonality. The forecast is a systematic component that consists of a level, trend, and seasonality. The level is deseasonalised, and the trend describes the rate at which demand increases or decreases. Lastly, seasonality predicts the seasonal fluctuations in the demand pattern. The different types of time series models can be seen in table 3.2.

The first method within the time series is the Moving Average (MA). This method calculates the forecast by using historical data from previous months or years. When new data is gathered, this is added to the forecast, and the forecast is moved over to the new data. It is a simple method applicable for demand with no or a low seasonality factor (Bondarev, 2012).

The exponential smoothing method calculates the average demand over all the historical demand. Then, new demand is observed, and based on this, a smoothing constant for the level is calculated. A weighted average is calculated with the old and new demand and the smoothing constant. The constant ensures that the new demand has a higher weight than the old demand to ensure that the forecast is responsive to recent observations (Chopra & Meindl, 2007).

The next method is Holt's model, which adds a trend factor to the exponential smoothing method. The calculation for the trend is adjusted to account for the changing trend factor. This consists of partly including the old level and, more importantly, including the new level, both with a determined and weighted trend factor (Gardner, 2006). In comparison to this, Winter's model adds a seasonality factor to Holt's model. This seasonality addition is constructed by partly the old seasonal factor and calculating a new factor. Demand forecasting involves various techniques, each altered to different types of demand and its patterns. Time series methods stand out because of the accuracy in forecasting demand with consistent patterns like seasonality and trend. With the focus on time series models, the forecasts can be established and also enhance decision-making processes.

Table 3.2: Forecasting methods and their corresponding description. The focus lies on the time series methods.

	Description
Qualitative	Uses human judgement
Causal	Determines correlation between demand and external factors
Simulation	Model consumer choices for arriving demand
Time series: Moving average	Estimation of average demand and no trend or seasonality is considered in forecasting future demand
Time series: Exponential smoothing	Estimation of average demand with smoothing constant and no trend or seasonality is considered in forecasting future demand
Time series: Holt's model	Trend-corrected exponential smoothing and trend is considered in forecasting future demand but no seasonality
Time series: Winter's model	Holt's model with seasonality and both trend and seasonality are considered in forecasting future demand

3.4.2 Staffing methods

After the workload prediction, the outcome can be used as input for the next phase, staffing. Different approaches to staffing exist, and this section discusses models from the literature that could be applicable to our scope and research.

A literature review is performed by Defraeye and Van Nieuwenhuyse, 2016 about staffing and scheduling under nonstationary demand, which is stochastic and with a time-varying rate. Nonstationary demand can happen because of several elements: product life cycles with multi-stages, technological innovation and reduced product life, seasonal effects, customer preferences, changing economic conditions and exchange rate fluctuations (Rostami-Tabar et al., 2015). In the literature review, different staffing methods are presented. The following methods are discussed: Square Root Staffing (SRS), Smallest Staffing Level (SSL), dynamic programming, mathematical programming and simulation-based heuristic. The SSL assumes that all service times follow an exponential distribution for the model. SRS does not evaluate the performance of the staffing. The references of the literature review are categorised according to the environment in which it is applied. The differentiation is made between general, emergency department, call centre and others. Postal services are considered to be part of a service company Borangiu et al., n.d. Therefore, the most relatable application to analyse is the call centre division. In this application, SSL and mathematical programming are the most mentioned staffing methodologies.

Three types of solutions were identified by Castillo-Salazar et al., 2016 in workforce allocation papers. The first approach is integer programming, which is based on a set covering formulation. This approach is then solved with a branch and price method. The second approach is the use of meta-heuristics. The last option is relaxing an integer programming formulation to determine lower bounds for the solution. In addition to the lower bounds, the upper bounds were then determined using constructive heuristics, and finally, it was solved using simulated annealing. This summation of methods already shows that many approaches and solution methods approach the problem differently based on assumptions and in and outputs.

When humans perform work, the skills of one employee can always differ from those of another. This is especially the case in work descriptions, where tasks are oriented differently. Firat and Hurkens, 2012 propose a MIP-based approach for a multi-skill environment. In this problem context, teams are formed, and the goal is to determine the workload per team while maximising the number of tasks performed per day.

Lastly, Villarreal et al., 2015 developed a mathematical model for staffing and demand planning while taking into account that it has a time window for on-time processing. The paper states that this model is applicable to all different types of service organisations. This mixed integer program aims to determine which employee is scheduled when to fulfil the demand on time. The model also makes use of penalty costs in the objective function to ensure that demand is fulfilled on time.

3.5 Application of models

In the previous sections, many models were described for different situations and in this section, the gaps are identified. The literature sources are summarized in Table 3.3 with their corresponding model and additional solution methods. For every source, it is specified whether the research is performed in a mail-specific environment or not. Next to this, the focus of the paper is stated. Lastly, the model formulation type and the additional solution methods that are used are mentioned.

The table shows that different types of model formulations can be used, and if applicable, different additional solution methods are also used. The sources in the mail-specific context all consider fluctuating uncertain demand. This is partly the case for our problem, but there is also a part of the demand that consists of time-window demand as considered by Villarreal et al., 2015. All the sources that are mail-specific have a basic model formulation that can be applicable to our research. However, none consider the time-window demand that is stated in Villarreal et al., 2015 so therefore a gap in literature is present.

Table 3.3: Overview of mail-specific and general workforce scheduling approaches.

Source	**Sample size**	**Mail specific**	**Research focus**	**Model formulation**	**Solution method**
Bard et al., 2007	-	Yes	Workforce planning using stochastic optimization	MIP and SIP	Target heuristic
Bard et al., 2003	-	Yes	Flexibility workforce planning scenarios	ILP	Exact
Brunner and Bard, 2013	-	Yes	Workforce planning	Set covering	Relaxation and Branch and price algorithm
Júdice et al., 2005	-	Yes	Volume lot sizing in workforce planning	MILP	Exact
Bard, 2004	-	Yes	Multi-skilled workforce planning	MILP	Relaxation
Castillo-Salazar et al., 2016	50 employees	No	Workforce planning	Set covering	Branch and price and meta-heuristics and relaxation
Firat and Hurkens, 2012	-	No	Multi-skilled workforce planning	MIP	Exact
Villarreal et al., 2015	700 employees	No	Time-window demand workforce planning	MIP	Exact

3.6 Conclusion

In this chapter, many different papers are discussed, and the answer to our research question is presented in this section. In Section 3.1, the problem was inspected, and problem characteristics were defined. We classify our problem as a stochastic static problem, but we will solve it deterministically because of computational intensitivity. Section 3.2 stated the different workforce management (WFM) phases which consist of workload prediction, staffing, shift generation and employee rostering. From these four phases, we will focus on the workload prediction and the staffing phases. In Section 3.3 and Section 3.4 different types of models and solution approaches were described that were combined in Section 3.5. The sources that contain mail-specific context all have a basic mathematical model that could be applicable to our research. Villarreal et al., 2015 considers a specific aspect of flexible demand that is also applicable to our research. To conclude, this chapter described the literature for our research in a mail-specific context and the WFM context.

4 Data analysis

To determine the best-fitting solution design for the workforce problem, we first analyse the demand volume data. This chapter focuses on the characteristics of the volume data that can be found. The first step of data analysis is collecting data. The data collection and the preparation of the data are described in Section 4.1. The analysis and results are given in Section 4.2. Lastly, Section 4.3 describes the main conclusions from the data analysis.

4.1 Data collection and preparation

This section describes how the data was collected and prepared before performing the analysis. MailNL already collected the mail volume data before this research started. All the mail that enters the process at a sorting centre is scanned and registered into the internal system. The volume data that is analysed, is gathered from the internal system. The volume data starts in 2022 and ends halfway through 2024 because the data before 2022 is stored away and not available for this research. In registering the mail items, a distinction is made between which machine it was sorted in and what type of item it is. The SMK abbreviation stands for sorting machine small, 'Sorteer Machine Klein' in Dutch and SMX is the sorting machine eXtented mail. The data is grouped per day and location to obtain one volume number per day and location. This data per day and location can show the possible patterns in the data. The demand data of the morning and afternoon process is analysed together. All the data that is shown is extracted for the location Nieuwegein.

4.2 Analysis

In this section, we analyse the presence of seasonality and a trend in the demand data. We perform this analysis to determine if the seasonality and trend are significant to include in the forecast method. There are a few things we can conclude from the data. First, we analyse if there is seasonality, weekly and annually in Sections 4.2.1 and 4.2.2 and lastly, we determine if there is a trend or not in Section 4.2.3.

4.2.1 Weekly seasonality

First, we analyse the presence of weekly seasonality in the data. This would concern a weekly occuring increase or decrease on specific days of the week. If this seasonality is present, a pattern can be detected depending on the days of the week and this influences the forecasting of demand.

Weekly seasonality can be distinguished in the demand data that is shown per day in Figure 4.1. A repeating pattern is shown in the data per work week. In the figure, clear ups and downs are visible, and each represent a week. The ups are mostly at the start of the week and the downs are the last days of the week. To further analyse the seasonality in a week, we zoom in into the demand data.

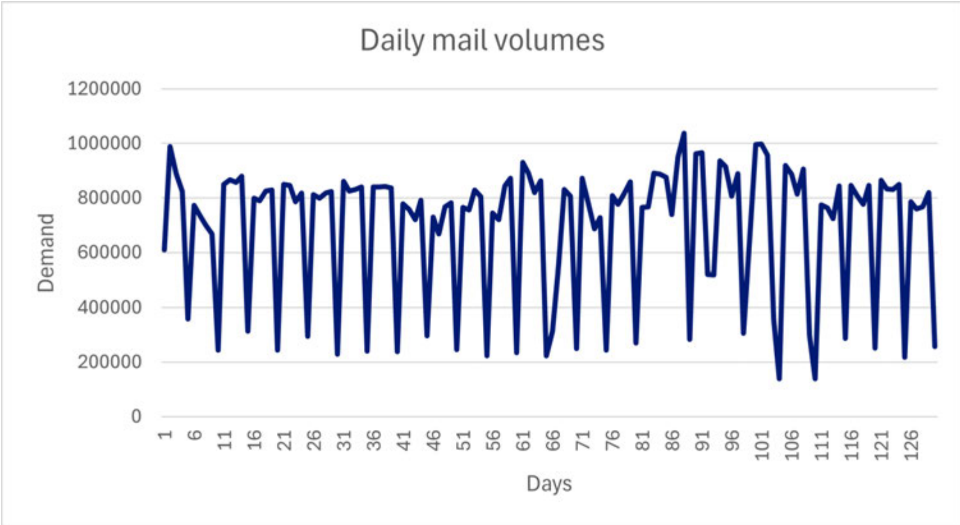


Figure 4.1: The mail volumes per day for the first half year of 2024, which show weekly seasonality.

