Examining Strategies for Shift Scheduling at FrieslandCampina

Msc TIL Thesis

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FrieslandCampina

Examining Strategies for Shift Scheduling at FrieslandCampina

by

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Preface

Dear Reader,

Thank you for taking the time to read my thesis, or maybe just the preface! It marks the end of my student years in Delft, and of my time at the TU. Despite some (self-induced) challenges I faced writing this thesis, I am extremely grateful for the experience and lessons I can take home. Sentimental (and maybe a bit sleep-deprived), I want to express my gratitude to everyone who was a part of this project.

For helping me with my model formulation and moral support in stressful times, I want to thank Mark Duinkerken. For his critical eye but structural and helpful feedback on my writing and reasoning, Ron van Duin. My texts were not always easy to read, nor my ideas to follow, but help from both of you pushed me through. I want to give thanks to Lóri Tavasszy for his ever-calm feedback and questions during my main meetings.

Although thesis writing can be a lonely process, I was hardly ever alone thanks to the team I was so warmly welcomed to at the DC. First of all, I want to thank Joost de Veth for giving me the opportunity and trust for this project, and for his patience and insights in my process. The door was never closed; thank you for always finding time to (offer) help! Jelmer, Bas and Roland, thank you for your lunch, distraction and food coordination. I'm afraid someone else will have to coordinate drinks from now on. If I wanted to separately thank everyone I wanted to at FC, I think I would end up with more pages than my appendix. So, for now, I want to thank all allround operators, coordinators, workflow control employees, teamleads, coordinators, front desk staff, transport professionals and technical operators for their warmth towards me and for making time for small talk, a laugh, or questions with regard to this study. Thank you for allowing me to be a part of your team for a little bit!

I want to thank my roommates and my friends for supporting me throughout these past months. A special thanks to Pauline for reading and commenting on the whole thing. My family for giving their unconditional support during my thesis and throughout my whole academic journey at the TU Delft. Finally, I want to thank Ben for always being there to collect my thoughts and help me puzzle them together.

Enjoy the read!

Quirine de Zeeuw
Delft, May 2024

Abstract

In their Distribution Centre in Maasdam, FrieslandCampina uses a four-crew shift schedule to prepare all necessary orders for their clients, 24 hours of each Monday to Saturday. Their large automated warehouse is home to 10 000 pallet places, containing fresh dairy products. From here, orders are either prepared as full pallets, machine-picked layers or hand-picked "colli". In the last department especially, personnel cost is high relative to the throughput. Definitive picking deadlines are often ambiguous, posing challenges in job and personnel scheduling. The study goal is twofold. Firstly, to find out whether full knowledge of picking deadlines can contribute to a more efficient job, and so, shift schedule. Secondly, to offer insight for a trade-off between shift types to absorb workload. To reach this study goal, a Shift Minimisation Personnel Task Scheduling Problem (Krishnamoorthy et al., 2012) and a Bin Packing Problem (Paquay et al., 2014) were combined and tailored to fit the scheduling problem at FC's DC. In three weekly scenarios, the Mixed Integer Linear Program (MILP) model scheduled picking jobs in the least expensive shifts through a cost minimisation function. Two model configurations were used, one to prefer the shift between 09:00 and 17:00 (flex), and one to prefer either one of the 06:00-14:00 (morning) or the 14:00-22:00 (afternoon) shifts. Both model configurations inherently avoided the most expensive 22:00-06:00 (night) shift. Main findings include the possibility to absorb workload using the morning and afternoon shift and to avoid the night shift. Additionally, it was confirmed that insight in picking deadlines can contribute to an efficient personnel schedule a great deal.

List of Acronyms

AO	Allround Operator
ATP	Available to Produce
BB	Best Before
BPP	Bin-Packing Problem
CCP	Coordinator Collipick
CLA	Collective Labour Agreement
CLP	Coordinator Layerpick
CP	Colli Pick
DC	Distribution Centre
DV	Decision Variable
FC	FrieslandCampina
JIT	Just-in-Time
JSSP	Job-Shop Scheduling Problem
KPI	Key Performance Indicator
LP	Allround Operator
MCLCMP	Multiple Container Loading Cost Minimisation Problem
NSSWD	Normalized Sum of Square for Workload Deviations
OPS	Order Picking System
OSSP	Open-Shop Scheduling Problem
OWBP	Operational Workload Balancing Problem
PTSP	Personnel Task Scheduling Problem
SL	Simon Loos
S-MILP	Stochastic Mixed Linear Program
SMPTSP	Shift Minimisation Personnel Task Scheduling Problem
TD	Technical Department
TL	Team Lead
TO	Technical Operator
WFC	Workflow Control
WLB	Workload Blancing

Contents

1 Introduction

1.1. Background

FrieslandCampina (FC) is a Dutch dairy corporation that has grown to host 9 927 member dairy farms since its establishment in 1871. They export dairy products to more than 100 countries worldwide and are responsible for a large part of Dutch dairy (product) production. A large number of logistic processes underlie the successful distribution of these products, part of which happen in their Distribution Centre (DC) in Maasdam. This is the basis for FC's distribution of fresh dairy products throughout The Netherlands, and is placed alongside their factory. Products conveyed directly from the factory or transported from external locations are stored in their automated warehouse, which is home to 10 000 pallet places. From here, customer orders are prepared for transport 24 hours each day from Monday to Saturday. Customer order requirements and product specifications dictate the picking process for order preparation. This is done either in full pallets, picked automatically in layers or manually in loose "colli". The time between initialisation of client orders and their deadline ranges between three days and three hours, resulting in different levels of criticality for the picking department.

The four crews at the DC are deployed in three eight-hour shifts each day and are complemented using a flexible pool of employees as indicated in Table 1.1. The morning, afternoon and night shifts are currently populated using permanent personnel and the flex shift using flexible employees. The shift schedule could also be manned using only flexible or only permanent personnel. As client orders come in at 09:00 each day, flexible employees are deployed for picking from that time.

Table 1.1: Shift Times

Shift Name	Time
Morning	06:00 - 14:00
Afternoon	14:00 - 22:00
Night	22:00 - 06:00
Flex	09:00 - 17:00

1.2. Problem Description

Based on client order deadlines, orders are divided into picking waves. However, these deadlines often differ from their definitive deadlines. This is shown for three different weeks in Figure 1.1. Due to the lack of transparency in definitive order deadlines, it is often unclear whether picking orders are contained in the correct waves, and so, whether picking on the colli picking department is done "at the right time". This ambiguity clouds judgement of whether orders can be pushed back in the schedule. To avoid risk of machine failure or unforeseen workload, picking orders are often completed quickly after they are placed at the DC.

Large variation in workload is perceived on the colli picking department especially, both within and between shifts. A challenge is found in determining which shifts are necessary to account for the workload in this department. The questions raised to this end are which shifts could be use to account for this workload, and whether the night shift can be avoided in the process. Shift types to use have their own advantages and drawbacks. Flex shifts contribute the lowest personnel cost, due to absence of shift pay for irregular hours. Using a combination of the morning and afternoon shift, in turn, contribute more flexibility to push back jobs when deadlines cannot be met in case of unforeseen circumstances.

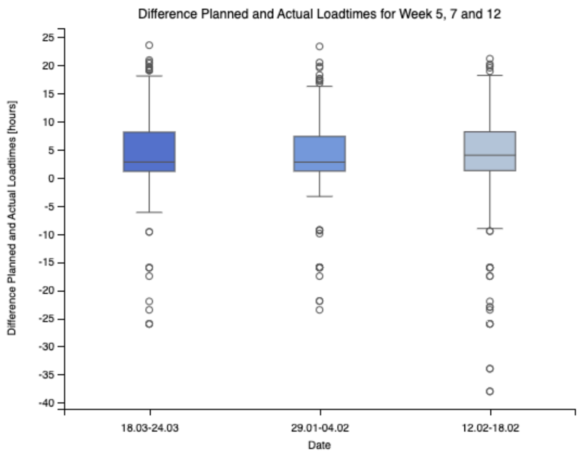

Figure 1.1: Box Plot for Difference between Actual and Planned Loadtimes for Week 5, 7 and 12

1.3. Literature Exploration

A great deal of research is done in job scheduling, workload balancing and shift cost minimisation, many of which use Mixed Integer Linear Program (MILP) formulations with objectives that minimise the difference between minimum and maximum workloads (e.g. Ouazène et al. (2016). Other formulations include cost minimisation (Golpîra and Tirkolaee, 2019) and minimisation of the maximal planned load over all used resources (Vanheusden et al., 2020). However, a shift schedule complexifies the problem. The Shift Minimisation Personnel Task Scheduling Problem (SMPTSP) as proposed by Krishnamoorthy et al. (2012) covers the issue of minimising the total number of shifts used for tasks, but their tasks have set start and end times, while the problem at hand requires task scheduling. To schedule tasks, determination of the start time was taken from the formulation by Rieck et al. (2012), who use start time of a job as a decision variable. To avoid overlaps between scheduled tasks, the 3D Bin-Packing Problem (BPP) as formulated by Paquay et al. (2014) is used. The number of dimensions is reduced to one to suit the problem at hand.

1.4. Research Goal and Methodology

This study's goal is to find out whether, and to what extent, improved insight in picking deadlines can contribute to a more efficient personnel schedule. By doing so, it aims to contribute to a trade-off between permanent shifts and flex shifts and to offer insights to assess the necessity of the night shift.

To this end, a MILP model was used, based on the SMPTSP formulation by Krishnamoorthy et al. (2012). To schedule jobs in shifts that carry minimal cost, jobs' start time was used as a decision variable (e.g. Rieck et al., 2012) and overlaps between jobs were avoided by using part of the formulation of a Bin-Packing Problem (BPP) approach (Paquay et al., 2014). It is often difficult to solve optimisation problems within acceptable time (Vanheusden et al., 2021), so the problem was reformulated to do so. For three weekly scenarios containing varying numbers of picking orders (an average, a busy and a slow week), daily subsets were made to solve the shift minimisation problem. A symmetry-breaking set of constraints was added to improve optimisation performance (Gent et al., 2006).

To contribute to a trade-off between different shift types, three scenarios containing different amounts of workload were run for two model configurations. Model Configuration 1 uses personnel costs taken from reality, in which flex shifts are least costly and most attractive for the model to schedule jobs in. In the second model configuration, a cost reduction was given to the morning and afternoon shifts. The afternoon shifts were given lower cost than the morning ones to avoid symmetry in the model, which is inherently more present in this model configuration.

1.5. Research Questions

To adhere to the main research goal of a more efficient personnel schedule and account for the trade-offs to be made, the main research question was formulated:

How can full insight in picking deadlines contribute to a more efficient shift schedule on the manual picking department at FrieslandCampina's Distribution Centre, taking into account the cost of these different shifts and regarding different scenarios for workload deviations?

To support the main research question, the sub questions are listed below.

1. Which opportunities can be identified in the current job scheduling method at FC?
2. Which models found in literature are most suitable to solve the job scheduling problem at FC?
3. How can the practical job scheduling problem at FC be represented in a mathematical formulation?
4. How can modeling results be related to the scheduling problem at FC?

1.6. Document Structure

The document is structured along the lines of the sub questions. In finding an answer to the first sub question, a system analysis is given in Chapter 2. In search for a suitable method, a literature review is given in Chapter 3. Chapter 4 contains model formulation and reformulation, answering sub question 3. Sub question 4 is answered through the experiments done in Chapter 5. The discussion and recommendations for further research, both at FC and in literature, are given in Chapter 6. The main research question is answered in the conclusion, in Chapter 7.

2
System Description of the Order Picking System

The system description in this chapter serves to answer the first research question: *"Which opportunities can be identified in the current job scheduling method at FC?"* The chapter starts with a context and system description to this end in Section 2.1. Activities on the picking department are examined in Section 2.2, followed by a description of personnel and structure in Section 2.3. Workload and workload distribution is reviewed in Section 2.4. Difficulties in job scheduling are reviewed in Section 2.5. KPIs and their expected interaction with the system are given in Section 2.6. A summary, answering the sub question, is given in Section 2.7

2.1. Context and System Description

An overview of the DC's departments is given in Appendix B.1. Inventory is kept in a large automated warehouse (home to about 10 000 pallet places, of which 9 000 are comfortably usable), from which orders are sent to the appropriate area in the DC automatically to be picked either manually (collipicked) or automatically (layerpicked). When an order is finished, it is taken back to the warehouse to wait for transport to the client. Whether or not a product can be picked using a layerpicker depends on the physical qualities of the product and on the client order. If a product cannot be picked in layers or a client requires loose products, the order is prepared on the colli picking department.

A combination of permanent and flexible workforce is employed to accommodate for the workload in the DC: the permanent workforce operates in four crews, spread over three eight-hour shifts to cover the 24 hours of Monday to Saturday (elaborated in subsection 2.3.1). When they are employed, flex personnel assist the permanent workforce during office hours, between 09:00 and 17:00. This is further elaborated in subsection 2.3.1.

Expensive in execution, the colli pick department especially is examined closely. A great deal of variation in workload is perceived within and between shifts in this department. As said earlier, this workload variation can be approached from two directions: personnel and activity scheduling. As found in Chapter 3, personnel deployment is often a result of the way activities are scheduled. These two aspects are explored from hereon. This context description contains an organisational chart of the DC and an IDEF-0 of the picking process, both to contextualise the following sections.

2.1.1. Organisational Chart

In their DC, FC employs about 75 people. To give an overview of the different roles in the DC and to give context to the system description, an organisational chart is given in Figure 2.1. An extensive description per role is given in Section B.2. For now, the functions highlighted in the figure correspond to the departments used for the IDEF-0 diagram in subsection 2.1.2.