The demand data is then plotted per workday for each week to see the overlapping pattern. On Sunday and Monday, no mail is delivered. The mail volumes of 15 different weeks are plotted in Figure 4.2. It can be seen that generally, the volumes rise a little bit during the week and descend on Saturday. Table 4.1 shows the statistical insights of the demand data. The average values show that on average the values increase towards Friday and increase significantly on Saturday. The coefficient of variation shows how much the values differ, measured relative to the mean value. The fluctuations show that each week, almost the same fluctuations happen on each day and therefore we assume that there is weekly seasonality.

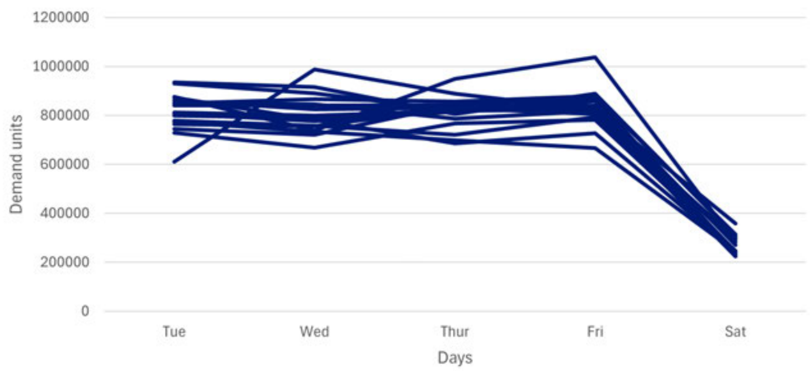


Figure 4.2: The seasonality per week plotted for 15 different weeks. This shows a small increase during the week and a decrease on Saturday.

Table 4.1: Statistics of the demand data. The average shows that the values do increase towards Friday and decrease on Saturday on average during a week.

Day	Average	Standard Deviation	Coefficient of Variation (%)
Tue	768465	146609	19.1
Wed	787729	100680	12.8
Thu	802700	59463	7.4
Fri	810946	55144	6.8
Sat	258739	38671	14.9

4.2.2 Yearly seasonality

To analyse the yearly seasonality, the day volumes are summed to obtain one value for the weekly volume. The weeks are compared for the different years in Figure 4.3. The years 2022, 2023 and the first half of 2024 of demand are plotted. All three years closely follow each other's high and low points. A difference occurs because the weeks include different days in one year than the other year. If the seasonality depends on specific dates of the year, for example, Christmas, it is dependent on which week these days occur in a year. A rise in volume is present at the end of the year, and lower volumes occur during the summer period. From the graphs, we can conclude that yearly seasonality is present.

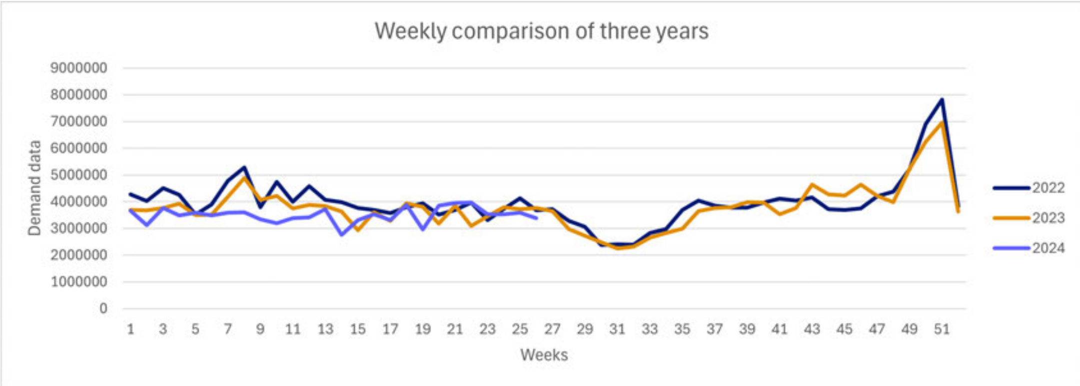


Figure 4.3: A comparison per week for the years 2022, 2023 and half of 2024. This shows the overlap in high and low points.

4.2.3 Volume trend

The weekly volume data from 2022, 2023 and 2024 is plotted in Figure 4.4. Because of the yearly seasonality that is probably present, it is hard to see if there is a trend in the data. Therefore, we fitted a linear trend line through the data points. This shows a negative slope of -2753.9, this corresponds to -0.07% of average weekly demand, which indicates a negative trend. This value shows the relationship between the two variables, time and demand. For every day that demand occurs, thus time increases, overall the demand value descends with a value of -2753.9. It can be seen that throughout the graph, the peaks are descending, and the low points are also descending more. Aside from the trend that could be concluded from this data, it is also researched more thoroughly by PostNL itself and a declining trend of more than 7% during the first half year of 2024 was established (*Press release PostNL Highlights Q2 2024*, n.d.). This does not correspond to our trend calculation but the PostNL calculation is probably done by comparing the first half year demand with the demand of previous year while we compare the overall demand trend over 2.5 year. Overall based on our own analysis and PostNL's analysis, a negative trend can be concluded from the data.

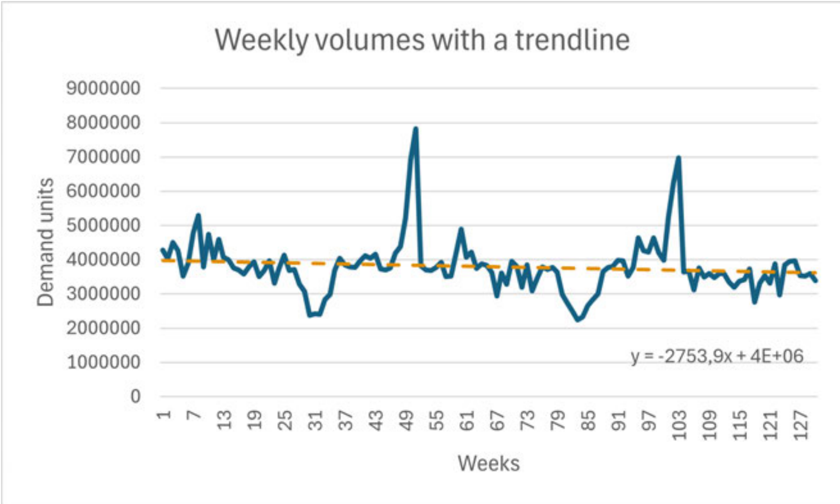


Figure 4.4: The weekly volumes plotted of 2022, 2023 and 2024 with a negative trend line.

In Table 4.2, the key statistics of the data are shown. The standard deviation is high, which means that the data varies around the mean value. This is also clear in Figure 4.4. The kurtosis of data represents both the tailedness and peakedness of the data, and it indicates if the data consists of possible outlier peaks (Booker et al., 1998). A value of three or higher indicates data with extreme values, which is the case for our demand data. The skewness of data indicates the asymmetry of data (Kim, 2013). The positive value indicates that the tail on the right side is longer than the left side, and this means that more extreme high values than extreme low values occur in the data. The maximum value shows us that the most significant deviation happens in higher values because this differs more from the mean than the minimum value. All these statistics together, indicate the characteristics of the demand data.

Table 4.2: Statistical data for volume numbers.

	Value
Mean	3799486
Standard Deviation	803486
Kurtosis	8
Skewness	2
Minimum	2246077
Maximum	7823120

4.3 Conclusion

In this chapter, we reviewed the characteristics of the data. Different data plots were showed, the daily and the weekly volumes of the demand data. Clear weekly seasonality can be seen in this data. An increase happens in the middle of the week and a decrease on Saturday. Aside from this, there is also yearly seasonality present in the data. During the summer period, a decrease occurs, and at the end of the year, the volume numbers show an increase. From the data, we conclude that there is yearly seasonality. Lastly, we performed a trend analysis and this showed a clear decreasing trend. From the data analysis, we conclude that there is weekly and yearly seasonality and a trend. These characteristics will be included in the solution design in our next chapter.

5 Solution design

In this chapter, the literature knowledge from Chapter 3 and the data analysis knowledge from Chapter 4 are combined to determine the solution design. The solution design consists of a mathematical model formulated as a Mixed Integer Program (MIP). In this chapter, the following research question is answered:

"How can the employee planning of PostNL be modelled as a mathematical model to determine the minimum number and types of employees needed to satisfy the demand service level while minimizing employee and demand costs?"

Section 5.1 motivates what model we use from the literature. Section 5.2 describes the approach for the demand forecast. Then, assumptions and simplifications are discussed in Section 5.3. From this, the mathematical model is explained in Section 5.4. The conclusions of this chapter are given in Section 5.5.

5.1 Solution approach

This research is concerned with matching the number of employees and their contracts with the fluctuating demand during a year, and to solve our problem, we undertake multiple steps in our approach. The steps are visualized in Figure 5.1. First, the workload prediction is made using a demand forecast method. This prediction is then used as input in the MIP model that is formulated to determine the staffing levels. In Chapter 4, we concluded that there is weekly seasonality, a trend and possibly yearly seasonality. Because of these characteristics, we decided to use Winter's forecasting model. The execution method of this model is stated in Section 5.2. We combine the models of Villarreal et al., 2015 and Bard et al., 2003 to construct our mathematical model. This is chosen because Villarreal et al. considers time-window demand within the workforce management context. Bard et al. designs a model in a postal environment and thus uses relevant constraints for our context. The goal is not to minimize the total workforce costs. Still, specifically, the penalty costs for scheduling employees too many or too few hours and modelling with penalties is also done in Villarreal et al. In comparison, Bard et al. considers demand without a time window but considers the specific mail applicable context, where the total number of employees is determined. The decision variables concern the number of employees and the total number of employees, which is also the output we want to achieve with our research. Villarreal et al. deals with a stochastic problem by solving it in a deterministic way. This is done by using a point forecast of demand data as input and we use the same method because a stochastic solution would be computationally intensive. The mathematical model and its description are stated in Section 5.4. The workload predictions are used as input in the mathematical model and the other input parameters are also set for our problem. Then the MIP can be solved and the corresponding output is the match between workload and employees in the form of number and type of employee contracts. All these steps together form the solution steps to our problem.

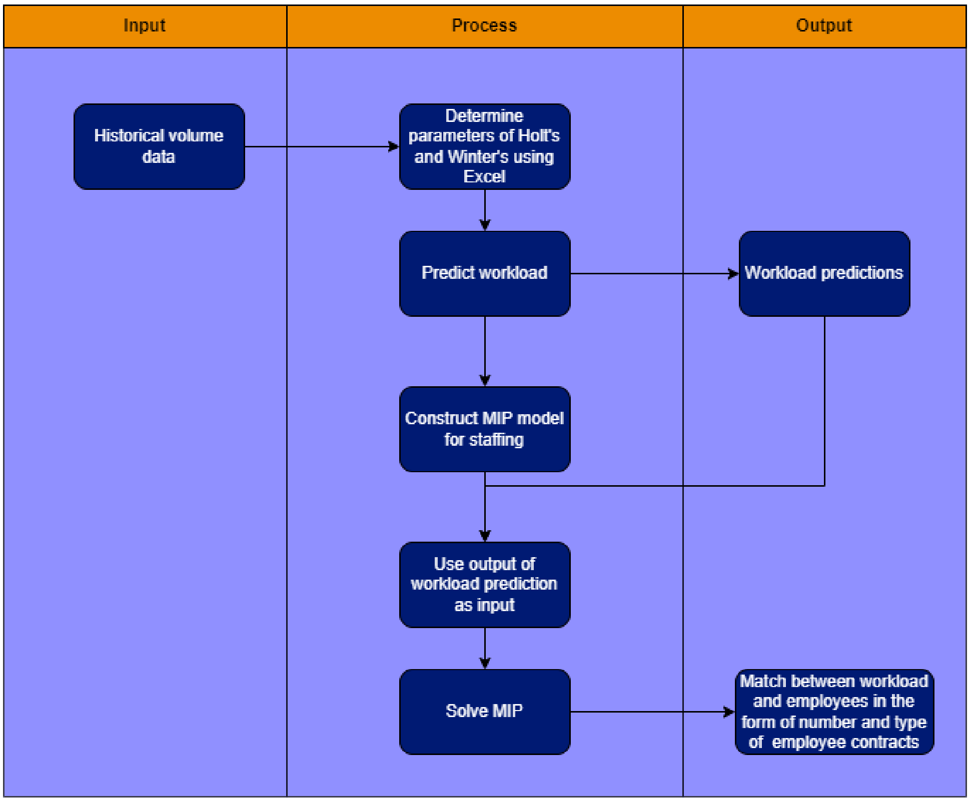


Figure 5.1: The solution steps and their relation to each other.

5.2 Demand forecast

This section describes what method will be used to forecast the demand for one year for the input for our MIP model. In Chapter 4, we concluded that the data shows patterns of seasonality and a trend. Because both these elements are present, we use Winter's forecasting model.

The first step to determining the parameter values is to determine the deseasonalized demand $\bar{D}_T$. This can be determined by calculating the moving average over a period, which is set to a year because we want to include the yearly seasonality. By performing a linear regression with the deseasonalized demand, the level and trend can be determined as stated in Equation 1. The trend is the slope of the deseasonalized demand and the level is the intercept of the deseasonalized demand.

L estimate of level
T estimate of trend
S_t estimate of the seasonal factor for the period t
F_t forecast of demand for period t

$$\bar{D}_t = L + Tt \tag{1}$$

The seasonal factors can be determined with the deseasonalized demand $\bar{D}_t$, which is shown in Equation 2. The seasonal factor for every period, S_i, can be determined by averaging the seasonal factors for that particular period p, as is shown in Equation 3. The factor should also be normalized by multiplying it with a normalizing factor.

$$\bar{S}_t = \frac{D_i}{\bar{D}_t} \tag{2}$$

$$S_i = \frac{\sum_{j=0}^{r-1} S_{jp+i}}{r} \tag{3}$$

The forecast value for a time t is finally determined by adding the trend and level and multiplying this with the according seasonal factor, as is shown in Equation 4. When multiple types of seasonality are present, the level and trend are multiplied by all seasonality factors.

$$F_t = (L + Tt)S_t \tag{4}$$

5.3 Modelling assumptions and simplifications

This section describes the key assumptions and simplifications made in modelling the problem. These assumptions and simplifications are taken into account in constructing the mathematical model and determine restrictions to our model. A key assumption that we make is that the employees work according to a fixed schedule with fixed break times. We assume that we are dealing with a fixed shift schedule. Because we are not researching the operational level, we do not include break time in our model. A simplification that we make is that the productivity of each employee is a constant factor and does not change over time. In reality, employees who are new hires have lower productivity than experienced employees. Another simplification is that we assume the same skills and productivity rate per employee. In reality, there is one mail handler present per working unit, and this employee performs other jobs aside from only preparing the mail. MailNL measures an efficiency rate that includes the activities of all employees, including the mail handler. Therefore, we assume that all employees work according to this same productivity rate. We assume that the hours that an employee works are always rounded to the nearest integer value and that contracts consist of 5,10,15,20 hours per week. In reality, employees have contracts varying between 0-5, 5-10, 10-15 and 15-20 hours per week. To draw a line in the type of contracts, these are set up per 5 hours per week. We assume that demand that is not treated today but moved to the next day is treated first. Therefore, it is not possible for the same demand to be delayed every day. In reality, it is also the case that the priority lies on mail that is delayed, and thus, this will be processed first instead of being delayed again.

5.4 Mathematical model

The goal of our model is to determine the minimum number of employees and the type of contracts needed to cover a predetermined percentage of demand while minimizing the costs for employee hours. A few constraints restrict the possible solutions. The excess employee costs are determined by calculating the worked hours per payment period with respect to the contract hours. Also, a part of demand can be treated with a time-window, but this part of demand should be treated within that time-frame. Demand that is not treated on a day is moved to the next day against penalty costs. In the end, demand should be completed with a certain percentage. The mathematical representation of the mixed integer programming model is shown below.

Sets
$E = \{1, ..., N_E\}$ Number of employees that can be scheduled
$W = \{1, ..., N_W\}$ Weeks in planning horizon
$T = \{5, 10, 15, 20\}$ Types of employee contract hours

$D = \{1, ..., N_D\}$ Days in the planning horizon

Parameters
N_E Total number of employees that can be scheduled
N_W Total weeks in the planning horizon
N_D Total days in the planning horizon
F_d Units of forecasted demand to arrive on day d that should be completed during the planning horizon, $d \in D$
h_t Contracted hours per payment period for employee type t, $t \in T$
c_p Penalty costs of one plus hour of an employee
c_m Penalty costs of one minus hour of an employee
c_d Penalty costs for one unit of unmet demand
α Fraction of demand that should be completed within the planning horizon
S Productivity of one employee (units of demand per time bucket)
σ Service level; minimum percentage of demand that should be processed
Max_h The maximum number of hours that employees can work on one day

Decision variables
p_{ew} Number of plus hours worked by employee e in week w, $e \in E, w \in W$
m_{ew} Number of minus hours worked by employee e in week w, $e \in E, w \in W$
n_d Unmet demand that is carried over to the next day d+1, $d \in D$
a_{et} binary variable that indicates if employee e is assigned to contract t, value 1, or not, value 0, $e \in E, t \in T$
s_{etd} Binary variable that indicates if employee e of type t is scheduled on day d, value 1, or not, value 0, $e \in E, t \in T, d \in D$
w_{etd} the number of hours that employee e of type t is scheduled on day, d $e \in E, t \in T, d \in D$

$$\text{Minimize} \sum_e \sum_w (c_p \cdot p_{ew}) + \sum_e \sum_w (c_m \cdot m_{ew}) + \sum_d (c_d \cdot n_d) \tag{5}$$

s.t.

$$\sum_{et} S \cdot w_{etd} \geq \sigma \cdot (F_d + n_{d-1}), \forall d \tag{6}$$

$$p_{ew} \geq 0.25 \sum_t a_{et} \cdot h_t, \forall e, \forall w \tag{7}$$

$$n_d \geq F_d + n_{d-1} - \sum_e \sum_t (w_{etd} \cdot S), \forall d \tag{8}$$

$$w_{etd} \geq 3 \cdot s_{etd}, \forall d, \forall t, \forall e \tag{9}$$

$$p_{ew} \geq \sum_t \sum_d w_{etd} - \sum_t a_{et} \cdot h_t, \forall e, \forall w \tag{10}$$

$$m_{ew} \geq \sum_t a_{et} \cdot h_t - \sum_t \sum d w_{etd}, \forall e \forall w \tag{11}$$

$$\sum_t s_{etd} \leq 1, \forall d, \forall e \tag{12}$$

$$\sum_t a_{et} \leq 1, \forall e \tag{13}$$

$$s_{etd} \leq a_{et}, \forall d, \forall t, \forall e \tag{14}$$

$$w_{etd} \leq Max_h \cdot s_{etd}, \forall d, \forall t, \forall e \tag{15}$$

$$\begin{aligned} \sum_e \sum_t w_{etd} &\leq \frac{S + F_d + n_{d-1}}{S}, d > 0 \\ \sum_e \sum_t w_{etd} &\leq \frac{F_d}{S}, d = 0 \end{aligned} \tag{16}$$

$$a_{et}, s_{ed} = \{0, 1\}, \forall e \forall t, \forall d \tag{17}$$

$$p_{ew}, m_{ew}, n_d, w_{ed} \in \mathbb{N}, \forall e \forall d \forall w \tag{18}$$

The objective function in (5) minimizes the costs for employee plus hours, employee minus hours and the costs for not meeting demand. The personnel costs are calculated by multiplying the costs of one employee plus or minus hour by the corresponding cost for all employees and every week. The costs for one unit of unmet demand are multiplied by the total number of unmet demand per day. The model provides a value for the number of employees and their corresponding types.

The solution values and variables are restricted to constraints that are explained in this section. The first constraint in Equation 6 ensures that the service level is met every day. The total productivity of all employees that are scheduled on that day should be higher than the demand of today and unmet demand of yesterday multiplied by the service level. Constraint 7 ensures that an employee works a maximum of 25% overtime hours. The following constraint calculates the unmet demand of a day. This consists of all the demand that could not be processed today by the employees. Constraint 8 shows that the forecasted demand and the unmet demand of yesterday make up all the demand that could be processed today. From this, the total productivity of that day is subtracted to calculate the unmet demand of that day. Constraint 9 shows that if an employee is working on a day, then they should at least work three hours. This is included because of work regulations, which state that an employee should work a minimum of three hours. The following two constraints, Constraint 10 and 11, calculate the values for the plus and minus hours. These are the difference between the contract hours of an employee and the actual worked hours per week. If an employee has worked more hours than their contract hours, then the extra hours count as plus hours. If an employee works fewer hours in a week than their contract hours, this is called a minus hour. Constraint 12 ensures that each employee can only be scheduled once per day. The summation over all contract types should be equal to one every day for each employee. Constraint 13 restricts employees only to be assigned to one contract type for a whole period. The summation over all the contract types should be equal to one or smaller for every employee. Constraint 14 links the scheduling of employees to their assigned contract type. An employee can only be scheduled for the shift and type if the type corresponds with the employee contract type. To ensure that an employee works a maximum hours per day, Constraint 15 limits the working hours per employee per day. In reality, it is only possible to work when there is work to do. We guarantee this in the model with Constraint 16, which states that the total hours worked cannot be bigger than the work there is to do. The available work consists of the forecasted demand of this day and the unmet demand of yesterday divided by the productivity per hour. This value is higher by one hour to ensure that employees can work one more hour than the demand available. In reality, employees will receive payment for rounded hours, and therefore, this represents reality. The demand for yesterday can only be included after the first day because otherwise, there is no demand for yesterday. Constraints 17 and 18 are the binary values and nonnegative values for the variables. This formulation of the objective and constraints with the sets, parameters and variables makes up the mathematical model.