2.1.2. IDEF0 for Process Description

The IDEF-0 diagram in Figure 2.2 shows the way an order arrives at and is processed by the DC. An elaborate explanation of this diagram is given in Appendix B. Inputs to a process step are given through the arrow on the left, controls come from the top and mechanisms from the bottom. The output of a process step is given on the right. An order starts with a client order, which is released as a sales order in process step 1 by the sales department after an Available to Produce (ATP) check. As the name implies, this check ensures that the order's contents are available for delivery. This is then put through to the DC, in which the EWM system makes picking waves in step 2, based on rules for picking waves and the time given in the client orders. If the client orders are not complete,

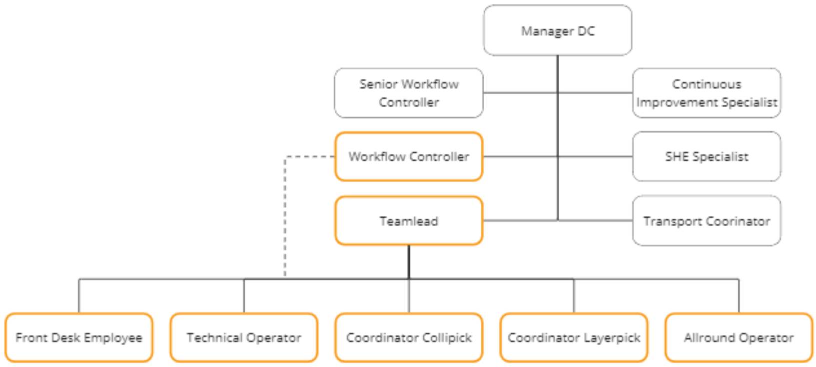

Figure 2.1: Organisational Chart of the DC

picking waves are determined using an old transport schedule. In step 3, the picking waves are "put in buckets" for picking, based on the times given in these waves, by EWM. Buckets are predefined time intervals in which picking tasks are placed to be picked on the picking departments in step 4, using necessary products, pallets and plastic foil as input and outputting a finished order. AOs, layerpickers, coordinators from the layer and colli picking departments and production support this step. Finished orders are stored in the warehouse in step 5 and staged for transport in step 6, giving the order ready for transport as output.

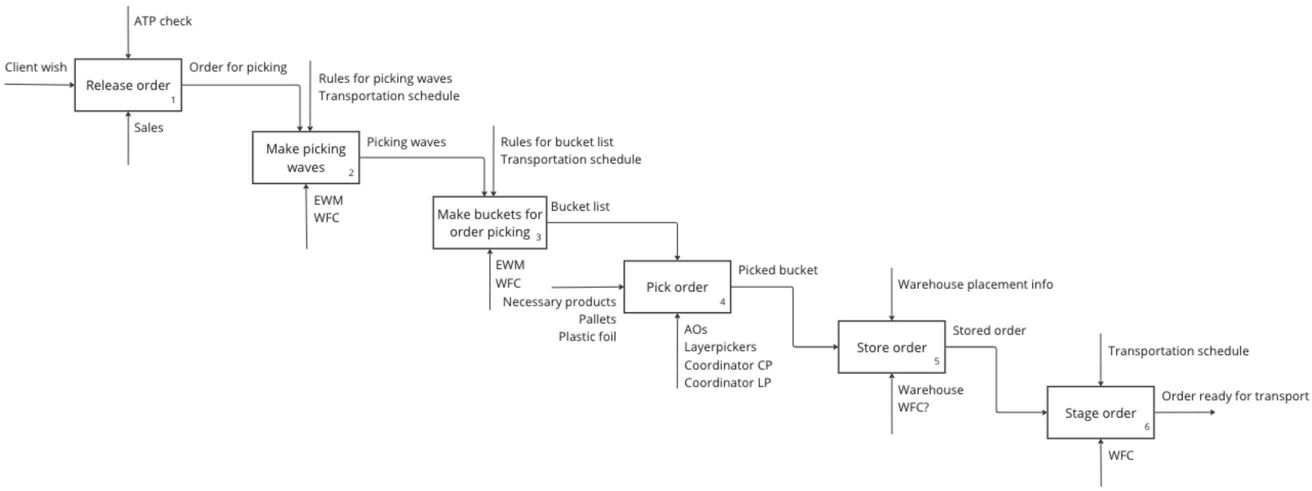

Figure 2.2: IDEF0 Diagram of the Order Picking Process

2.1.3. Explanation of Order Terminology

The following sections use terminology to describe the contents of client orders. However, categorised as sensitive information, volumes are kept out of the main text. An explanation of this terminology is given in Appendix F.1.

2.2. Activities

This section serves to give insight in and overview of the activities done in the colli pick department and how the different departments and processes interact.

2.2.1. Swimlane Diagram

To show the interplay of departments and systems when an order passes through the system, a swimlane is used, shown in Figure 2.3.

As shown in the figure, a great deal of interaction happens between departments, which mainly comes together at WFC. A great deal of work that should be done by the system is taken up by WFC employees, such as organising orders at the Layerpicker. As shown in the figure, waves are created in the EWM system and divided over time buckets. These time buckets are set intervals in time over which the determined picking waves are divided. A choice is made for colli or layerpicking in EWM, after which waves are released by WFC to be picked on either department. As previously shown in the IDEF-0, picking waves are based on the time given in sales orders or on an old version of the timetable, which means the times the waves are based on are not always accurate. As can be seen in the swimlane, the transporter, Simon Loos (SL), matches the unloading time to an order and puts through the definitive loading times to FC afterwards. This is then used by the EWM system at FC to add the definitive due dates to the different orders, which sometimes changes the buckets orders are put into.

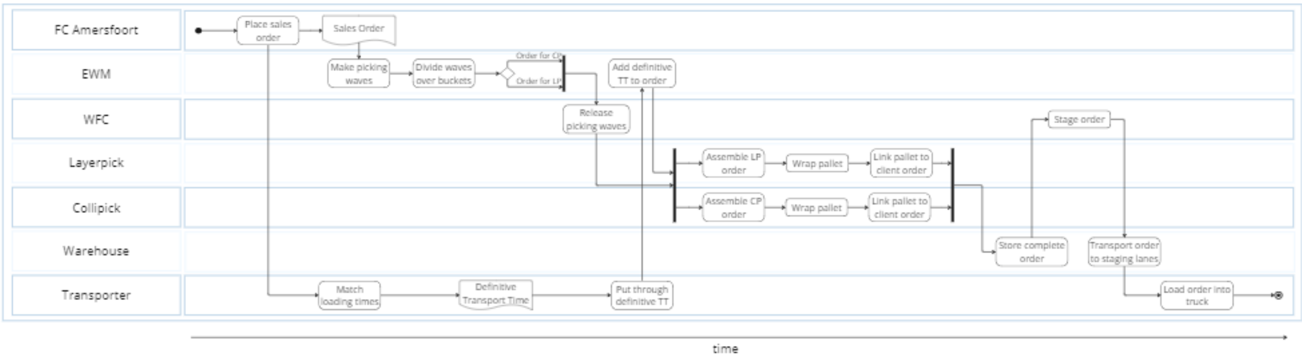

Figure 2.3: Swimlane Diagram for the picking process in the DC

As shown in Figure 2.3 and the description of the process, a great deal of interaction happens between departments and even companies in determining the "right time" to pick. Using an estimation based on experience, WFC can determine more accurate picking times by hand, but they have more on their plate. The interaction between parties calls for clear agreement to the end of obtaining a more efficient task division, which allows for making substantiated decisions regarding a tighter personnel schedule.

2.2.2. Types of Client Orders

Picking wave determination is complexified by the different client orders they contain, which leave different levels of room for flexibility in scheduling due to the time between their creation and deadline. These different types of client orders also contribute to peaks and drops in workload. The different types of orders are given in Table 2.1. The dataset used contains 62 074 picking tasks in total, of which 7 656 are part of A-for-A orders, 46 818 of A-for-B orders and 7 600 A-for-C, resulting in the shares given in the same table.

The distribution of the time between the creation time of a picking task and its planned load time, categorising the tasks into order types, is given in the histogram in Figure 2.4.

The first category, A-for-A orders, leaves little room to move around tasks in the schedule, and cause a peak in workload at 09:00, when they come in. A pool of flex workers is used to account for this peak, which is still available in the afternoon when the A-for-A orders have already left the DC. Even though the volumes in this category are quite predictable, these hours contain a large peak in workload, and employees are kept or put on the schedule to match. However, as explained in subsection 2.3.1, a shift is 8 hours, meaning employees can come to a standstill if the time is not filled up with tasks.

The second category comprises the largest number of tasks, and can be moved around in the schedule. The third, a small category, has the most time between order creation and deadline. Logi-

Table 2.1: Types of Client Orders

Order type	Description	Time gap	Share
A-for-A	Order on same day as delivery	5 hours before loading time	12.3%
A-for-B	Order between 13:00 and 16:00, one day before delivery	5 - 24 hours	75.4%
A-for-C	Order at least two days before delivery	24-48 hours	12.3%

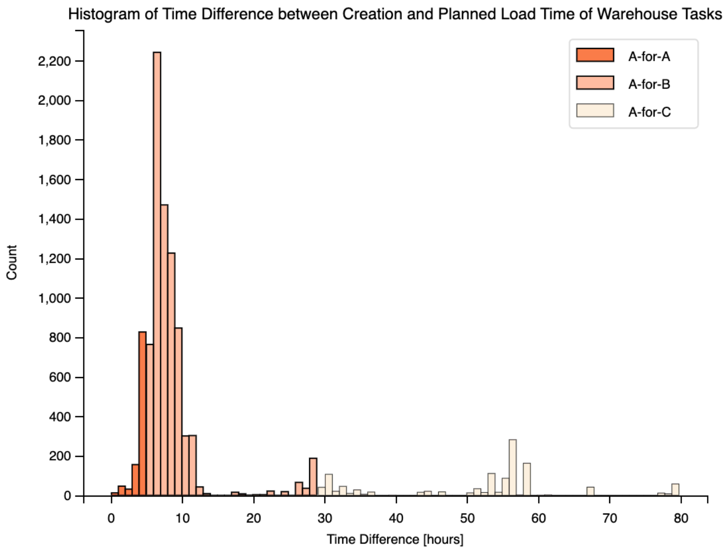

Figure 2.4: Histogram of Tasks, labeled by Order Type, on the Colli Picking Department

cally, the last two categories are most flexible in the schedule to be either pushed forward or backward, but they are often used to fill up time as employees are present for picking anyway. Additionally, uncertainty in true loadtimes of orders as well of a desire to mitigate risk of machine failure in the DC causes risk-averse order scheduling. These elements make it difficult to determine whether picking is done at "the right time": early enough to still deliver orders on time in case of delay, but later in case of a more efficient personnel schedule.

2.3. Personnel and Structure

To be able to operate 24/6 and to account for the work to be done as explained in the previous sections, manpower is an inherent attribute to the DC. To this end, this section describes its shift schedule and associated cost.

2.3.1. Shifts

In its 24/6 principle, the DC operates 24 hours on each day except Sunday; its shift schedule is shown in Figure 2.5. The figure shows the way shifts are spread over four weeks through a four-crew shift schedule, which are shown chronologically in the figure. As seen in the figure, the different types of shifts follow one another in line with the collective labour agreement. Additionally, on a day-to-day basis, people have a break schedule. The DC has 36-hour work weeks through the schedule as it is now. Employees work in the same crews most of the time, but flex personnel is deployed during office hours (09:00-17:00), as shown in the schematic representation of the shift schedule in Figure 2.6.

Flexibility in the schedule is not only found in the deployment of flexible personnel, but also in the

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Week A	Night	Night	Night			Afternoon	Afternoon
Week B		Morning	Morning	Night	Night	Night	
Week C				Morning	Morning	Morning	Morning
Week D		Afternoon	Afternoon	Afternoon	Afternoon		

Morning
Afternoon
Night

Figure 2.5: The Four-Week Shift Schedule

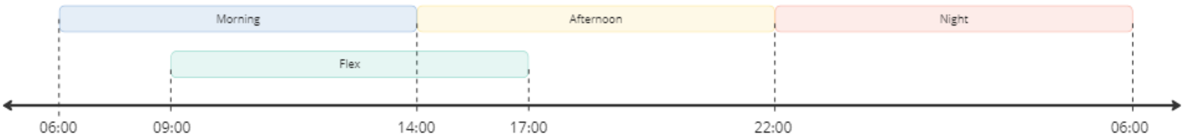

Figure 2.6: Schematic Representation of how Permanent Shifts overlap with Flex Shifts

use of senior days. Twice every four weeks, an employee 58 years and older can choose a free shift.

In the current shift schedule, the permanent crews are deployed in the morning, afternoon and night shifts, supported by flexible personnel in the flex shifts. However, both personnel types could be deployed in all shifts.