5.5 Conclusion

In this chapter, we present the steps of the solution approach and the mathematical model to solve our research problem of matching demand fluctuations with employee contracts. We also state the calculations for the workload predictions. Because seasonality and trends are present, we use Winter's model calculations to obtain forecast values. The modelling simplifications and assumptions follow this. These are the basis of the mathematical model that is presented in this chapter. The model objective is to minimise employee hour costs and unmet demand costs for one year while still reaching a predetermined service level. This is achieved by assigning employees to different contract types to process the daily demand. In conclusion, this chapter provides the steps for forecasting demand using Winter's model and using this as input with the mathematical model for determining the employee contract number and types.

6 Experiments

In this chapter, the solution method and experiments are explained. The following research question is answered:

"What solutions are proposed for different problem scenarios by the mathematical model?"

The performance and results of the forecast model are discussed in Section 6.1. This is followed by a description of the input and the performance of the mathematical model in Section 6.2. Then, the experimental design, Section 6.3 is described, and the corresponding results are analysed in Section 6.4. The current situation and the problem solution are compared in Section 6.5. This is followed by validation of the mathematical model and forecast in Section 6.6. A sensitivity analysis is performed on the parameters of the mathematical model in Section 6.7. Lastly, the conclusion of this chapter is described in Section 6.8.

6.1 Forecast model performance

In the base scenario, the forecast is performed as mentioned in Chapter 5. Figure 6.1 shows the performance of the demand forecast, which is measured against the known demand. The bias is -0.05%, and this measures the structural deviation in the forecast from the actual demand (Gu & Wu, 2003). The negative value indicates that the forecast is structurally lower than the realised demand. If the bias is 0, the forecast fits the actual demand exactly on average. Therefore, a value close to zero is ideal. The value of -0.05% is close to zero, such that the forecast is comparable with the actual demand. The root mean squared error indicates the units of demand the forecast deviates from the realised demand. The root mean squared error of our forecast is 166961.96, which is 69.17% of the standard deviation. This means that the error in our forecast is significantly smaller than the standard deviation of the demand, and thus, the fluctuations could be predictable behaviour (Gu & Wu, 2003). Figure 6.2 shows a part of the demand that is plotted against the forecast values.

Forecasting performance	
Bias (%)	-0.05
MSE	27876297553
rootMSE	166962
StDev(demand)	241396

Figure 6.1: Forecasting performance of the process

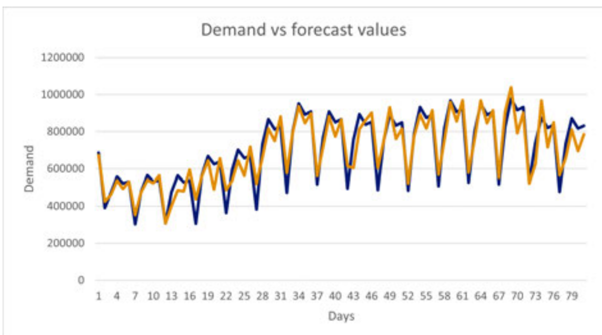
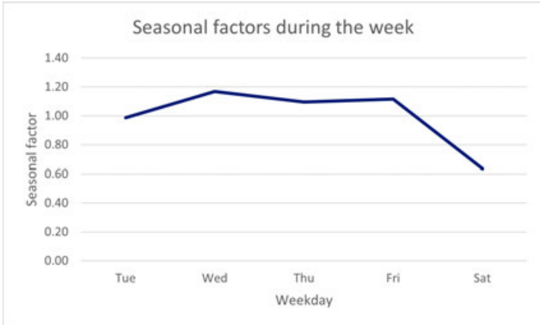


Figure 6.2: The demand values plotted against the forecast values.

The historical demand shows patterns throughout the week and also throughout the year. If these patterns increase or decrease repeatedly at the same time, day, or week of the year, then a seasonal factor can be calculated to include this pattern in the forecast. The in- or decrease is captured in a factor that is used to multiply the forecast value to accommodate for the structural in- or decrease on this day or date. The seasonal factors are calculated for the days of the week and the weeks of the year. This is done because there is a clear seasonality during a week, which we analysed in Chapter 4, and also seasonality during the year. The seasonality during the year is mainly related to holidays and events, which are tied to a specific time in the year and not months. Therefore, we choose to use the seasonality of weeks instead of months. Figure 6.3 shows the values and graph of the seasonal factors during a week. The demand values on Saturday are a factor of 0.64 lower than on an average day. The days in the forecast are multiplied by the corresponding factor of that day to incorporate the seasonality during a week.

Tue	Wed	Thu	Fri	Sat
0.99	1.17	1.09	1.11	0.64

(a) The values of the seasonal factors during a week.



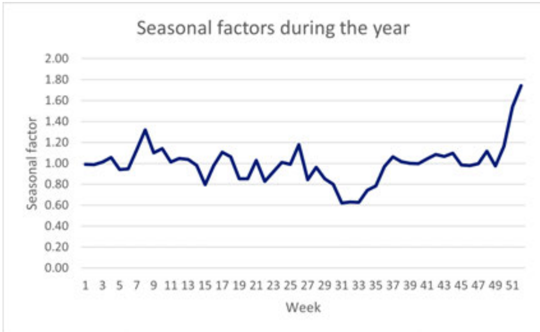
(b) The graphical representation of the seasonal factors during a week.

Figure 6.3: The seasonal factors during a week which show an increase in the middle of the week and a decrease on Saturdays.

The seasonal factors during the year are shown in Figure 6.4. The graphical representation is shown in Figure 6.4b. This shows a pattern of fluctuating demand in the beginning, with low demand during the summer and high demand at the end of the year. The demand values are multiplied by the corresponding seasonal factor of each week. Incorporating these seasonal factors into the forecast allows for adjustments that more accurately reflect expected demand variations across both the week and the year. This method ensures that the forecasted demand aligns closely with historical patterns, accounting for both weekly and annual demand fluctuations. The forecasted values of 2025 are used as input for demand in the mathematical model.

1	0.99	27	0.84
2	0.99	28	0.96
3	1.01	29	0.85
4	1.06	30	0.80
5	0.94	31	0.62
6	0.95	32	0.63
7	1.13	33	0.63
8	1.32	34	0.74
9	1.10	35	0.78
10	1.14	36	0.97
11	1.01	37	1.06
12	1.05	38	1.02
13	1.04	39	1.00
14	0.98	40	1.00
15	0.80	41	1.05
16	0.98	42	1.09
17	1.11	43	1.07
18	1.06	44	1.10
19	0.85	45	0.98
20	0.85	46	0.98
21	1.03	47	1.00
22	0.83	48	1.12
23	0.92	49	0.98
24	1.01	50	1.16
25	0.99	51	1.54
26	1.18	52	1.74

(a) The seasonal factors throughout the year based on historical demand of 2022 and 2023. A colour scale is applied to the values to show the distribution of high and low values throughout the year.



(b) Graphical representation of the seasonal factors throughout the year.

Figure 6.4: The seasonal factors throughout the year.

6.2 Mathematical model

The mathematical model is constructed as stated in Chapter 5 and in this section, we describe the used input values and computational limitations of the model. Table 6.1 shows the input parameter values for the mathematical model. These values are fixed values for the experiments that are performed in the following sections. By using the mathematical model, we choose to solve the problem in an exact way. This comes with its advantages and disadvantages. One big disadvantage is that this model is not suitable for a long planning horizon and fluctuating demand input values because it is hard to determine one employee level that fits demand over a whole period. The experiments are performed with horizon values of a maximum of 4 weeks, because the runtime can be high for larger instances, but especially with more fluctuations in demand. These solutions for 4 weeks can be combined to form a larger employee level planning solution. A deep analysis of the runtime performance of the model is stated in Section 6.11. The mathematical model can be helpful in case of stable demand during a year with small demand values. Still, when the demand values increase and many fluctuations are present, this model is not suitable because of runtime of more than a day. The advantage of solving it with this mathematical model is obtaining an exact solution for the problem. This returns an outcome that is predictable because it always returns the same outcome and this is more accessible to interpret. One big advantage is that less historical data is needed, in comparison to solving it stochastically, for the deterministic mathematical model because the data is not readily available within the company. Mainly because the company wants insights into the future situation, for which there is no data yet available, this exact method fits the problem. Overall, the model performs the best for planning horizons that have stable demand or are not longer than 4 weeks.

Table 6.1: Mathematical model input parameters

Input	Value
Days per week	5
Contract types	5h, 10h, 15h, 20h
Service level	0.95
Efficiency rate	400
Hours per day	5
Costs for unmet demand	1
Costs for hiring one employee	1000
Demand	Forecast values

6.3 Experimental design

In this section, we describe the experimental design for different scenarios to gain insights into different problem scenarios and determine the model performance. First, we determine the input penalty costs for the mathematical model, and we construct the experiment for the runtime performance of the model. Then, the future scenario and different demand scenarios are set up. Lastly, the experiential set up for demand input, which is divided into different periods, is described.

6.3.1 Penalty costs

To use the mathematical model, we first have to determine the penalty cost for the minus and plus hours. The exact costs of the hours are hard to estimate, but a few indications of the range of costs are known. A plus hour consists of an average employee salary, which costs around 30 euros. Aside from these base costs, an employee working an extra hour also incurs other costs, such as a manager who is also working extra hours, more employee breaks, and other personnel-related costs. Therefore the plus hour costs should be higher than 30 euros per hour. For the minus hours, these are hours that employees did not work but do receive payment for because of their contract hours. The company focuses on not paying any minus hours because it loses money, and therefore, the costs of a minus hour should be significantly higher than for a plus hour. To determine the input values for the costs, we experiment with different values. The mathematical model was executed with different values for the minus and plus hours in the range of [50,100,200,300,400]. Figure 6.5 shows the outcomes of the different cost settings. The company is more interested in reducing the minus hours than plus hours because, for a minus hour, an employee receives payment for not working. Therefore, the minus-hour penalty costs should be at least larger than the plus-hour penalty. The values are grouped based on the outcomes that are generated. From this, the values of 50 and 200 are selected for the plus and minus hours, respectively. This is because there should not be a big weight difference between the two types of hours, such as 50 and 400. The chosen values give a value of zero for minus hours and low plus hours. Therefore, the penalty costs for plus hours are 50 and for minus hours are 200.