2.3.2. Personnel Costs

Surcharge is applied to salaries in line with the Collective Labour Agreement (CLA), on top of the base pay. Normal working hours (from 06:30 until 17:00) get no surcharge, except for 45% on Saturday and 100% on Sunday. From the end of that time interval until 00:00, 34.2% is paid on top of the normal hourly wage from Monday until Friday and 100% on Saturday and Sunday. During the night, from 00:00 until 06:30, surcharge is 37% from Monday until Saturday and 125% on Sunday. An overview of these costs is given in Table 2.2. Using this surcharge, cost of deployment was calculated per shift, which was used for the model. Categorised as sensitive information, this calculation and its outcomes are given in Appendix F.2

Table 2.2: Surcharge on for Irregular Hours

Start	End	Mon	Tue	Wed	Thu	Fri	Sat	Sun
06:30	**17:00**	0.0%	0.0%	0.0%	0.0%	0.0%	45%	100%
17:00	**00:00**	34.2%	34.2%	34.2%	34.2%	34.2%	100%	100%
00:00	**06:30**	37%	37%	37%	37%	37%	37%	125%

2.4. Workload and Workload Distribution

This section shows the way workload is distributed over and between shifts As said earlier, the general perception of workload is that there are peaks and drops in its volume and pattern. This fits the image generated by the different types of client orders and the cooperation between FC and its transporters.

Workload distribution alone is made more interesting by adding the discrepancy between workload fluctuations and personnel deployment, through which the problem obtains its price tag. As explained before, a pool of flex employees is used to handle A-for-A orders that come in each morning. According to a team lead, the volume of these orders require at least 2 manual pickers. This phenomenon is accompanied by the problem of employee idleness later on in the shift, when the high workload people are deployed to absorb sizzles out.

2.4.1. Box Plots of Picking Tasks

This section contains a box plot for the workload distribution on the colli picking department. Data used for this workload were taken between the 15th of May and the 11th of June 2023. Due to the sensitivity of exact volume patterns, only the box plot for Tuesday was enclosed in this section. Hours of the day are shown on the x-axis and picking volume in number of colli on the y-axis. Boxes for the night shift are shown in red, the morning shift in green and the afternoon shift in blue.

As seen in Figure 2.7, picking activities are generally less during the night and shrink during this time as well. At 08:45, the first A-for-A orders are released to the DC, and the hours before this time are generally slow, as can be seen in Figure 2.7. As the shift starts at 06:00, this means that the first three hours of this shift are not used very effectively by the people that are deployed during this time. One way FC counters this effect is by deploying flex workers from 09:00. The A-for-A orders are done before 12:00 and the workload looks quite constant over the period of time the data was aggregated. These orders are loaded at 12:00, after which the afternoon shift generally has a large spread in workload.

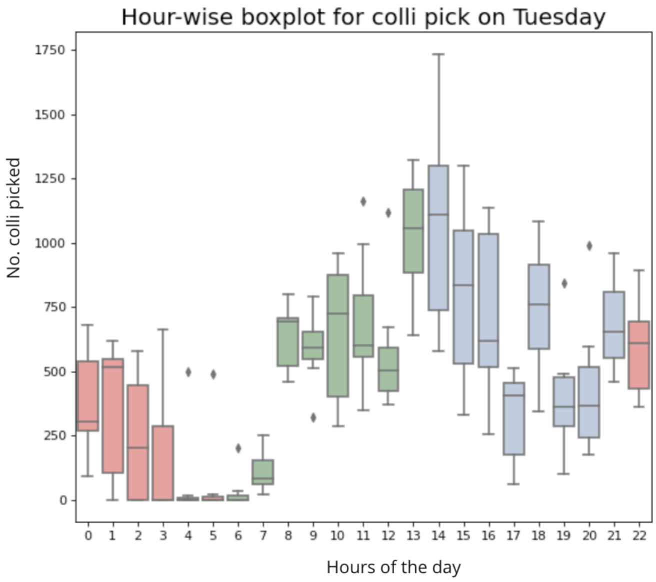

Figure 2.7: Workload Distribution on Colli Pick Department for Thursday

2.4.2. Picking Activities compared to Picking Norm

Due to the sensitivity of picking volumes over time periods, a graph comparing the picking norm with productivity was added to Appendix F.3.1. A histogram for this difference is shown in Figure 2.8. Taken from the descriptive statistics, the mean difference between the norm and the number of colli picked is 572, with a standard deviation of 395. This shows both the overcapacity present at the DC and the large deviations in workload. In this representation of data, it is important to note that the number of people present were counted from the data, using the number of different people that confirmed orders. This would be a more representative measure is counts were taken from past personnel schedules.

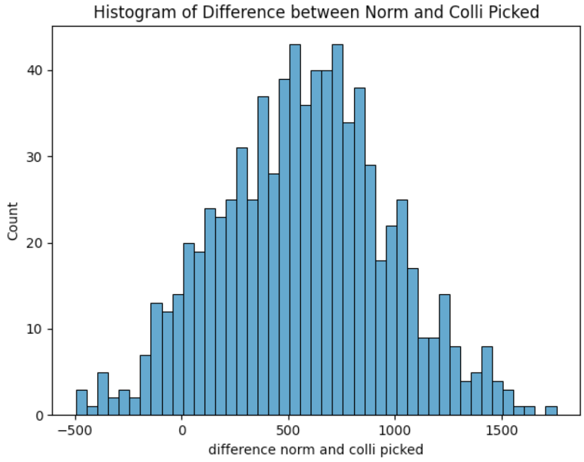

Figure 2.8: Histogram for Difference between Actual Picked Colli and Norm between 11.05.2023 and 31.06.2023

2.5. Job Scheduling and Difficulties

2.5.1. Insight in Load Times

As discussed through the swimlane at subsection 2.2.1, one of the interactions in the picking system is found between SL and the DC. The first picking deadlines are put through with the client orders, and the final load times are added once SL links their transporting schedule to these load times. Picking orders are placed in waves based on the first load times passed to the DC. Although these waves are changed when the definitive deadlines by SL come through, it is initially often unclear whether picking jobs are spread over shifts effectively.

The difference between the initial and final load times are shown for three different weeks in 2024 in Figure 2.9. For the weeks between 18.03 and 24.03, 29.01 and 04.02 and for 12.02 and 18.02, a discrepancy is seen between the load times put through in the client order and the final one, put through by SL.

Even though it is expected to result in a higher amount of scheduling efficiency, it is difficult to determine which jobs can be left to be completed later due to this uncertainty. With full insight in deadlines, it would be possible to determine when jobs can be completed minimised risk of not delivering to the client in time.

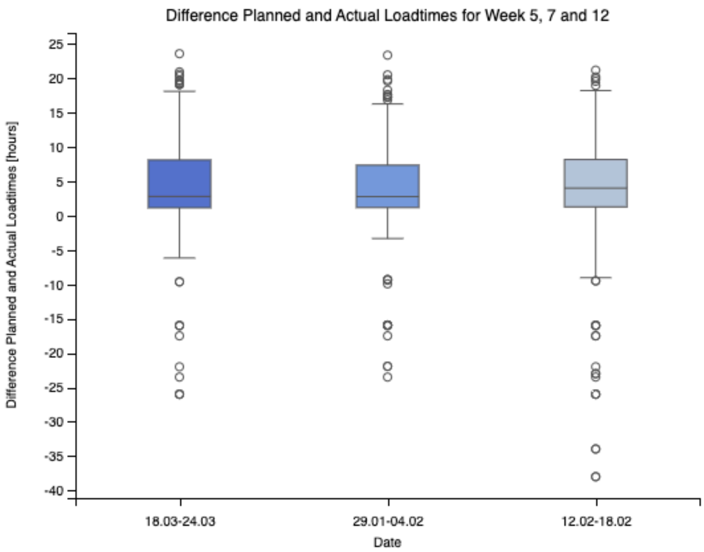

Figure 2.9: Box Plot for Difference between Actual and Planned Load Times for Week 5, 7 and 12

2.5.2. Job Scheduling with respect to their Deadlines

As a result of uncertainty in definitive job deadlines, they are completed quickly after their creation times. En example of when jobs are completed with respect to their creation times and deadlines is shown in Figure 2.10. It was masked as it contains picking volumes; the unmasked figure was moved to subsection F.3.2. It is shown for week 12 of 2024, between 18.03.2024 and 24.03.2024. In the figure, the moments jobs are completed are shown in orange and the intervals to schedule them in in blue. Jobs' creation times follow a pattern with wave releases. As shown in the figure, some days contain a great deal of jobs that are completed quickly after their creation times and others show jobs distributed over the course of their scheduling intervals more.

2.5.3. Stock

As the DC in Maasdam processes fresh dairy products most of the time, they depend on stock delivered by their factory. Relatively tight due dates cause stock to be limited and sometimes not sufficient. This can be in the way of order picking at times.

2.6. KPIs

Parmenter (2007) defines KPIs to represent a set of measures focusing on those aspects of organisational performance that are most critical for the current and future success of the organisation. In the context of this research, the backdrop of measuring the KPIs for the problem serves to contrast solution alternatives to. A table with the chosen KPIs is given in Table 2.3, after which they are both elaborated on.

Table 2.3: Key Performance Indicators

No.	KPI	Unit
1	Number of redundant hours	#
2	Cost of used shifts	€
3	Number of people scheduled	#

2.6.1. KPI 1: Number of People Scheduled

The first KPI encompasses the number of people scheduled over all shifts

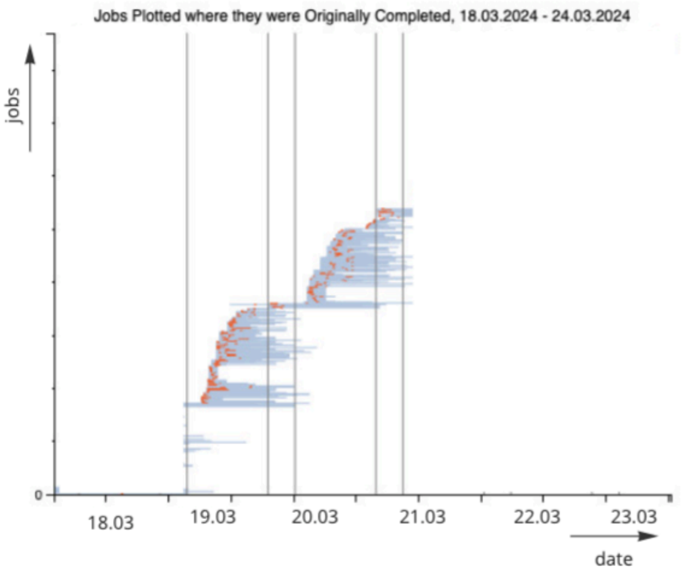

Figure 2.10: Visualisation of Job Creation Times, Deadlines and their Completion Times between 18.03.2024 and 24.03.2024 (masked)

2.6.2. KPI 2: Number of Redundant Hours

The first KPI is used to measure the difference between personnel presence and the total duration of orders. It indicates the efficiency of personnel deployment.

2.6.3. KPI 3: Cost of Used Shifts

As shifts carry different costs, using a smaller number of shifts for workload does not always result in a cost decrease. This KPI was added to assess this effect

2.6.4. KPI Interaction with System

KPIs are put into context of the system in the causal diagram shown in Figure 2.11, in which the KPIs are outlined in red. As shown, the first KPI, **the cost of used shifts**, increases with the deployment of more personnel, both from the permanent and flexible workforce. Additionally, when using expensive shifts (such as the night shift) to complete picking tasks in, this cost increases.

For the second KPI, **the number of redundant hours**, the discrepancy between workload as a result of an uneven workload distribution influences the number of redundant hours through the amount of employee idleness it causes. The uncertainty in order load times is a result of the cooperation with FC's transporter, Simon Loos. There is a gap between the systems both parties use to link orders to transporting units, so an early estimation of which client order needs to be done at what time is lost in translation. However, leveling out the uneven workload distribution can be used as a control mechanism to this end, by scheduling orders efficiently in the used shifts.

The third KPI, **the number of used shifts**, is a direct result of the number of permanent and flex employees put on the schedule and in turn directly influences total personnel cost. When personnel norms can be altered through a more level workload distribution, this number of used shifts can be decreased.

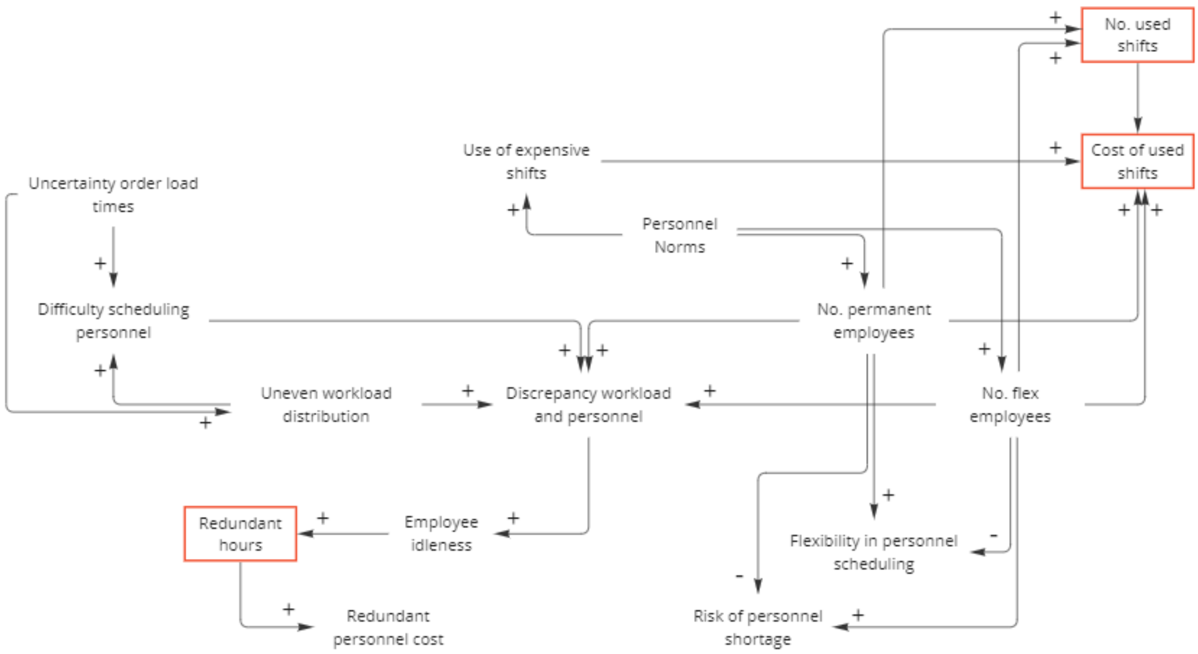

Figure 2.11: Possibilities for control and their influence on KPIs

2.7. Summary System Description

In answering the first sub question, *"Which opportunities can be identified in the current job scheduling method at FC?"*, this chapter comprises a system analysis.

The first opportunity is identified in the wave determination. As explained in subsection 2.2.1, jobs are not scheduled explicitly in the current system. They come in and put into picking waves and buckets based on the deadlines that accommodate client orders. However, as explained in Section 2.5, large differences are seen in the deadlines received with client orders and those put through by SL in a later stage. This results in uncertainty in when picking should be done to meet deadlines. As shown in subsection 2.5.2, orders are often completed quite closely to the time they are initialised.

The second opportunity is found in distributing jobs to the end of an efficient personnel schedule, so that norms used for personnel scheduling (Section 2.3) can be adjusted accordingly. This means that personnel is put on the schedule at night in some cases. Being the most expensive shift (subsection 2.3.2), this is undesirable. However, it is unclear whether picking jobs can be distributed in a way that the night shift is avoided. To this end, it is expected that jobs can be moved into the flex shifts or into the morning shifts and afternoon shifts.

The third opportunity is found in the senior days as explained in Section 2.3. Using these senior days cleverly can contribute to less redundant hours in shifts with low workload.

3
Literature Review

In finding a method to realise a better workload distribution, this chapter aims to answer the second research question: *"Which models found in literature are most suitable to solve the job scheduling problem at FC?"* It starts with literature regarding workload balancing and workforce allocation in Section 3.1. Separate workload balancing literature is given in Section 3.2. Task Scheduling is discussed in Section 3.3, followed by shift scheduling in Section 3.4. Different workload balancing criteria and time representation literature are discussed in Section 3.5, followed by a summary of the literature review in Section 3.6

3.1. Workload Balancing and Workforce Allocation

Irastorza and Deane (1974) have defined workload balancing as "managing the variability of workloads over a time horizon". This can be done through activity or personnel distribution. A general strategy for personnel scheduling is letting it depend on the workload forecast, a shown schematically in Figure 3.1a. Vanheusden et al. (2020) have added the workload balancing step to this equation in Figure 3.1b.

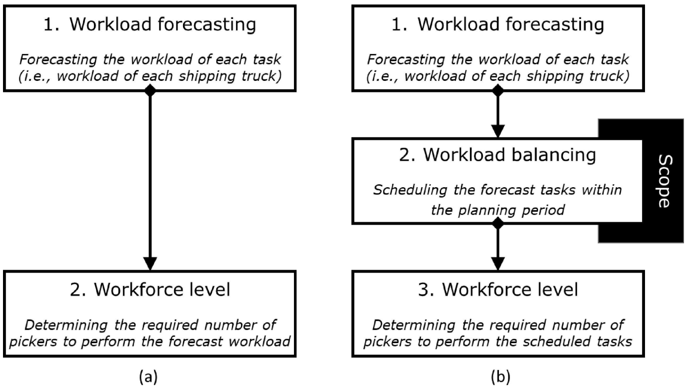

Figure 3.1: Approaches to Workforce Determination (Vanheusden et al., 2020)

In their literature review regarding personnel scheduling, Van Den Bergh et al. (2013) note that personnel scheduling is hardly ever combined with unforeseen activities, even though scheduling of different aspects are bound to interact. They suggest testing a model's robustness through simulation experiments in different settings, with varying input parameters to account for different workload peaks. They stress the importance of integrating real-life difficulties into personnel scheduling to make the solutions more suited for practical implementation.

In their study, Smet (2023) aims for a balanced workload distribution over hospital employees, taking into account the types of patients that arrive and the types of care they need. In their equity objective function formulation, they encapsulate both spatial (between hospital wards) and temporal (between days in the planning period for individual wards) workload balancing. Their objective is a min-max equity function, which minimises the maximum workload in their timeframe. The maximum workload is taken over all hospital wards as well as over all days, which envelops the spatial and temporal aspect of the problem, as said earlier. This paper also contains a formulation for constraints ensuring hospital patients are admitted to the hospital within the feasible time window. To do so, they use a set of feasible admission dates per patient. This element of scheduling a task within an available time frame and keeping a deadline in mind can be used from this study in the current problem formulation.

3.2. Workload Balancing

A stated earlier, Vanheusden et al. (2020) have formulated a model to solve the issue of Operational Workload Balancing Problem (OWBP) in warehouses. They aim to balance the workload to prevent workload peaks, describing the problem as assigning groups of customer orders to predefined time slots to this end. Their objective function is a minimisation of the maximal planned workload over all timeslots. They do state that the OWBP issue is a difficult problem to solve optimally when the aim is a practical computational time. In 2021, Vanheusden et al. did a new study to compare different workload balancing approaches, using restricted time windows to retrieve customer orders. They found that the effectiveness of different balancing measures is influenced only very little by warehouse layout characteristics and customer order parameters (in an e-commerce setting). The effectiveness of measures is more often influenced by underlying managerial reasons, such as transportation schedules.

Huang et al. (2006) state the importance of a clear definition of workload balancing, in which they use the maximal workloads and the sum pairwise difference as objectives for their Stochastic Mixed Linear Program (S-MILP). They use the model for workload balancing in an aircargo terminal situation, in which they aim to balance the workload between handling terminals and over the given time horizon. They assume a fixed aircraft schedule, and a stochastic workload from each flight. This can be compared to the situation at FC in the sense that there is a fixed schedule for a part of the order picking activities that need to be completed, and there is the stochastic element of unforeseen orders with short deadlines that also need to be done. However, the problem set to be solved is deterministic rather than stochastic.

Workload balancing can also be done through task division over personnel, to which end Azmat et al. (2004) formulate different approaches to an annualised problem, in which the holiday schedule and yearly demand planning constrain the objective of leveling workload for the manufacturing company the case is built on. They aim to minimise overtime hours over the year and per employee to formulate a workforce schedule. In their objective, they minimise a pairwise comparison of the workload difference between employees. In this comparison, they sum the number of hours one employee works more than the other and the number that the other works more than the one. They add this to the number of overtime hours for workers.

Golpîra and Tirkolaee formulated a MILP model for stable maintenance task scheduling, using sets of time buckets to divide maintenance tasks over (2019). These time buckets, however, are pre-purchased and the objective is to minimise cost and stability over the different buckets.

Simulation is a broad term for methods that allow the user to imitate a real-life simulation and assess the effects of different measures on the simulated system. Kim (2020) have formulated a simulation approach to schedule jobs more efficiently to meet compressed response times in an e-commerce setting. They applied priority-based job scheduling using shop-flow models for their warehouse job scheduling. A joint evaluation criterion was used to assess the performance of different priority rules, which integrates the objectives of low earliness, low tardiness, low labour idleness and low work-in-process stocks. This evaluation criterion is in line with the solution aimed for at FC. However, in an e-commerce setting, orders come in stochastically, making this simulation a handy approach to test different scenarios.

Some other studies have been found using simulation, but those were mainly used for production planning. An example is Haeussler and Netzer (2019), who made a comparison between an optimisation-based and a rule-based approach to workload balancing in a production planning environment. They conclude that the optimisation-based model outperforms the rule-based one on most of the aspects they tested, but that it is still not developed enough to serve as a user-friendly way to conduct activity planning. In case of a deterministic model, however, this could be useful.

3.3. Task Scheduling

Brucker (2004) and Leung (2004) both give an extensive explanation of scheduling and different algorithms, most of which concern deterministic scheduling. Lawler et al. (1993) restrict some of the characteristics in deterministic problems, for example defining that only one job can be handled by one machine at a time.

Pinedo (1996) categorised scheduling problems for machine environments. They make a distinction between environments with single machines, multiple machines, uniform and varying completion times of jobs, based on the processing times of machines. Problems in which jobs need to move through the problem in series are touched upon, as well as cases of parallel machines. In line with this categorisation, the problem at FC can be viewed as problem with m identical machines that act in parallel (P_m), in which a job j requires a single operation. In this case, order pickers can be seen as the machines and picking tasks as jobs, which contain a release date, deadline and duration (based on the processing speed of the order pickers). This problem contains no preemption. They define the minimisation to always be a function of task completion time, which an be divided in earliness by subtracting the deadline and tardiness as the same measure with a minimum of 0.

Completion times are used for makespan minimisation in this group of problems. However, the total makespan depends on the times orders come in and their deadlines at the DC, and the objective is not a makespan minimisation but a spread of this workload to bring about manpower minimisation.

Rieck et al. (2012) formulated MILP models for project scheduling, in which each project comprises a set of tasks to be done before a deadline. These tasks have different needs with respect to resources, such as machinery, personnel and time. In this formulation, the problem is a resource allocation problem as opposed to a task scheduling one but people and shifts can be seen as resources. Their definition of the decision variable contains a start time only, instead of scheduling over all time blocks the task needs to be scheduled in

3.3.1. Job Shop and Machine Scheduling Problems

In line with the previous definition of task scheduling problems, many manufacturing formulations of the workload (im)balance problem are formulated as a serial operation, in which one machine operation needs to be done before the next and tasks or machines have different processing times. These formulations contain Job-Shop Scheduling Problem (JSSP) formulations, in which an execution on all or some machines in a specific order is necessary and the goal is to minimise overall makespan (Błażewicz et al., 2000).

It can be formulated in a multi machine environment, in which machines would be people in the context of this study. Abdolrazzagh-Nezhad and Abdullah (2017) view various formulations of the JSSP, categorising fourteen classes of JSSPs. By their definition, the classical JSSP contains three types of constraints: precedence, capacity and release and due date. Precedence constraints contain the precedence of different machines for one job and not the precedence relative to another job, capacity constraints ensure that machines cannot be idle if there is a job in the queue and that one machine handles one job at a time. The last set of constraints ensure no negative starting time, specific processing times and no interruption of these processing times. Objective functions aim for minimal (weighted) tardiness, lateness and makespan.

In the study performed by Rudek (2022), another problem in which tasks are scheduled over parallel machines is given. In contrast to the other formulations, tasks do not all have the same release time, but are released at different points in time and also have different deadlines. It also contains a deterioration function for the different machines to account for maintenance, which is not needed in the formulation of the model at hand. In many of the Job Shop and Machine Scheduling problems, the start time of all jobs is 0. As the envisaged deterministic model contains tasks that arrive at different moments than 0 on the timeline. This formulation needs to be altered to be suitable for the problem at hand.

As opposed to a JSSP, an Open-Shop Scheduling Problem (OSSP) aims to schedule a number of jobs over a number of machines in no specific order. It is also categorised as an NP-Hard problem and is often solved through heuristics.

In Parallel Machine Scheduling Problems, the goal is to schedule J jobs to M machines. Gharbi and Haouari (2005) have done so, taking into account availability constraints of the machines. Feldmann et al. (1994) have also done so using a network approach. Mokotoff (n.d.) considers the parallel machine scheduling problem in her survey, and concludes that large steps are made towards solving the problem. These steps are seen especially in the objective of makespan minimisation, a relevant subject in computer science. Models minimising total tardiness are also found to the end of parallel machine scheduling (eg. Yalaoui and Chen (2002)).

3.3.2. The Bin-Packing Problem

In the Bin-Packing Problem (BPP), the objective is to pack all rectangular shaped objects in to a number of bins that is as small as possible (Martello and Vigo, 1998). The generalised BPP aims to add two sets of compulsory and non-compulsory items to bins, minimising the cost in the process and taking into account profit of packing specific items (Baldi et al., 2012).

The BPP is often found in cloud computing as a way to place Virtual Machines onto different servers (Berndt et al., 2018). An example of this is Komarasamy and Muthuswamy (2016), who took on the problem of storage allocation using this approach. They classified jobs and prioritised them to place them inside bins. In its objective, the number of bins used can be minimised, but cost can also be allocated to different bins so that cost is minimised in these problems. An example of this is the Multiple Container Loading Cost Minimisation Problem (MCLCMP) as discussed by Hou et al. (2011), in which objects are placed into containers under the objective of cost minimisation.

In the aircraft industry, BPP is used for task scheduling by Witteman et al. (2021), who used this method for maintenance scheduling taking into account different ability levels of mechanics. They added a fictitious bin to their definition to add space in the model tasks could be placed in if they did not fit in the planning horizon. Their objective function contains a cost minimisation. In their study conducted in 1978, Coffman et al. used a Bin Packing formulation for multiprocessor task allocation.

The use of a BPP formulation for WLB is also seen in a cloud computing setting. An example is the paper by De Cauwer et al. (2016), who created BPP model with a temporal component, in which they also minimise total cost of used bins. In their study, Hou et al. (2011) examine the multiple container loading cost minimization problem (MCLCMP) using Linear Integer Programming and getting superior results to previous studies. Fleszar and Hindi (2002) have formulated new heuristics for solving the 1D-BPP, which have better performance than previous algorithms.