Costs plus hours	Costs minus	Number of minus hours	Number of plus hours	20 h employees	10 h employees	15 h employees
equal to minus	equal to plus	9	146	426	0	0
50	100	0	177	425	0	0
50	300	0	177	425	0	0
100	200	0	157	424	2	0
100	400	0	157	424	2	0
50	400	0	157	424	2	0
50	200	0	157	425	1	1
100	300	0	157	425	0	1
200	400	0	157	425	0	1
200	300	4	151	425	1	0
300	400	4	151	425	1	0

Figure 6.5: Analysis of penalty costs for minus and plus hours.

6.3.2 Runtime performance

In this section, we set up the experiments to evaluate the runtime performance of the mathematical model. This is done by determining the relation between the demand input values and the runtime because the input demand input values have the most impact on the runtime. From the other performed experiments, it was derived that the variation in demand shows the most impact on the runtime. The other input values that are used are shown in Figure 6.1. These values are fixed for every experiment. The demand can be varied in different ways, by varying it throughout the week or each week in comparison to the previous week. The difference between the highest demand value and the lowest demand value is the range of the demand. The first type of demand variation is increasing the range of demand during the week. This means that all demand values are multiplied with a multiplier value, as is shown in Figure 6.6 and thus the difference between the lowest and the highest value of demand increases. For this first type of variation, Figure 6.2 shows the experiment set up. The corresponding demand values are used as input, and the corresponding runtime per experiment is reported in Section 6.4.1.

Table 6.2: The experiment settings to research the effect of larger demand ranges during a week. The demand range increases with the number of experiments.

Experiment	Multiplier	Demand range
1	1.0	[349263, 641412]
2	1.1	[384189, 705553]
3	1.2	[419116, 769694]
4	1.3	[454042, 833836]
5	1.4	[488968, 897977]
6	1.5	[523895, 962118]

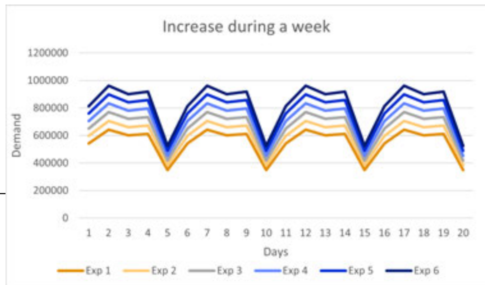


Figure 6.6: The corresponding demand values for the different experiment settings. The difference between the highest and the lowest value increases for every setting.

The second type of demand variation is increasing the demand every week in comparison to the first week. Figure 6.3 shows the multiplier values per week for the experiments and the corresponding demand range values in Figure 6.7. The multiplier value increases the demand with the corresponding factor of that week, where the factor also increases every week. Both the demand variation experiments are performed, and the results are discussed in Section 6.11.

Table 6.3: Demand ranges for different multipliers over 4 weeks in the experiments

Exp.	**Multiplier week 1**	**Multiplier week 2**	**Multiplier week 3**	**Multiplier week 4**	**Demand range**
1	1.00	1.01	1.02	1.03	[349263, 660654]
2	1.00	1.02	1.04	1.06	[349263, 679897]
3	1.00	1.03	1.06	1.09	[349263, 699139]
4	1.00	1.04	1.08	1.12	[349263, 718381]
5	1.00	1.05	1.10	1.15	[349263, 737624]
6	1.00	1.10	1.20	1.30	[349263, 833836]
7	1.00	1.20	1.40	1.60	[349263, 1026259]

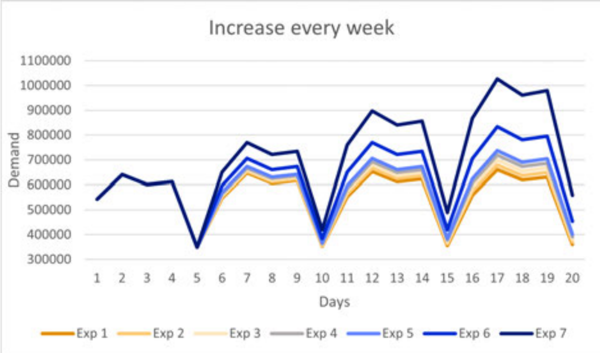


Figure 6.7: The corresponding demand values for the different experiment settings. The difference between the demand values increases every week for each setting.

6.3.3 Future logistics scenario

[redacted]

6.3.4 Demand scenarios

This section describes experiments for different demand scenarios in case of low, average or high demand. The goal of the experiments is to determine how the results change in regard to demand. In our mathematical model, we assume that the actual demand is precisely the value of the forecast. Because, in reality, this is not the case, we investigate different demand scenarios, high and low values, and their influence on the results of the mathematical model. Because of long run times, we investigate the changes to the solution for one month in case of different demand values. The initial demand values are used as the average scenario, and for the low and high demand, multipliers of 0.9 and 1.1 are used, respectively. This results in the demand values as shown in Figure 6.8, where each demand is 10% higher or lower. The demand values of the figure are used as input for the mathematical analysis of low, average, and high-demand scenarios. The results of the experiments are discussed in Section 6.4.3.

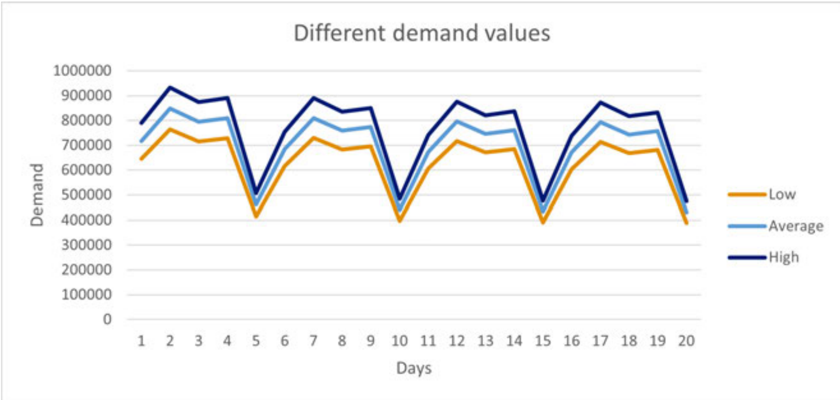
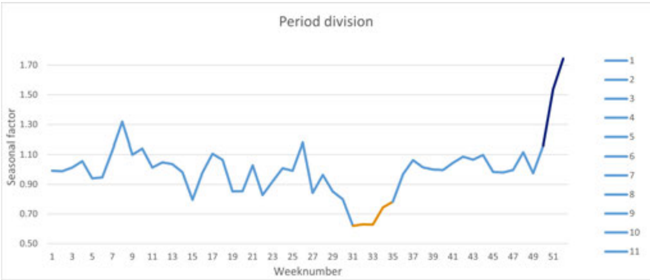


Figure 6.8: The demand values in the case of low, average or high demand.

6.3.5 Demand division into periods of low, average and high demand

In this section, we set up the experiments to determine the number of employees for different periods of demand. The goal of the experiment is to determine the level of employees for low, average and high demand periods, which the company can use as guidelines for the number of employees throughout the year. In reality, the number of employees during a year differs because people leave the company and new people are hired. Therefore, it is not realistic to maintain one level of employees for a whole year, and in these experiments, guidance can be given on when to hire new people and when to let people go on leave. First, we divide the demand into periods of high, average, and low demand. This does not change the forecast method, but it influences the outcome of the mathematical model. The mathematical model can provide outcomes per period instead of over all the periods in a year. To determine which periods are classified as high, average and low demand, we classify the seasonal factors into different categories. Figure 6.9 shows the division for the low, average and high values. The low and average values consist of a period of four weeks to restrict the running time of the mathematical model. The high-demand period consists of the last three weeks of the year; here, the most extreme high values occur. The graph in Figure 6.9a shows the visual of the low values in orange, which mainly occur during the summer period. For the mathematical model, the values of week 31 to week 34 are used because these are stable values in the same range. The average demand values are all the values that are not classified as low or high because, naturally, there are fluctuations during the year, but these are stand-alone values and not a period. For the mathematical model, weeks 37 to week 40 are used because these generate stable demand values for four weeks. The number and corresponding values are shown in Figure 6.9b. The demand for the selected weeks is used as input for the mathematical model, and the model determines the optimal values for the employees and their contracts for that specific period. This approach allows the mathematical model to generate more accurate employee solutions by optimising for specific demand periods rather than treating the entire year as one time period. The results are discussed in Section 6.4.4.



(a) The visual representation of the seasonal factors with the low, average and high demand values coloured.

Week number	Seasonal factor
31	0.62
32	0.63
33	0.63
34	0.74
37	1.06
38	1.02
39	1.00
40	1.00
51	1.54
52	1.74

(b) The corresponding seasonal factor numbers and week numbers per period of low, average and high demand.

Figure 6.9: The visual representation of the low, average and high demand values with the corresponding week numbers and factor values.

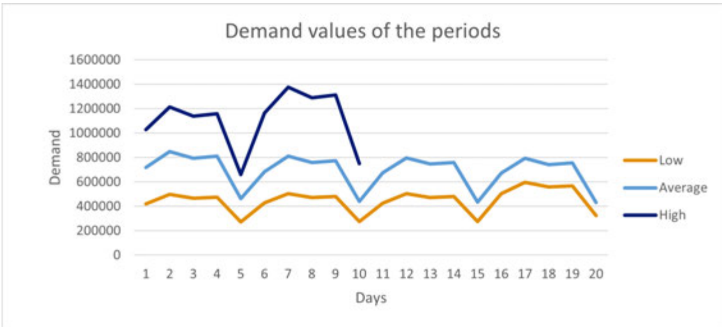


Figure 6.10: The demand values per day for the different period divisions. This shows the different ranges and levels of the values.

6.3.6 Sample Average Approximation

In the previous sections, we experimented with a deterministic model, but in reality, the demand input is stochastic. We also experimented with a stochastic version of the model. The stochastic model instance of our problem is too big to be solved within a reasonable runtime. Therefore, we create a small problem instance to show that the model can be solved stochastically for small instances. The average demand values of one week are divided by 100 to obtain a smaller input. For the stochastic forecast errors, we assume a normal distribution with a mean value of 1500 and a standard deviation of 500. With this distribution, we generate different demand scenarios as input for the model. For the different scenarios, one solution is obtained that is used in all scenarios. This method is called a Sample Average Approximation (SAA) (Pagnoncelli et al., 2009). In this experiment, we set the number and type of contracts as the first-stage variables, so these are determined based on the best solution for all scenarios, and all the other decision variables are second-stage variables, which are determined based on the decision of the first-stage variables. The different values used for the SAA are shown in Table 6.4.

Table 6.4: Model inputs for the SAA which shows the corresponding values.