3.4. Shift Scheduling

Shift allocation of work force must meet requirements of the workforce. This shift allocation problem is seen as trivial to solve, but too rigid in the case workforce demand fluctuates too much during a shift (Baker, 1976). This shift scheduling problem requires a predetermined workforce demand, which would mean that personnel scheduling could be done more efficiently based on current workload. However, this would mean a suboptimal schedule as workload fluctuates a great deal the way it is filled in now. Smet et al. (2014) formulated a new method to solve the Shift Minimisation Personnel Task Scheduling Problem (SMPTSP), in which they use an extra binary variable that indicates whether an employee has a task during a shift.

Krishnamoorthy et al. (2012) introduced this problem, in which the objective is to minimise overall personnel cost to schedule all tasks. Again, this formulation contains a heterogeneous workforce to complete tasks with a fixed start and end time, while this study aims to move tasks around to be able to schedule the workforce more efficiently. The difference with the FC case is that start and end times of tasks are not fixed, which means that a model formulation is needed to account for both shift and task scheduling.

3.5. Workload Balancing Criteria

To formulate a model in balancing the workload over different shifts, measures are needed to show the workload (im)balance. Many JSSP model formulations aim to minimise total makespan, which does not necessarily add to a balanced workload for reduced cost in this study. As they see workload imbalance amongst employees or machines as a large problem, Ho et al. (2009) propose a measure for workload balancing called Normalized Sum of Square for Workload Deviations (NSSWD), which is adopted by Schwerdfeger and Walter (2018). In their study, they aim to schedule a set of jobs n over a set of parallel machines m by minimising NSSWD. They show that minimising this measure acccounts for a minimal maximum completion time. However, as it is not the minimal maximum completion time this study is interested in but a cost minimisation through workload balancing, this is not necessarily useful for this study.

Ouazène et al. (2016) use this measure for their study on a minimisation problem for parallel machines. They use both the NSSWD and a C_{max} - C_{min} criterion (ΔC) for workload distribution over parallel machines. They show that the latter criterion theoretically gives the same results as the former in a parallel machine workload imbalance minimisation environment. Building on this theory, Ouazène et al. (2021) have given a theoretical and computational analysis of various workload balancing models, in which their main objective is to schedule workload over different machines or operators to decrease idle time. In the workload balancing problem this study is faced with, this could mean seeing the machines as hours of the day, in which the employees that need to be deployed are a result of the workload distribution. This formulation of a workload balancing objective may however be computationally demanding for large datasets.

In their study in 2014, Ouazène et al. formulated a mathematical programming method to solve the workload balancing problem. They did so by minimisation of workload between the machines with the highest and lowest workload, through the ΔC criterion as named above. Their decision variables comprise two binary variables x_{ijm} and y_{jm}, respectively denoting whether job j immediately follows job i on machine m and whether job j is assigned to machine m.

The shift minimisation objective in the SMPTSP as proposed by Krishnamoorthy and Ernst (2001) is in line with the task scheduling problem viewed in this study.

3.6. Summary of Literature Review

The literature studied in this chapter aims to answer the second sub question: *"Which models found in literature are most suitable to solve the job scheduling problem at FC?"*.

Based on the SMPTSP as defined by Krishnamoorthy et al. (2012), the model objective is to minimise shift use over all shifts using a weighted objective function. To determine which job is done at what time and which shifts are in use (the latter for cost calculation of the objective), binary variables are used.

The model formulation by Krishnamoorthy et al. (2012) differs from the model needed in this study on a critical aspect: job scheduling. In their model, jobs have set start and end times, based on which jobs are placed in "cliques" of jobs that overlap. Using these cliques, a minimal shift schedule is devised. However, the start and end times of jobs in the model required in this study are not set, meaning that the minimal clique algorithm may be used to define sub sets of possible job scheduling combinations, and a separate job scheduling addition needs to be made.

Using a continuous time horizon for scheduling, jobs can be scheduled both between their creation time and deadline and between the start and end time of a shift. Jobs' start time is portrayed as a decision variable to this end (Rieck et al., 2012). However, when multiple jobs are scheduled in one shift, they cannot overlap as one person cannot work on multiple orders. To this end, non-overlapping constraints are inspired by the BPP approach as formulated in 3D by Paquay et al. (2014). As the temporal dimension is the only one this study requires, these overlapping constraints can be reformulated into 1D constraints. In their BPP approach to a job scheduling problem, Witteman et al. (2021) created a fictitious bin in which jobs can be placed if they cannot be planned in the given bins in the model. In this vein, more shifts than necessary are defined in the model to leave room for jobs that do not fit into the desired shifts.

4
Model Formulation

This chapter contains the model formulation to answer the third research question: *"How can the practical job scheduling problem at FC be represented in a mathematical formulation?"* Mdel requirements and assumptions are given in Section 4.1, followed by the problem description in Section 4.2. Sets, Parameters and Decision Variables are given in Section 4.3. Section 4.4 contains the model's objective function and constraints, followed by a conceptual model. Model development is elaborated in Section 4.5 and a model discussion in Section 4.6. The chapter concludes with a summary in Section 4.7.

4.1. Model Requirements and Assumptions

Model requirements are found in subsection 4.1.1 and assumptions in subsection 4.1.2

4.1.1. Requirements

To determine whether the model does what it is supposed to do, model requirements were devised in this section.

- An order must be completed within one shift;
- An order must be completed between its creation time and deadline;
- No job preemption is allowed;
- All jobs must be completed;
- No overlap is allowed between jobs assigned to the same shift;
- A time gap is added between the end of one job and the start of the next to account for processing time between orders.

4.1.2. Assumptions

The model assumptions are given in this section

- There are no skill requirements to complete jobs;
- In real life, orders contain different picking tasks. These picking tasks are contained in an order and an order is indicated using the word "job";
- Jobs are finished in one go;
- A shift represents a worker in that shift;
- Building on the previous assumption, the shifts are not paired to a person. This means the model does not take into account time between workers' shifts as defined in the Collective Labour Agreement;
- The model is focused only on picking jobs, and not on any other tasks employees must perform in this department;
- The model does not contain a break schedule.

4.2. Problem Description

The different shifts in the model represent an employee deployed in that shift. This is based on the definition by Krishnamoorthy et al. (2012) and is shown conceptually in Figure 4.1. In their model, the objective is to schedule tasks in a minimal number of shifts. There are two large differences between their model and the problem description given for this model. The first is that their employee qualifications should meet task requirements, which is not present in the problem description in this study. The second difference is that the tasks in their model have a set start and end date, even though the point in the study at hand is to schedule tasks to be able to see whether they fit in less, or a different composition of, shifts.

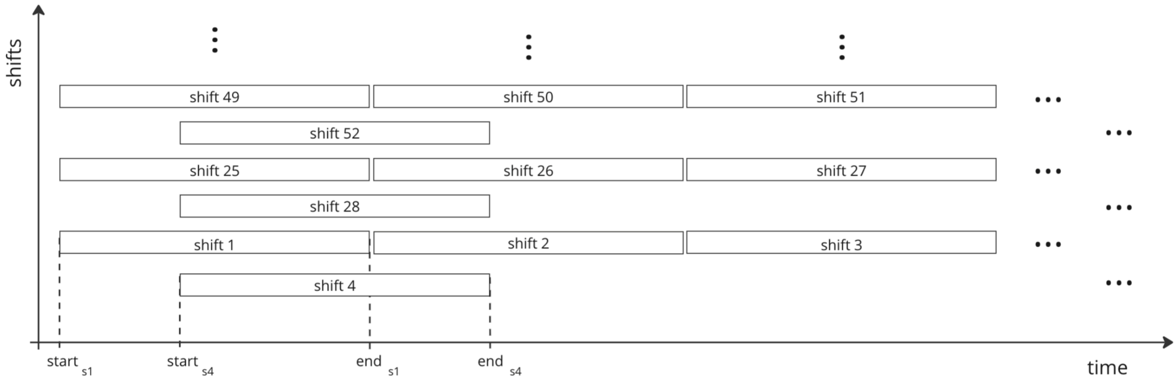

Figure 4.1: Schematic representation of shifts

Part of this job scheduling formulation follows directly from the problem description, in which jobs need to be scheduled between their time of creation and deadline, and need to fit into shifts completely. To this end, the start time of a job is seen as a continuous variable (Rieck et al., 2012). The challenge is found in ensuring jobs do not overlap within a shift, as one person cannot work on two orders at any given moment. To this end, non-overlapping constraints are inspired by the BPP approach as formulated in 3D by Paquay et al. (2014). As requires only a temporal dimension, these overlapping constraints were reformulated into 1D constraints.

In their BPP approach to a job scheduling problem, Witteman et al. (2021) created a fictitious bin in which jobs can be placed if they cannot be planned in the given bins in the model. To this end, more shifts than necessary should be defined so that the model has room for scheduling.

Due to the NP-hardness of BPPs, the next challenge was found in making the formulation suitable for practical use. This process is described in Section 4.5.

4.3. Sets, Parameters and Decision Variables

This section contains the model Sets and Parameters in subsection 4.3.1 and Decision Variables in subsection 4.3.2.

4.3.1. Sets and Parameters

The sets for the mathematical model are given in Table 4.1 and parameters in Table 4.2.

Table 4.1: Sets used for the mathematical formulation

Set	Definition
J	Set of picking tasks
S	Set of shifts

As shown in Table 4.1, the set of jobs to be done is denoted by J, and the set of shifts by S. A job j is a given deadline DL_j, a creation time CT_j and a duration D_j. A shift carries cost C_s and has a start time and end time ST_s and ET_s, respectively. The time used by an operator to switch between jobs is indicated with BAT; this time includes placing the finished order in a bin to be moved into the warehouse and driving to the next start bin. The model also uses a large positive a large positive time value V.

Table 4.2: Parameters

Parameter	Definition	Unit
DL_j	Deadline of job j	[seconds]
CT_j	Creation time of job j	[seconds]
D_j	Duration of job j	[seconds]
C_s	Cost of shift s	[€]
ST_s	Start time of shift s	[seconds]
ET_s	End time of shift s	[seconds]
BAT	Between-activity time	[seconds]
V	Large temporal value	[seconds]

4.3.2. Decision Variables

The decision variables used in the model are given in Table 4.3.

Table 4.3: Decision Variables for the Mathematical Model

Variable	Definition	Sets
x_{js}	Binary variable indicating whether job j is assigned to shift s	$j \in J, s \in S$
u_s	Binary variable indicating whether shift s is used	$s \in S$
$start_j$	Continuous time variable indicating the start time of task j	$j \in J$
b_{jk}	Binary variable indicating whether task j is scheduled before task k	$j \neq k \in J$

The first binary variable x_{js} evaluates to one if task j is assigned to shift s, and the second, u_s, indicates whether shift s is in use. For the task scheduling constraints, two additional DVs were devised, denoting the scheduled start time of a job j, $start_j$, and whether task j is scheduled before task k, b_{jk}.

4.4. Objective and Constraints

4.4.1. Objective

As explained in Section 4.2, the model's goal is to minimise cost of used shifts over the planning horizon. As the cost per shift differs per shift and weekday, the objective function in Equation 4.1 follows from this goal, in which the cost of used shifts is summed.

$$min : \sum_{s \in S} C_s * u_s \tag{4.1}$$

4.4.2. Constraints

An overview of the constraints that bound the objective is given in Equations 4.2 up to 4.10.

Task Scheduling and Shift Capacity Constraints

$$\sum_{s \in S} x_{js} = 1 \qquad \forall j \in J \tag{4.2}$$

$$x_{js} \leq u_s \qquad \forall\, s \in S, j \in J \tag{4.3}$$

$$\sum_{j \in J} x_{js} * D_j + \sum_{j \in J} x_{js} * BAT \leq ET_s - ST_s \qquad \forall s \in S \tag{4.4}$$

Start Time Scheduling Constraints

$$CT_j \leq start_j \qquad \forall\, j \in J \tag{4.5}$$

$$start_j + D_j + BAT \leq DL_j \qquad \forall\, j \in J \tag{4.6}$$

$$start_j \geq ST_s - (1 - x_{js}) * V \qquad \forall\, j \in J, s \in S \tag{4.7}$$

$$start_j + D_j + BAT \leq ET_s + (1 - x_{js}) * V \qquad \forall\, j \in J, s \in S \tag{4.8}$$

Overlapping Constraints

$$b_{jk} + b_{kj} \geq (x_{js} + x_{ks}) - 1 \qquad \forall\, j \neq k \in J, s \in S \tag{4.9}$$

$$start_j + D_j + BAT < start_k + (1 - b_{jk})V \qquad \forall\, j \neq k \in J \tag{4.10}$$

The constraints in Equation 4.2 ensure that all jobs are scheduled in exactly one shift. A shift is marked as used in Equation 4.3. Equation 4.4 impose that the total duration of jobs scheduled in a shift, with the addition of BAT, does not exceed shift duration. Equation 4.5 denotes that a job's start time must be larger than its creation time, and Equation 4.6 prevents a job from exceeding its deadline, using its duration. The large temporal value V was used to schedule a job between the start and end time of a shift, respectively in Equations 4.7 and 4.8.

Through the constraints in Equations 4.9 and 4.10, overlap between jobs is avoided. If two jobs j and k are scheduled in the same shift s, Equation 4.9 forces one of the two jobs to be scheduled before the other. If job j is scheduled before job k (i.e. b_{jk} = 1), the start time of job j (with the addition of its duration and the BAT parameter) is constrained by the start time of job k.

4.4.3. Conceptual Model for Task Scheduling

Using the sets, parameters and decision variables as formulated in the previous sections, a conceptual model for the way constraints ensure task scheduling is shown in Figure 4.2. It shows two shifts, s and t, over which tasks j and k must be scheduled, respectively shown in green and orange. The creation time and deadline CT and DL for both tasks are shown in the same colours and with corresponding subscripts.

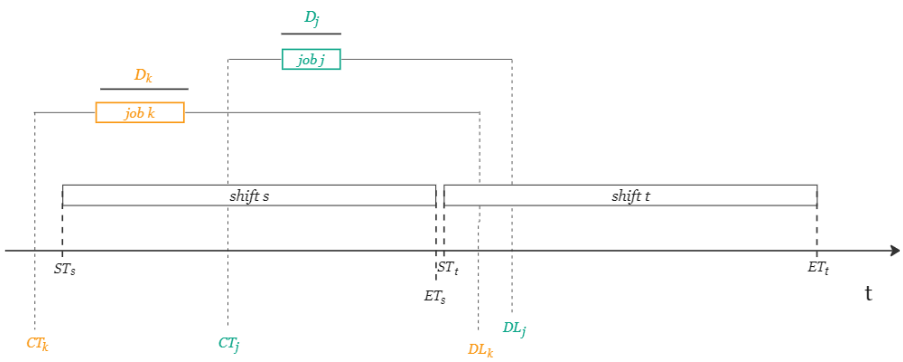

Figure 4.2: Visual Representation of Example Jobs and Shifts, with Creation Times and Deadlines

Figure 4.3 shows a possible way these tasks can be scheduled in the given shifts, adhering to all constraints and including the corresponding evaluation of decision variables in red. As shown in the figure, the two tasks must be scheduled between their creation time and deadline (Equations 4.5 and 4.6), and must each be completed during a shift with no preemption (Equations 4.8 and 4.7) or overlap between tasks (Equations 4.9 and 4.10).

Taking into account that the two tasks to schedule both fit into the same shift due to their creation times, deadlines and durations, the DVs corresponding to this situation are given in red: the scheduled start times $start_k$ and $start_j$, the binary variables that are equal to one x_{js}, x_{ts} as both tasks j and k are scheduled in shift s, u_s as shift s is in use and b_{kj}, as task k is scheduled before task j

The case in which job creation times, deadlines and durations do not allow for jobs j and k to be scheduled in the same shift is shown in Figure 4.4. In this case, both shifts are in use ($u_s = 1$ and

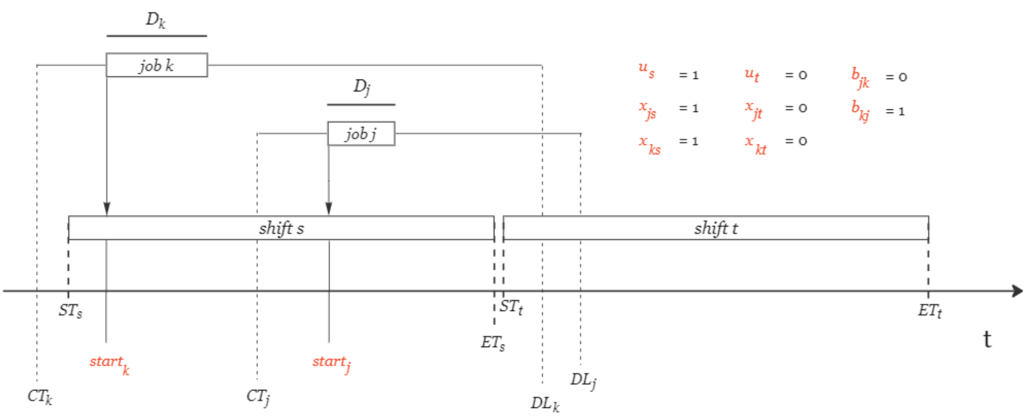

Figure 4.3: Conceptual Representation of Task Scheduling of jobs j and k that fit into Shift s

$u_t = 1$), job j is scheduled in shift t and job k is scheduled in shift s ($x_{jt} = 1$ and $x_{ks} = 1$, respectively). Neither b_{jk} nor b_{kj} evaluate to one, as the jobs are scheduled in different shifts, and the start times of the jobs $start_k$ and $start_j$ allow for both jobs to be finished within the shifts they are scheduled in.

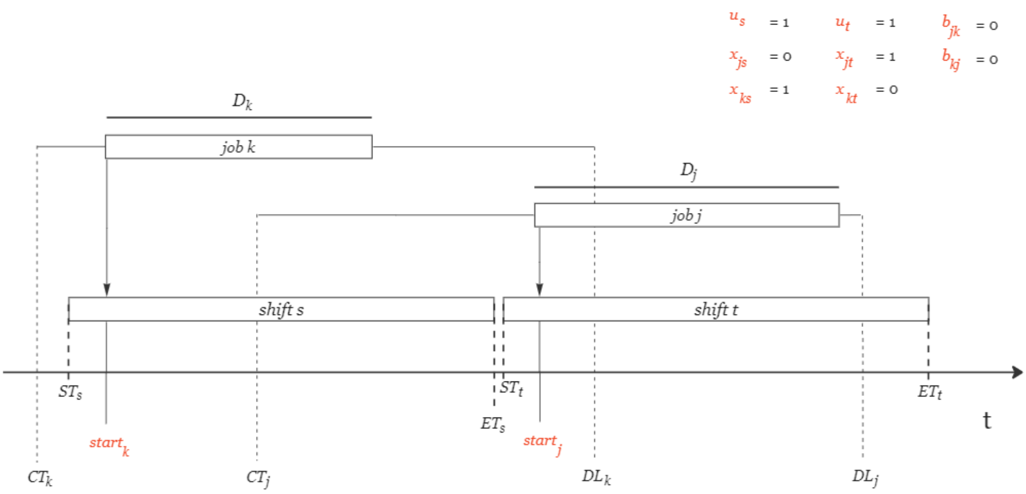

Figure 4.4: Conceptual Representation of Task Scheduling of jobs j and k that do not fit into Shift s together

4.5. Model Development

Due to the decision variables b_{jk} ensuring no overlap, the number of constraints was very high in the model's formulation. This resulted in a slow model that had trouble finding optimality. Some approaches were used to mitigate this effect, which are elaborated in this section. The first was taken from the formulation of maximal cliques in graph theory. The approach and outcomes are given in subsection 4.5.1. To further reduce the problem size, alterations were made to task creation and deadlines, described in subsection 4.5.2.

4.5.1. Cliques

An algorithm to find maximal cliques as given by Krishnamoorthy et al. (2012) is used to make sub sets of tasks that can be scheduled together. This way, sub problems are made so that the model does not need to compare tasks that could not have been scheduled in the same shift in any case. The algorithm to do so is given in Figure 4.6, based on the visual representation of cliques as given in Figure 4.5 (Krishnamoorthy et al., 2012).

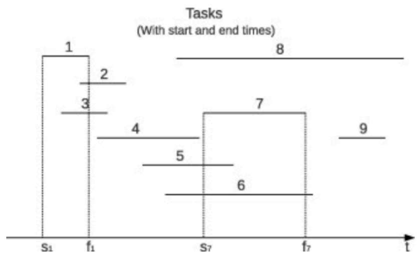

Figure 4.5: Visual Representation of Tasks in Cliques

Initialize:	p=0, C=∅,
	s=$\min_{j\in J} s_j$, ***stop***=0;
do	$f = \min_{j:s<f_j} f_j$
	p=p+1
	K_p={j∈J|s_j<f≤f_j}
	C=C⋃{K_p}
	if ∃s_j≥f **then** $s = \min_{s_j \geq f} s_j$
	else ***stop***=1
while	***stop***=0

Figure 4.6: Maximal Clique Algorithm

In using cliques, a shorter runtime was expected from the model. However, due to the large number of overlap between tasks over different days of the week, large overlap of tasks in between cliques is seen. This is displayed in Figure 4.7, where darker orange means that a job is contained in more cliques. Using this clique formulation of the model, the optimality gap did not go lower than 70% within a 30-minute runtime for tasks scheduled , meaning the model was so far from optimal that it was not practical to use it for the end goal of this study.

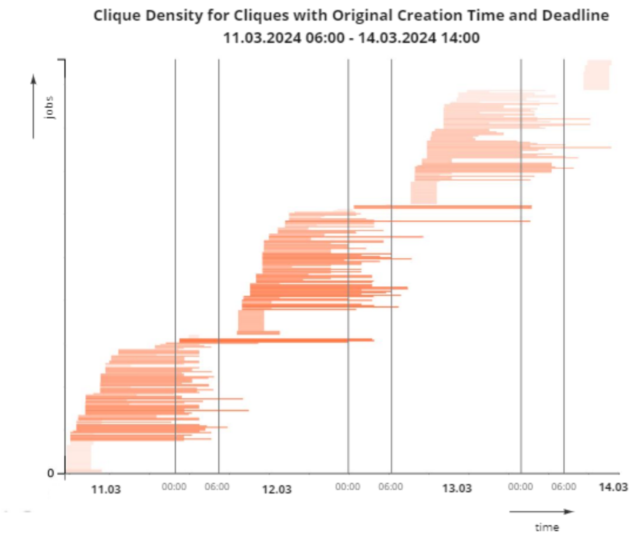

Figure 4.7: Visualisation of Clique Densities for Jobs between 11.03.2024 06:00 and 14.03.2024 14:00

An alteration was made to this clique formulation to reduce the number of overlaps in the data by assigning a new creation time to the different jobs in the model. This creation time was equal to the job deadline, minus its duration minus 2 hours. This alteration resulted in the new creation times and deadlines as shown in Figure 4.8. This new formulation gave the model very little room to schedule tasks and resulted in an infeasible model.

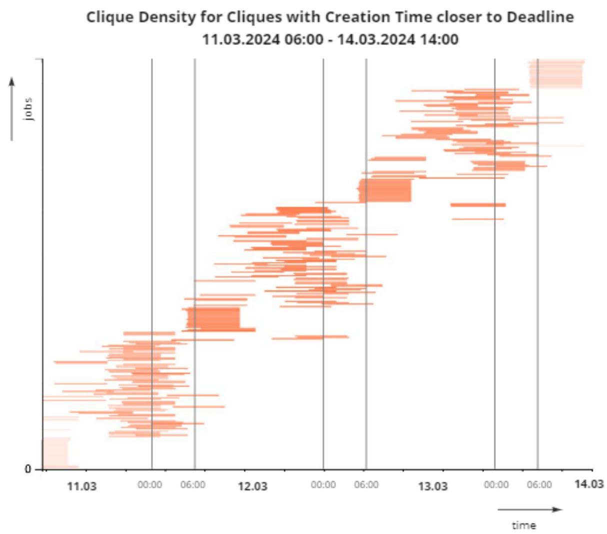

Figure 4.8: Visualisation of Clique Densities for Jobs between 11.03.2024 06:00 and 14.03.2024 14:00, Short CTs

4.5.2. Subset Creation

After the clique attempts at increasing optimisation speed that did not bring about a great deal of improvement, it was decided to make sub sets to solve separately. However, as visible in Figure 4.7, there are tasks that overlap into the next day. To ensure that these tasks were not overlooked in the model, their deadlines and creation times were altered to fit into the day used for modeling by the conditions given in algorithm 1. An important step in making these sub sets is deciding which cut-off time is logical with respect to the model formulation and study goal. As the largest number of orders come in during the day, the cut-off time was decided to be at 06:00 each day.

Both the cutoff deadline DL^{cutoff} and the cutoff creation date CT^{cutoff} were set to their respective original values (i.e. $DL^{original}$ and $CT^{original}$). Through the conditions given below, it was first determined whether the deadline is found after 06:00, one day after the creation date of the task. If this is the case, the first cut-off deadline DL^{cutoff} is set to be at 05:59, the morning after the creation date. Different conditions are then used to determine the right DL^{cutoff}s and CT^{cutoff}s, based on the times between their original values and new values. These conditions ensure that tasks are cut off so that the greatest interval remains between CT^{cutoff} and DL^{cutoff}, and that they are cut off at the beginning or end of a daily interval in case the job completion interval stretches over multiple days.

Algorithm 1: Conditions to cut off Creation Time and Deadline of a Task

$DL^{cutoff} = DL^{original}$;

$CT^{cutoff} = CT^{original}$;

if $CT^{original}_{date+1} \quad 06:00 \leq DL^{original}$ **then**

  $DL^{cutoff} = CT^{original}_{date+1} \quad 06:00$;

end

if $CT^{original}_{date} == DL^{cutoff}_{date}$ & $CT^{cutoff}_{time} < 06:00$ & $DL^{original}_{time} \geq 06:00$ **then**

  $DL^{cutoff} = CT^{original}_{date} 05:59$

end

if $CT^{cutoff}_{date} < DL^{cutoff}_{date}$ & $00:00 \leq CT_{time} \leq 06:00$ & $00:00 \leq DL_{time} < 06:00$ **then**

  $DL_{cutoff} = CT^{original}_{date} 05:59$

end

if $CT^{cutoff}_{date+1} \quad 06:00 \leq DL^{cutoff}$ & $CT^{cutoff}_{time} < 06:00$ & $06:00 \leq DL^{cutoff}_{time}$ **then**

end

if $DL^{original} - DL^{cutoff} > DL^{original} - CT^{original}$ & $DL^{original}_{date} \leq CT^{original}_{date+2}$ **then**

  $CT^{cutoff} = DL^{cutoff}$;

  $DL^{cutoff} = CT_{date+2} 05:59$

end

Figure 4.9 shows the way these conditions cut off the job creation times and deadlines and Figure 4.10 shows the results for jobs between 11.03.2024 06:00 and 14.03.2024 14:00, showing the stretch from the cut-off creation time or deadline in dark orange and the parts that are left in light orange.