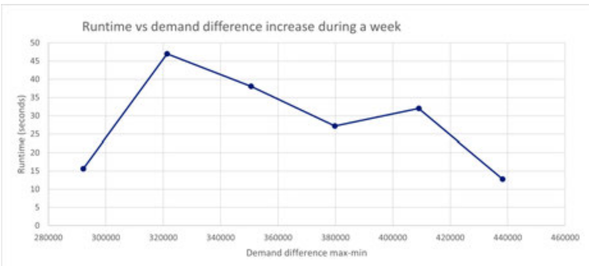
Input	Value
Distribution mean	1500
Distribution standard deviation	500
First-stage variable	a_{et}
Second-stage variables	$\{p_{ew},\ m_{ew},\ n_d,\ s_{etd},\ w_{etd}\}$
Number of scenarios	{10, 20, 30, 40, 50, 60, 70, 80}

6.4 Experimental results

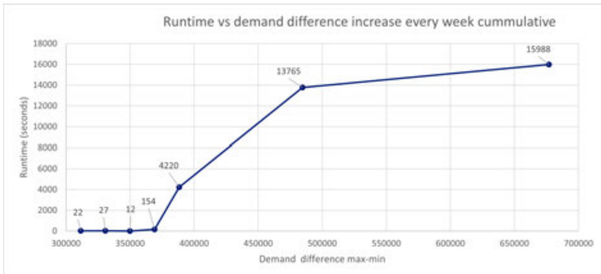
This section describes the results of the experimental setup that is described in the previous section. The runtime performance is analysed. Then, the future scenario, demand scenarios and period division results are stated.

6.4.1 Runtime performance

This section describes the results of the experiments on the runtime performance. First, we experimented with the demand variation during a week. The runtime is shown per demand range value in Figure 6.11a. The runtime of the mathematical model depends highly on the performance of the machine on which it is executed. Therefore, it is possible that the same model instance can result in a few seconds more or less every time the instance is solved. Figure 6.11a does not show a clear relation between the increasing demand range and the runtime. The mathematical model reviews the contract hours per employee every week. Therefore, it is logical that one set of employees performs the same way for different weeks, at least if the demand is constant every week. The second demand range variation that we experimented with was increasing demand every week. Figure 6.11b shows the results of the runtime for this experiment. From this figure, we can distinguish a significant increase in runtime with every increase in demand range. From this experiment, we conclude that the difference in demand range each week has a significant influence on runtime performance. Thus, the model runtime performs better for stable week demand values.



(a) The runtime results of increasing the demand range during a week. All runtimes are less than a minute.



(b) The runtime results of increasing the demand range every week. The runtimes show a cumulative increase in the demand range.

Figure 6.11: The runtime results of increasing the demand range during or every week. This shows that the demand range during a week has a low influence on the runtime, while the demand range every week has a significant influence.

6.4.2 Future logistics scenario

[redacted]

[redacted]

[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]

6.4.3 Analysis of demand scenarios

The low, average and high demand values are used as input for the mathematical model, and we will analyse the results. Table 6.6 shows the performance outcomes of the mathematical model. The optimal number of employees to hire changes at almost the same rate as the demand values change for a stable demand scenario. In a low-demand scenario with -10% demand, the number of employees is around 10% lower than in the average scenario, and the same counts for the high scenario. With this, the plus hours also increase and decrease at almost the same rate as the demand values. The minus hours stay around the same values. This is the case because these costs are significantly higher than the plus-hour costs. Therefore, the number of employees decreases by one, and employees make extra plus hours rather than incur minus hours. Overall, the number of employees changes at the same rate as the demand changes. This means that the average value can easily be used by scheduling employees. If the demand differs a little bit on a weekly basis, the scheduling employees can adjust the number of employees at the same rate as the demand changes.

Table 6.6: Performance output of the mathematical model in case of low, average and high demand input.

	Low	Average	High
Demand in/decrease	-10%	0	10%
Demand range	374966	416629	458292
20 h Number of employees	382	424	467
15 h Number of employees	0	1	0
Plus hours	738	800	891
Minus hours	0	4	1
Objective value	418900	465800	511750
Runtime (seconds)	489	456	112

6.4.4 Analysis of demand division into periods of low, average and high demand

The mathematical model is executed three times in total with the low, average and high demand as input. This performs as shown in Table 6.7. The average demand indicates what demand values correspond to that period, and the difference between the highest and lowest values is shown as the range. For the high-demand period, it is more beneficial to hire employees with a five-hour contract as well. This results from the wide range of demand values for the high-demand period; the values in this period fluctuate more from each other than compared to the low and average periods. Employees with a five-hour contract can quickly be scheduled for one day in the week when the demand is exceptionally high. The extensive range of demand values makes it harder to find one fitting set of employees, and thus, plus and minus hours costs are higher, and the solve time is drastically higher. Figure 6.10 shows the demand values graphically per period, and this shows how different the demand ranges are and the demand levels. In general, employees with lower contract hours, for example, 5 hours, offer flexibility in scheduling if the demand range during a week is high. These employees can be scheduled for one shift on days when demand is high, and then their contract hours are completed for that week. By running the model for different periods, the company can obtain guidelines for when to hire extra employees or when employees can take leave. During the low period, the level of employees is lower than in an average period, and with the low level, the planners can keep track of the amount of employee leave during the summer. The proposed number of employees in the low period can also be translated to the needed employee capacity and, thus, how many employees can go on vacation. For the high period, the opposite can also be reasoned. During this period, more employees are needed, and thus fewer employees can go on holiday.

Table 6.7: Performance output for low, average, and high demand periods.

	Low	**Average**	**High**
Average demand	449678	695308	1109073
Demand range	324331	416629	714636
Weeks	4	4	2
20 h Number of employees	266	425	645
5 h Number of employees	0	0	51
Plus hours	98	785	1576
Minus hours	0	9	153
Objective value	270900	466050	805400
Runtime (seconds)	2397	75	6925

6.4.5 Analysis of Sample Average Approximation

The objective value results and the runtime performance of the SAA scenarios are shown in Figure 6.12 and Figure 6.13. From the number of scenarios against the objective value, we can see that the value flattens out for more than 60 scenarios, which would mean that more than 60 scenarios are necessary to obtain a significant result to reduce the sample bias. If we calculate the sample bias for each number of scenarios and we compare it to the exact value for the average demand for each solution, we can see that for 70 scenarios, the sample bias is close to the exact value, with a sample bias of 6.3, all the average costs per scenario are shown in Table 6.8. Figure 6.12 shows that the runtime increases drastically after 40 scenarios, and thus, 70 scenarios would still be within a reasonable time to perform. These results show that the model is able to perform with stochasticity for a small instance. Therefore, our mathematical model could also be helpful for other smaller problem instances that contain stochasticity.

Table 6.8: The comparison of the sample bias for the different number of scenarios where 70 scenarios would be enough to obtain a significant small sample bias.

Number of scenarios	**Average costs per scenario**
10	1170
20	1803
30	992
40	1355
50	1282
60	1486
70	**990**
80	992

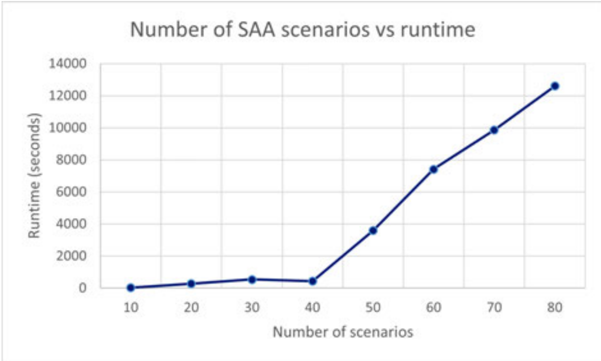


Figure 6.12: The number of SAA scenarios against the runtime which shows that the runtime drastically increases for more than 40 scenarios.

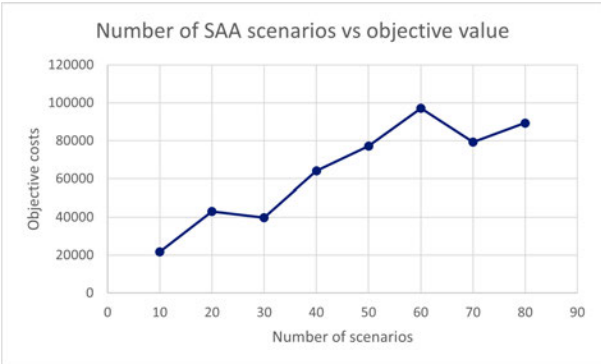


Figure 6.13: The number of SAA scenarios against the objective value which shows that after 60 scenarios the value flatttens.

6.5 Current situation comparison

This section describes the comparison between the proposed solution and the current situation. We use data from employees and plus and minus hours per week to compare the current situation with the results of the mathematical model and determine how much can be gained with the mathematical model. The data of the current situation and the solution for a 4 week comparison is shown in Table 6.9 for a period of 4 weeks with average demand. This shows that in the current situation, there is a mix in the type of contract and the number of employees for each contract type. This occurs because of naturally occurring supply and demand in what type of contracts employees prefer. The total number of employees is 398, while the solution proposes 425 employees. From this, we can conclude that a significant amount of demand cannot be processed daily in reality. Still, the employees work many plus hours every week, and there are also flex workers in addition to their employees. The exact number of flex workers is not available for this research, but it is known that flex workers are used. Aside from the number of employees, it is remarkable that the number of plus and minus hours are drastically reduced. The number of plus hours is lower in our solution because extra-hired employees work these hours in comparison to the current situation where employees work extra hours. The difference in the number of plus and minus hours also depends on the operational scheduling of employees. As described before, the company's operational process is still being improved because of the changes in responsibilities after a reorganisation. The difference in the number of plus and minus hours shows that there is still a lot to gain from improving the scheduling on the operational level. In reality, there are more factors included in scheduling employees than are currently in the mathematical model, such as preference for working days and vacations. The comparison of data shows a mix of contract types and a big difference in plus and minus hours.

Table 6.9: Employee allocation and hours distribution comparison between the current situation and solution. This shows a big difference in the number of plus hours because in the proposed solution more employees are hired. This comparison is made over 4 weeks.

	Current situation	**Proposed solution**
5h employees	1	0
10h employees	15	0
15h employees	43	0
20h employees	339	425
Plus hours	5065	785
Minus hours	975	9

We multiply the data with the corresponding costs for each input, and this results in a cost comparison as is shown in Table 6.10. If we compare the costs with the proposed solution, we are able to save up to 380250 euros in total for this period of 4 weeks, which is 44.9%. More costs are made in the solution than in the current situation for employees, but this is because more people are hired, and the data about flex workers is not available for the current situation. Thus, most cost savings are gained by reducing plus and minus hours. This could hypothetically save many costs, but in reality, most of the costs are reliant on the operational planning of employees, and thus, if this solution would be implemented in reality, it would save costs but probably not the high percentage that we conclude from the data. Aside from this, in our solution we also miss a natural mix in contract types because in reality employees have different needs for the type of contracts and this would also incur extra costs on top of our current solution.

Table 6.10: Cost comparison between the current situation and solution, showing a large decrease in costs for the proposed solution. This comparison is made over 4 weeks.

	Unit costs (€)	**Current situation (€)**	**Solution (€)**
5h employees hiring costs	1000	1000	0
10h employees hiring costs	1000	15000	0
15h employees hiring costs	1000	43000	0
20h employees hiring costs	1000	339000	425000
Plus hours	50	253250	39250
Minus hours	200	195050	18 00
Total		846300	466050
Savings			380250

To compare the proposed solution and the current situation on a yearly horizon, we combine the period division of the experiment in Section 6.4.4 to form a whole year solution and compare it with the current solution of 4 weeks multiplied for a year. The low period solution consist of 4 weeks and the high period solution of 2 weeks and the rest of the year we assume that there is average demand. The number of employees and their contracts stay the same for the average demand period but the plus and minus hours are multiplied by 11.5 to accommodate for the 46 average demand weeks. The values of the periods are shown in Table 6.11 and the corresponding costs of a yearly horizon are shown in Table 6.12. The adjustments on the employee level can be made by matching the absence of employees to the levels for low periods and by adding flex workers to the levels to obtain more employees for high periods.

Table 6.11: Overview of weekly employee allocation and hours for a yearly horizon in total.

	Low	Average	High
Weeks	4	46	2
20h employees	266	425	645
5h employees	0	0	51
Plus hours	98	9027.5	1576
Minus hours	0	103.5	153

Table 6.12: Cost comparison between the current situation and the proposed solution for a yearly horizon, showing significant savings.

	Current situation (€)	Solution (€)
20h employees	339000	645000
5h employees	59000	51000
Plus hours	3292250	535075
Minus hours	2535000	51300
Total	6225250	1282375
Savings		4942875

6.6 Validation

In this section, we validate the mathematical model. Two types of validity, internal and external, are explained. First, internal validity is concerned with whether the model is working correctly, and secondly, external validation is concerned with the generalisation of the model (Heerkens & Winden, 2017). For internal validation, the mathematical model has been validated to the best of our ability within this research. To show this validation, we create a simple input demand instance which generates random demand for each day for one week. This demand varies between 1500 and 2000, and considering the productivity of one employee of 400 demand pieces, one or two employees should be hired. Figure 6.14 shows the result of the mentioned demand input. This shows that the demand varies, and on day four, the employee works four hours, which is equal to 1600 pieces of demand, while demand is 1620. Therefore, the orange bars show a slight increase in the unmet demand on the fourth day, and on day five, the same situation occurs. The result of the model is to hire one employee with a 20-hour contract and let this employee work 24 hours because this is cheaper than hiring an extra 5-hour employee. With this simple scenario, we show that the model works as we would expect in this case.

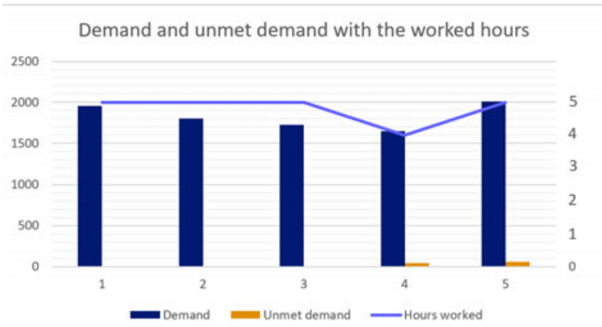


Figure 6.14: Internal model validation through showing the demand per day and the unmet demand with the worked hours per day.

For external validation, we validated the model with company experts. The input values, objectives and constraints of the model were discussed thoroughly. The model was checked to see if the constraints were representative of the real-world logistic process. With both the internal and external validations performed, we have validated the model to the best of our abilities in this research.

6.7 Sensitivity analysis

In this section, we perform a sensitivity analysis of the proposed mathematical model and forecast. We will change model parameters and measure how much the performance outcomes change. The parameters that we test are the productivity of employees and service level.

6.7.1 Productivity of employees

The effect of the productivity parameter on the results is tested and discussed in this section. The productivity of employees is a measured value by MailNL. This value includes all employees, as well as new employees and employees who perform other tasks during the preparation process. Therefore, this parameter is already accurate, but this analysis could show what benefits can arise from increasing and decreasing productivity. Figure 6.15 shows the result of different values of productivity used as input. The forecast input was average demand values of 4 weeks in total because of run times. The first thing that we see in the graphs is the decrease in the objective value and the employees. These both gradually decrease around the same rate for every increase in productivity. This can be explained by the fact that more productivity means that fewer employees are needed to perform the work and thus fewer costs for employees as well. Because of this, both these results decrease at the same rate. The minus hours decrease with the rise in productivity because fewer employees are hired, thus reducing the chances of not being able to schedule an employee. The plus hours differ in reduction or increase because this depends mainly on the number of employees and whether they match the demand. Because there are fewer employees hired, the employees that are hired can be asked to work more plus hours.

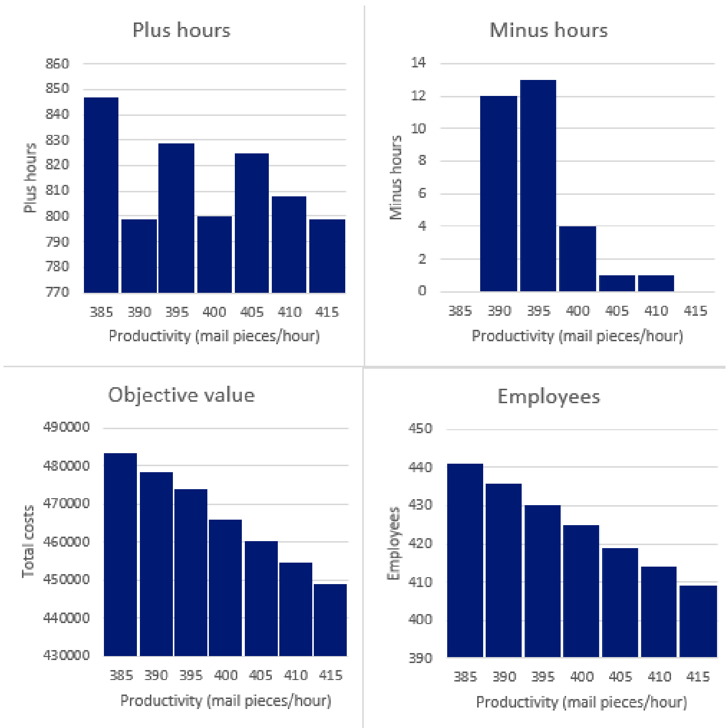


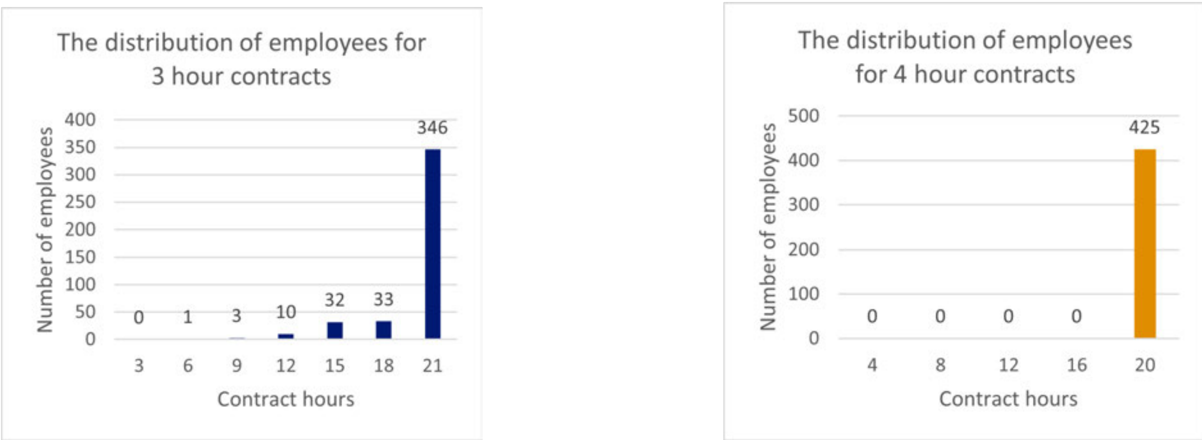
Figure 6.15: The different performance outcomes with different levels of productivity.

6.7.2 Service level

We used different service level values as input to investigate the effect on the demand solution values. The values that were used as input ranged from 0.90 to 0.99. For all these values, the results of the mathematical model remained the same, which is that all demand is processed every day. This happens because if demand is not treated today, it is moved to tomorrow, which only increases the demand for tomorrow. To be able to process the extra demand, an extra workforce should be necessary, and this does not benefit the total solution. In reality, the whole supply chain at MailNL should perform at a service level of at least 0.95, and therefore, it is beneficial to have a high service level for this one process in the supply chain. In comparison with the other processes, this is a process which can quickly reach a high service level and leaves room for a lower service level at the other processes. In general, for a smaller instance of demand, it can be beneficial to move demand to tomorrow. This is the case because then the match between demand and employees can fluctuate more. For example, if the units of demand on day 1 are equal to an amount that 2 employees should process, the demand can be processed by one employee for the rest of the week. Then, it can be beneficial to move demand one day to be able to process it all with one employee. This only counts for small instances of demand, as with more significant demand instances, there is always one employee who can work one extra hour to process the few units of demand extra. Overall, for this specific company case, the service level variations do not have any effect on the solution value, while in general, they influence the results for smaller demand instances.

6.7.3 Contract types

The input settings are set at contract types in steps of 5 hours, which fits the shifts of a maximum of 5 hours perfectly. We changed the contract types to steps of 3 and 4 hours. Figure 6.16 shows the distribution of contracts for 3 and 4-hour contracts. The 3-hour contracts are more distributed over more minor contrasts as well; this increases scheduling flexibility, while the 4-hour contracts still only use 20-hour contracts. Figure 6.17 shows the corresponding costs for both settings. The total costs for both settings are in the same range, and from this, we can conclude that even with different input contract hours, the results will stay almost the same. This means that the model can also be used in situations where a company would prefer different contracts than 5-hour contracts. In reality, there is a more natural mix between the different contract types than only 20-hour contract, thus the 3-hour contracts also provide guidelines for a more natural mix of contract types.



(a) The contract results if contracts were offered with 3-hour steps.

(b) The contract results if contracts were offered with 4-hour steps.

Figure 6.16: The results of offering different types of contracts. With 3-hour steps contracts, the mix between larger and smaller contracts is high. While with 4-hour step contracts, 20-hour contracts are the best fit.