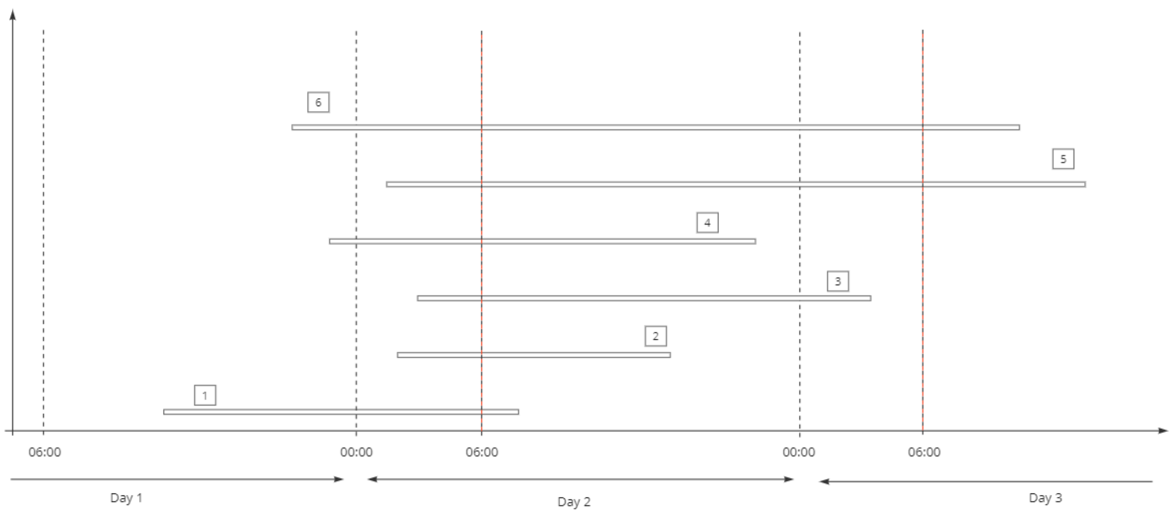

Figure 4.9: Visualisation of Conditions for Job Creation Time and Deadline Cutoffs

Effects of Cut-off Deadlines and Creation Times

Cutting off creation times and deadlines allowed to reduce problem size and tighten the solution space, as it took out jobs with possible scheduling intervals spanning over multiple days. As a result, some combinations of jobs that would have otherwise been possible are taken out and the model could be run for different subsets instead of multiple days, which would result in a much slower model due to the growth in problem size. Cutting of these deadlines and creation times do take away some part of reality, as it may cause the model to schedule some jobs in more expensive shifts than would have

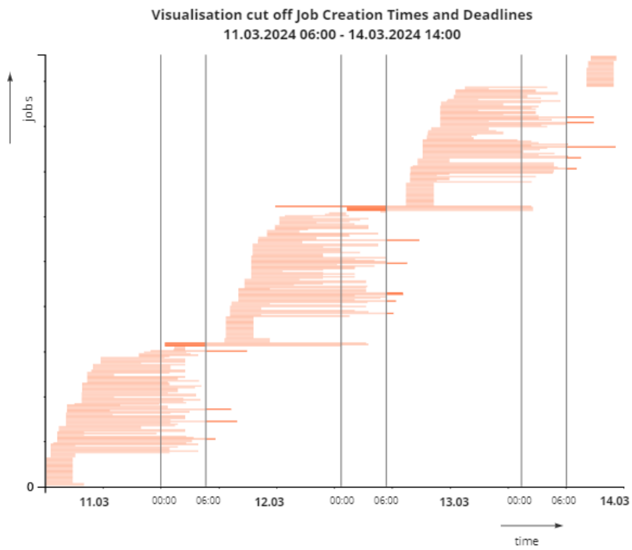

Figure 4.10: Visualisation of Job Creation Time and Deadline Cutoffs, for Jobs between 11.03.2024 06:00 and 14.03.2024 14:00

been necessary when using the original creation times and deadlines. This sometimes does not allow the model to avoid the night shift in its optimisation, which of course causes for more jobs to be scheduled during these shifts as it is in use anyway.

4.5.3. Addition of Extra Set of Constraints

The final addition to the model to reach a smaller optimality gap within an acceptable amount of time is found in an extra set of constraints, given in Equation 4.4 and repeated below.

$$\sum_{j \in J} x_{js} * D_j + \sum_{j \in J} x_{js} * BAT \leq ET_s - ST_s \qquad \forall s \in S \tag{4.4}$$

The set of constraints given in Equation 4.4 is implied by the combination of 4.8, 4.7 and 4.10, which respectively ensure that a job is scheduled before the end time of a shift, after the start of a shift, and with BAT seconds between jobs within a shift. However, the addition of Equation 4.4 resulted in a drop in optimality gap from 70% to 0.0% for a model run of 30 minutes. It scheduled 106 jobs in 4 flex shifts, 1 afternoon shift and 1 night shift. The addition of these constraints allows larger steps in optimisation, effectively resulting in a more efficient model.

4.6. Model Discussion

This section contains a discussion of the model with respect to the different modeling elements.

4.6.1. BAT Parameter and Effects of Number of Shifts in Model

The BAT-parameter in some cases can be used to improve optimisation performance. In different dataset runs, an optimal solution was found for a higher BAT-parameter value than for another. This is regarded as a logical consequence for two reasons. The first builds on the idea that less room for scheduling is better in this model formulation, which is also used in the addition of the extra set of constraints as explained in subsection 4.5.3. By increasing the BAT value, the model is given less room for scheduling. This set of constraints is also the root of the second reason for performance improvements: a higher BAT value may cause the model to need an extra shift for scheduling, which increases the lower bound. This results in an increase in redundant hours, but also in more shifts being used anyway, in which more jobs fit more easily. The effects different BAT values have on model outcomes, so that decisions can be made regarding which BAT values to use, are evaluated in the sensitivity analysis in Appendix D.

For the sensitivity analysis, the model was run for Monday until Saturday of the week between 18.03 and 24.03 (days containing respectively 109, 124, 115, 142, 81 and 6 jobs) with varying values of the BAT-parameter (0, 30, 60, 120 and 240 seconds), all for 75 minutes and with 9 shifts defined in each shift type category. It was interesting to see that the BAT value of 120 resulted in an optimality gap 0 in all cases but the one containing 124 jobs, without adding more shifts to the model and even reducing the number of shifts with respect to the BAT vale of 60 in the case with 115 jobs and the one containing 142. An increase in shifts necessary to accommodate for the duration of jobs when BAT is included was seen in the sub sets containing 81 and 109 jobs, respectively when changing the BAT value from 0 to 30 and from 30 to 60.

The cases where an extra shift is necessary to schedule all jobs including BAT logically cause peaks in the number of redundant hours. This is seen as one ascent that stays constant for the cases in which BAT causes the turning point for needing an extra shift, and rises and drops again for the ones where the BAT parameter allows for enhanced optimisation. Due to its desired performance in most cases in the sensitivity analysis, a BAT parameter of 120 seconds was used for the first run. This sometimes did not allow for an optimal outcome, as not only the BAT parameter, but also problem size and shape influence model outcomes.

4.6.2. Number of Shifts

In Appendix D, the influence of the number of shifts defined was examined with respect to model performance. It was found that a tighter definition of shifts allowed for better model performance, but optimality does not always mean the absolute optimal outcome. With a tighter defined number of shifts, there is a risk that the jobs do not all fit into the least expensive ones and a more expensive shift is chosen. To avoid this, a less-tight shift definition was chosen to avoid the risk of choosing a number of shifts that was too small.

4.6.3. Duration of Jobs

As explained earlier, the actual picking duration is used for job durations in the model to avoid using a picking norm. However, there are cases in real life where an order is put aside when stock does not suffice to finish the order. This would not be a problem is jobs could overlap, which they cannot in this formulation of the model.

4.6.4. Discussion of Subset Creation

In the process of cutting of jobs' creation times and deadlines as described in subsection 4.5.2, the model further deviates from reality and is restricted in its possibilities for scheduling. When creation dates and times are cut short as shown in Figure 4.10, one result is that some jobs that may have been scheduled over a course of two days (A-for-B of A-for-C orders, as explained in subsection 2.2.2) are limited to be scheduled in a day. This especially results in a less useful result when new creation times and deadlines hinder the model from avoiding night shift scheduling, which in turn tampers with the study's goal of finding out whether the DC can refrain from using this shift. Additionally, as shown in algorithm 1, both creation times and deadlines are cut off with creation times as a basis, meaning they are cut off earlier rather than later. This may cause a reduction in number of tasks that can be scheduled closer to their deadline.

4.6.5. Discussion with respect to Model Assumptions

One of the modeling assumptions is that the model does not take into account the time between shifts employees need to get according to the Collective Labour Agreement. When using the model as decision support to consider different shift schedules or shift coverage, it is important to keep in mind that some shifts are generally busier than others in terms of picking jobs. This means that even when some shifts allow for less personnel, the crews that operate those shifts keep the same size.

A break schedule and cleaning activities were not included in the model formulation, which may cause a bit of bias in the number of hours that is available during the day. However, the complete break schedule was expected to add an unnecessary layer of complexity to the already NP-hard problem at hand, as redundant time is found in the model in any case. These hours can be interpreted with regard to the number of hours that are necessary for break schedules each day. The hours for cleaning were also left out in consultation with FC, but should not be overlooked in result interpretation. The same holds for the coordinator present in the picking department during each shift. As this study only considers picking jobs and not the tasks that need to be completed by coordinators, they need to be taken into consideration for further studies at the DC. When certain shifts are not used, consideration can be done of whether a coordinator is still necessary during these shifts.

Varying the BAT may help broaden the model's common boarder with reality. Additionally, the model looks solely at picking tasks and does not consider other operations that need to be done by employees at the DC, such as cleaning. This means these elements should be considered in interpretation of model outcomes.

4.7. Summary Model Formulation

This section answers the second research question: *"How can the practical job scheduling problem at FC be represented in a mathematical formulation?"*

The model was formulated using the SMPTSP (Krishnamoorthy et al., 2012) for shift definitions, adding the start times of jobs as decision variables (Rieck et al., 2012). It uses a BPP approach to ensure no overlap between jobs within a shift (Paquay et al., 2014).

To use the model in practice, daily sub sets were made from the weekly datasets through algorithm 1 in subsection 4.5.2. As explained in subsection 4.6.4, this results in some bias in the model as not all combinations of orders can be scheduled together. This means that some A-for-B and A-for-C orders cannot be considered unambiguously. However, the effect is not expected to be large as the workload of these jobs is spread evenly over the different sub sets.

Another addition to the model formulation was the addition of symmetry-breaking constraints as explained in subsection 4.5.3. For the test set, it allowed for the optimality gap to drop from 70% to 0.0% in 30 minutes. Varying the BAT parameter was found to have an effect on optimisation performance, as well as the number of shifts defined within the model.

Through these alterations and additions to the model formulations found in literature, model performance was improved to be usable for the practical job scheduling problem seen at FC.

5 Results

In answering the final sub question, *"How can modeling results be related to the scheduling problem at FC?"*, this chapter contains experimental results. It starts with a recap of the study's goal and the experimental setup in Section 5.1. A comparison of the different scenarios is given in Section 5.2 and determination of input parameters in Section 5.3. Section 5.4 contains results of model runs for the chosen weeks under the different model configurations. A discussion of the results is given in Section 5.5, followed by verification and validation in Section 5.6 and an answer to sub question 3 in Section 5.7.

5.1. Study Goal and Experimental Setup

As a recap, the study's goal is to find a minimal shift schedule and find out whether workload can be distributed in such a way that the night shift is avoided. The sole purpose is not to find the shift schedule that is absolutely minimal (this results in a model scheduling mainly flex personnel, due to its lower cost compared to other shift types), but also to compare its outcomes to a shift schedule that regards whether the workload can be absorbed by the morning and afternoon shifts. In both of these model configurations, avoidance of the night shift is inherent to the model's formulation, in which the night shift is a more expensive shift. Model configurations are based on the cost structures as defined in the input data. Due to sensitivity of personnel cost, the relative cost of different shifts is given using "+"-es in Table 5.1. As the cost of shifts differs per weekday, it was chosen not to work with percentages. The absolute cost used as model inputs can be found in Section F.4.

Table 5.1: Relative Cost of Shifts under MC1 and MC2

Shift Name	Time	Cost MC1	Cost MC2
Morning	06:00 - 14:00	++	++
Afternoon	14:00 - 22:00	+++	+
Night	22:00 - 06:00	+++++	+++++
Flex	09:00 - 17:00	+	++++

Under these model configurations, scenarios are used to determine how robust a minimal shift schedule is with respect to workload: one considers an average, one a busy and one a slow week. The way the experimental setup is summarised in Figure 5.1. As explained in Chapter 4, the model uses some assumptions to enhance optimisation performance. These have implications for the model's deviation from reality, which are taken into account in the interpretation of results in Section 5.5. Experiments were run using Gurobi (a commercial solver) in Python. A Macbook Pro 2017 was used with a 3,5 GHz Dual-Core Intel Core i7 processor and 16 GB RAM.