Figure 6.17: The costs resulting from the different contract settings.

6.8 Conclusion

In this chapter, we analysed and evaluated different problem scenarios and their effect on the solution. The runtime performance of the model was analysed, and the runtime increases significantly when the demand fluctuates between weeks. In contrast, the runtime stays the same if demand is increased during one week but stays the same every week. We looked into different scenarios for the mathematical model. Different demand scenarios for low, average, and high demand were analysed to determine the relation between demand changes and the model results. This showed that the number of employees increased or decreased at the same rate as the demand changed. Because of this relation, the planners can adjust the number of employees easily to accommodate for last minute changes in demand volumes instead of having to run the model again. The minus hours stayed around the same value while the plus hours also changed at the same rate as the demand. Next, we divided the data into periods of low, average, and high demand and determined the outcomes to determine different employee levels for different periods throughout the year. This resulted in 425 employees with a 20-hour contract corresponding to 466050 euros costs for employees and minus and plus hours for an average period. For a low period, the summer, 266 20-hour employees would suffice and for a high period, end of the year, 645 20-hour employees and 51 5-hour employees. With these values the planners can adjust the employee holidays to this and the hiring and contract lengths can be adjusted to accommodate for these periods in the year.

We compared the solution with the current situation and concluded that it is possible to save up to 380250 euros, 44.9% by adjusting the number of employees and their contracts. In the current situation, the scheduling on the operational level still needs improvement, and therefore, there is a significant difference in the plus and minus hours. In reality, there will be extra costs made on operational level because of planning errors and in hiring to accommodate for the different level of employees and thus the actual costs savings will be lower. The validity of the model was confirmed with a simple scenario explanation. Lastly, we performed a sensitivity analysis of the productivity of employees, service level and the contract types. This showed that the objective values increase and decrease at the same rate that the productivity increases. The minus and plus depend on the match between demand and employees, and thus, the minus hours, decrease and the plus hours differ per productivity. The service level difference between 0.9 and 0.99 does not have any effect on the number of processed demands for these large-demand instances, but for small-demand instances, this does have an effect. Changing the steps of the contract types does affect the mix of the contracts that fit optimally, but the total costs do not change significantly. Overall, the results demonstrated that the mathematical model provides valuable flexibility for planning by enabling adjustments in employee contracts and levels to match varying demand patterns throughout the year, significantly reducing costs while maintaining operational efficiency.

7 Conclusions and recommendations

This chapter provides the conclusions and recommendations of this research. The following research question is answered:

"What conclusions and recommendations can be made to MailNL based on the outcomes of the mathematical model?"

The conclusions of the research are described in Section 7.1. Section 7.2 discusses the recommendations for MailNL, and the scientific contribution is described in Section 7.3. Lastly, the limitations and future research are described in Section 7.4.

7.1 Conclusions

This section states the conclusions that are drawn from this research. In this research, we solved the core problem of 'it is unclear how many employees with what type of contracts are needed for the demand volume numbers throughout the year'. MailNL encounters high costs for extra worked hours and for hours that employees did not work in comparison with their contracts because there is a mismatch between demand and the number of employees. This research focuses on the mail preparation process because it involves a lot of manual labour. A literature review was performed on workforce problems and the postal services industry. From the literature, we distinguished four phases: workload prediction, staffing, shift generation and employee rostering. In this research, we focus on the first two phases: workload prediction and staffing. The workload prediction is performed by developing a demand forecast model. The demand data shows a yearly and weekly seasonality and trend pattern; thus, based on this, we choose Winter's model to incorporate these characteristics in the forecast. To perform the staffing, we developed a mathematical model based on the models from Villarreal et al., 2015 and Bard et al., 2003. The first source, Villarreal et al., 2015 includes elements to deal with flexible demand, that can be moved to another day and focusses on minimizing overall costs for scheduling employees and processing demand, while Bard et al., 2003 focusses on minimizing the total number of employees in a postal environment. The constraints and objectives of the models are combined, and different employee contract types are added to develop our mathematical model. We performed multiple experiments using this mathematical model to investigate scenarios and research how the model is performing. The experiments showed that the runtime performance of the model depends highly on the variation of demand every week. With this research, we conclude that the proposed core problem is solved. The gap between the core problem and action problem, 'MailNL pays high employee costs for minus and surplus hours', is made smaller by solving the mismatch between the number of employees and the demand.

Several conclusions can be drawn from this research. The first conclusion is that for an average demand setting, 425 employees with a 20-hour contract are needed to minimize the plus and minus hours. With the result of 425 employees, there are also 785 plus hours and nine minus hours for 4 weeks. All this together results in a total cost of 466050 euros for this scenario of 4 weeks. From these costs, the employee hiring costs are fixed costs for this time period and the plus and minus hour costs are variable costs for this period. When this is compared to the current situation, this would mean 380250 euros cost savings in total which is a reduction of 44.9%. In the current situation, the scheduling on the operational level still needs improvement, and therefore, there is a higher difference in the plus and minus hours. In reality, there will be extra costs made on operational level because of planning errors and in hiring to accommodate for the different level of employees and thus the actual costs savings will be lower. Different demand scenarios for low, average, and high demand were analysed to determine the relation between demand changes and the model results. From this, we conclude that the number of employees increased or decreased at the same rate as the demand changed. Because of this relation, the planners can adjust the number of employees easily to accommodate for last minute changes in demand volumes instead of having to run the model again.

In periods of high demand, at the end of the year, there would be 645 20-hour employees necessary and 51 5-hour employees to process the high amounts of demand, while in periods of low demand, during the summer, 266 20-hour employees suffice. With these values the planners can adjust the employee holidays to this and the hiring and contract lengths can be adjusted to accommodate for these periods in the year. [redacted] To conclude, MailNL can improve its employee level planning by adjusting the total number of employees and their contracts to the advised numbers. During the year, the hiring of MailNL and flex employees can be guided by the advice for the number of employees for high and low demand during the summer and Christmas holiday periods.

7.2 Recommendations to MailNL

In this section, we first describe how the solution can best be implemented at MailNL and then we describe the recommendations. The solution consists of a forecast and a mathematical model. At MailNL, some employees focus on demand planning within all the processes. This forecast is not used because of data availability for the future situation but the forecast can be implemented in the future. Therefore, when MailNL obtains its forecast for demand for different situations, this can be used as input. MailNL can use the mathematical model and its results in different ways within the company. The mathematical model is made on a tactical level and, therefore, provides insights into an average or period basis. The results of the model can serve as a guideline for the strategic plans for hiring employees and flex workers during high or low periods. The employee levels for different periods can be combined to serve the low, average and high demand periods throughout the year. The mathematical model results show the number of necessary employees, and this employee level can be obtained by matching employees' absence to this in low demand periods and by hiring flexible workers during high periods. By guiding the employee levels throughout the year in this way, a more stable and matching employee level is present for demand.

On an operational level, it can also provide guidance. Different demand levels correspond to a different total number of employees and corresponding hours. The results of the mathematical model can be used as a guideline for scheduling the employees on a weekly basis. The number of employees has a linear relation with the demand, and therefore, employees on the operational level can adjust the guideline to the actual demand. Thus, to start using the model, the employee levels should be included in the operational guidelines that planners use on a daily and weekly basis. To keep the model results up to date, it should be executed every year for multiple scenarios to evaluate the new demand forecast.

Based on the execution of this research and the previously stated conclusions, we provide several recommendations for MailNL in this section. The first recommendation is to implement the results of the mathematical model in the way stated before. By implementing the results, the planners will have better guidance on the number of employees to plan, improving workforce allocation efficiency. Secondly, perform research on the operational level within the company. The mathematical model provides insights into the necessary workforce by scheduling employees in a very simplified way. In reality, the operational level comes with more challenges than are included in this tactical level. Currently, a lot can be gained from improving operational planning because the planning employees spend many hours per week on operational scheduling. At the same time, part of this process could also be standardized. An essential planning framework per week, which the planning employees can manually adjust, would be an excellent start for the company. Additionally, aside from the actual planning of employees, research into the appropriate shift times with the changing demand at the company can also be beneficial. In the upcoming years, there will be changes to the demand arrival days and times, which will impact the company's shift schedules. Lastly, the communication process between the different parties involved in planning employees should be improved. Currently, employees in the workplace cannot contact planners directly and must go through their people coach, who handles communication with planners. To improve efficiency, people coaches need to maintain close collaboration with planners, ensuring that employee concerns and updates are communicated effectively. This should become a structural process with clearly defined responsibilities for both parties. Overall, these recommendations highlight the importance of integrating the tactical insights provided by the model with improved operational processes to ensure a more streamlined, efficient, and adaptable workforce planning system for MailNL.

7.3 Scientific contribution

This section discusses the scientific contribution of the research. There are multiple types of models in the literature that match the workforce with demand. The focus of our model is on fitting the number of employees and their contracts with the demand while maintaining flexibility in demand planning. By combining the demand flexibility of Villarreal et al., 2015 and minimizing the number of employees in the postal industry from Bard et al., 2003, we designed a mathematical model that combines the two concepts. We also included the element of determining the employee's contract hours by reviewing the worked hours every week and determining the fitting contract hours. Our combined mathematical model in this industry is our scientific contribution.

7.4 Limitations and future research

In this section, we discuss the limitations of this research and the options for future research to extend the research and mathematical model. In this research, the problem is approached with a deterministic model. In reality, we are dealing with uncertain demand, and therefore, the model can be extended by providing a stochastic program. A small experiment is performed to research if the stochasticity can be used for smaller instances, but this stochasticity can be researched in depth. The value of stochastic information can be calculated by comparing the deterministic and stochastic solutions, and this will provide information about the added value of using a stochastic program. By doing this, the model will represent reality even more. During this research, a stochastic model was developed, but with the current version of the deterministic model, the runtime is too high to perform well. Therefore, first, a simpler version of the model should be developed, or a smaller problem instance should be created, and then stochasticity could be included. By including this, the model is more similar to the real world and the variations that can happen. A stochastic model will produce more resilient solutions that correspond better to reality. Another point for future research is how to create flexibility in the workforce. As described in this research, the demand fluctuates during the year and the week. There are multiple ways to increase flexibility in workforce (Qin et al., 2015), for example, using multi-skilled employees that can be employed in different parts of the supply chain. Research in this direction can offer a lot of possibilities for improving the planning and scheduling of employees and the performance of the overall supply chain. With more flexibility in the workforce, the runtime of the mathematical model could also be lower. Other points for future research could be extending the model by including the skills of employees and sickness. An average percentage of the sickness and vacation hours could incorporate absence of employees throughout the year. Currently, this is not included in this model, and this could extend the model to be even more like reality. To conclude, future research consists of designing a stochastic model, determining flexibility in the workforce, and including employee skills and sickness.

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