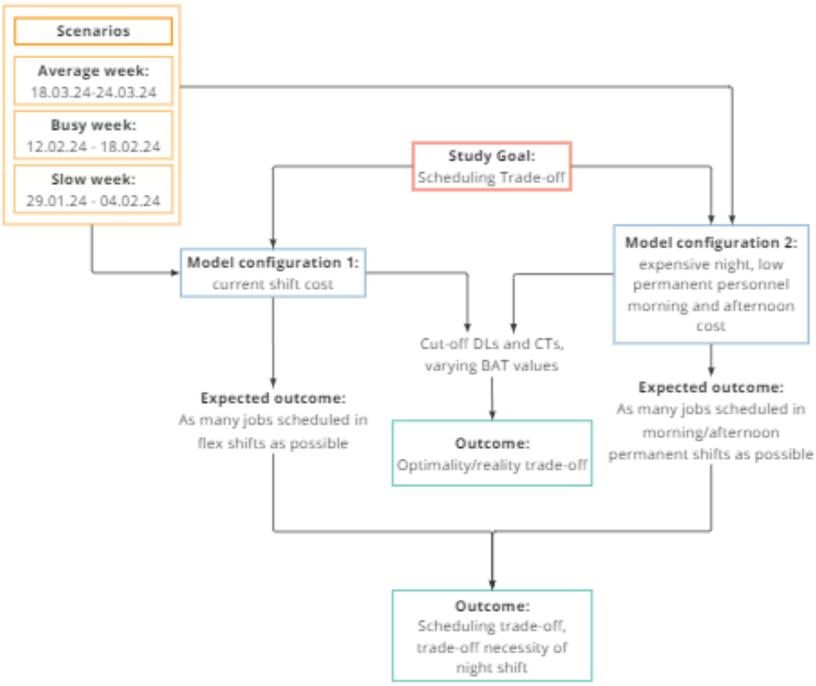

Figure 5.1: Study Goal, Model Set ups and Outcomes

5.2. Comparison of Scenarios

This section contains a comparison in number of jobs and job durations between the different scenarios used in this study. The number of orders present in each weekly dataset, given per weekday, is shown in Figure 5.2. The total number of orders in the average week is 577, in the busy week 628 and in the slow week 504.

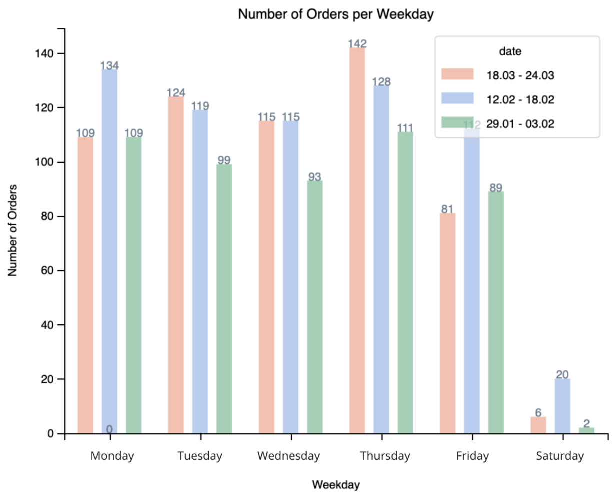

Figure 5.2: Comparison of the Numbers of Orders between Weekdays of the different Weeks

5.3. Determination of Input Parameters

For the different model runs performed in this study, the BAT parameter and number of shifts to be used for optimisation were chosen beforehand. For all model runs, the BAT parameter was set to 120. This resulted in an optimal outcome in the sensitivity analysis given in Appendix D for most cases. In the same appendix, it is explained that the number of shifts chosen matters for modeling outcome and performance.

For the average week, the number of shifts used for optimisation was 9 for the original cost structure. As more shifts are used side-by-side for the case of the cheap morning and afternoon shifts, this model run was performed with 6 shifts. When first running the model for the busy scenario in the first model configuration, a shift number of 14 was chosen to ensure the model had enough room to schedule in. Model outcomes were suboptimal for a large part through these model runs, so the number of shifts was re-evaluated to 9 for the first model configuration. Again, the number of shifts used in the second model configuration was 6. The same numbers were chosen for the slow scenario.

5.4. Experimental Results

This section contains the experimental results for model runs in an average, busy and slow week in Sections 5.4.1, 5.4.2 and 5.4.3. Due to sensitivity of personnel cost, cost of model outcomes is given as a percentage compared to actual personnel cost for that scenario. Absolute cost is found in Appendix F.5.

5.4.1. Results Average Week (18.03.2024 - 24.03.2024)

For the average week, optimality was found in most cases when running for the first model configuration but the second model configuration generated results that were suboptimal. The results for both of these model configurations are given in this section.

Model Configuration 1

The job scheduled as a result for the model runs of the average week is given in Figure 5.3. The different shift types correspond to the colours as given in the legend, and the scheduled jobs are shown in red. As shown in Figure 5.3, a large number of jobs is scheduled in the flex shifts. This is in line with expectations due to the cost structure in the first model configuration, in which the flex shifts are cheapest.

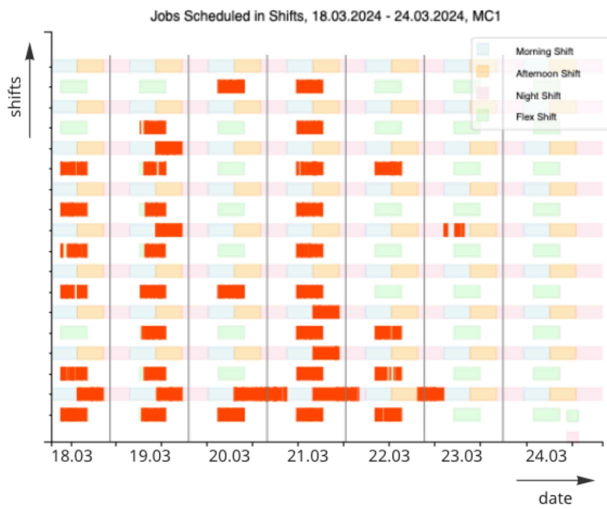

Figure 5.3: Job Schedule shown in Shift Schedule for Model Configuration 1, Average Week (18.03.2024 - 24.03.2024)

Model Configuration 2

In line with the cost structure in the second model configuration, the model tried to schedule as many jobs as possible in Figure 5.4. However, these model runs resulted in large optimality gaps (around 20%), which is also visible in the number of jobs scheduled in flex shifts over the course of the week.

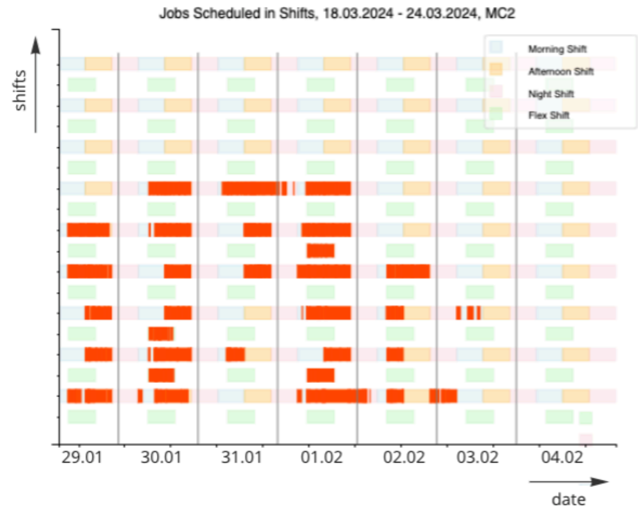

Figure 5.4: Job Schedule shown in Shift Schedule for Model Configuration 2, Average Week (18.03.2024 - 24.03.2024)

KPI Measurement and Comparison of Cost Configurations for an Average Week

As shown in Table 5.2, the model outperformed reality in both cases. Even though the number of people scheduled in the model under MC2 is higher than the actual number of people scheduled, cost is reduced. In the model run for MC2, it was more difficult to find optimality. This resulted in a much higher number of redundant hours in the model in total.

Table 5.2: Key Performance Indicators for Average Week (18.03.2024 - 24.03.2024)

Model Config.	KPI	Actual	Model	Unit
1	No. Redundant Hours		55.94	hours
	Cost diff Used Shifts		-18.29	%
	No. People Scheduled	45	42	
2	No. Redundant Hours		95.94	hours
	Cost diff Used Shifts		-3.49	%
	No. People Scheduled	45	47	

5.4.2. Results Busy Week (12.02.2024 – 18.02.2024)

The results for the scenario containing 628 jobs is given in this section.

Model Configuration 1

The results for the first model configuration is shown in Figure 5.5. The different shift types correspond to the colours as given in the legend, and the scheduled jobs are shown in red.

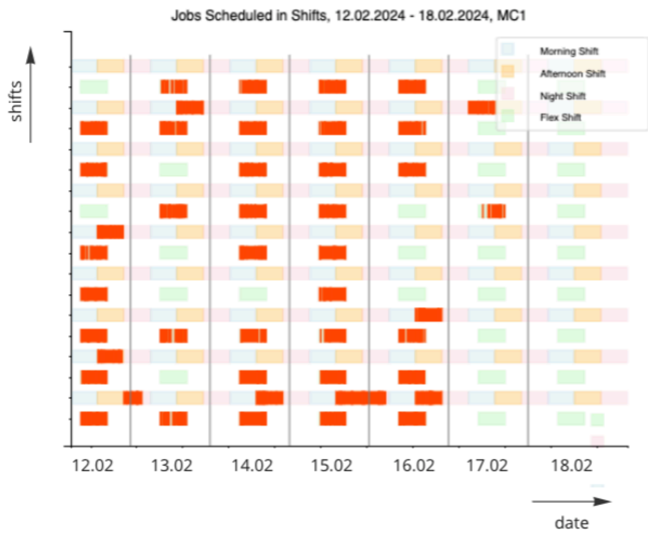

Figure 5.5: Job Schedule shown in Shift Schedule for Model Configuration 1, Busy Week (12.02.2024 - 18.02.2024)

Model Configuration 2

The second model configuration also resulted in large optimality gaps and numbers of shifts, as seen in Figure 5.6.

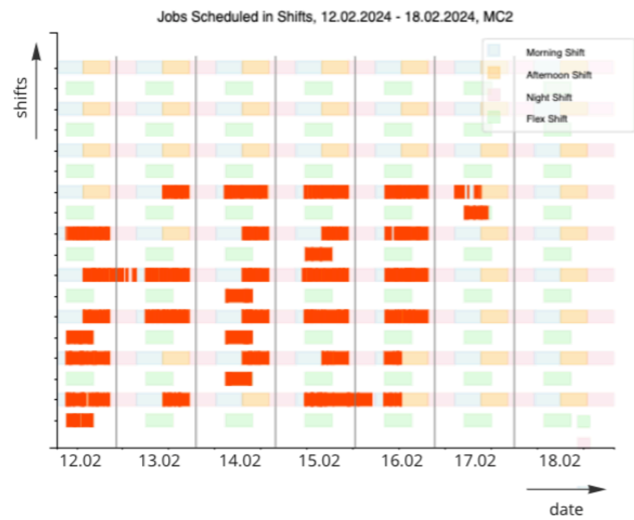

Figure 5.6: Job Schedule shown in Shift Schedule for Model Configuration 2, Busy Week (12.02.2024 - 18.02.2024)

KPI Measurement and Comparison of Cost Configurations for a Busy Week

The comparison of KPI performance for the model run for a busy week is given in Table 5.3.

Table 5.3: Key Performance Indicators for Busy Week (12.02.2024 - 18.02.2024)

Model Config.	KPI	Actual	Model	Unit
1	No. Redundant Hours		55.19	hours
	Cost of Used Shifts		+0.34	%
	No. People Scheduled	41	46	
2	No. Redundant Hours		87.19	hours
	Cost of Used Shifts		+16.69	%
	No. People Scheduled	41	50	

5.4.3. Results Slow Week (29.01.2024 - 04.02.2024)

The results for the scenario containing504 jobs is given in this section.

Model Configuration 1

For the slow week, job scheduling results of the first model configuration are shown in Figure 5.7. The different shift types correspond to the colours as given in the legend, and the scheduled jobs are shown in red. For these model runs, the model found optimality for all days except for Tuesday (8.1% gap from optimum) and Thursday (25.8% gap from optimum). As shown in the figure, the main shifts in which jobs are scheduled are the flex shifts, in line with the cost structure used in the first model configuration.

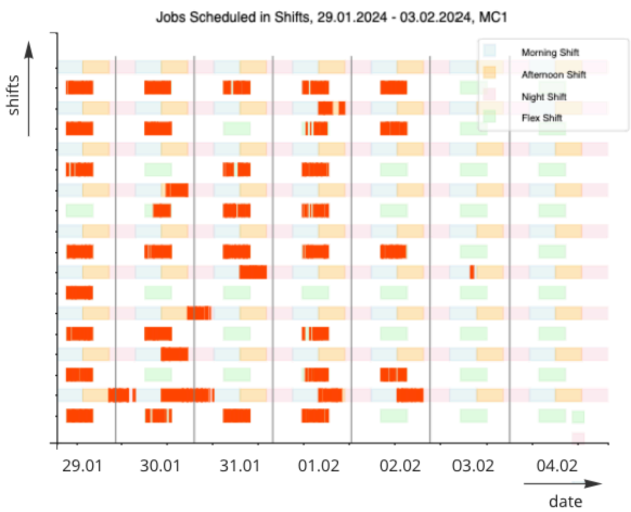

Figure 5.7: Job Schedule shown in Shift Schedule for Original Cost, Slow Week (29.01.2024 - 03.02.2024)

Model Configuration 2

As with the previous cases of runs under the second model configuration, the model had suboptimal outcomes. This is also seen in the number of shifts jobs are scheduled in.

KPI Measurement and Comparison of Cost Configurations Slow Week

For the slow week, model performance did not exceed FC's personnel deployment. High numbers of redundant hours are seen in both model configurations.

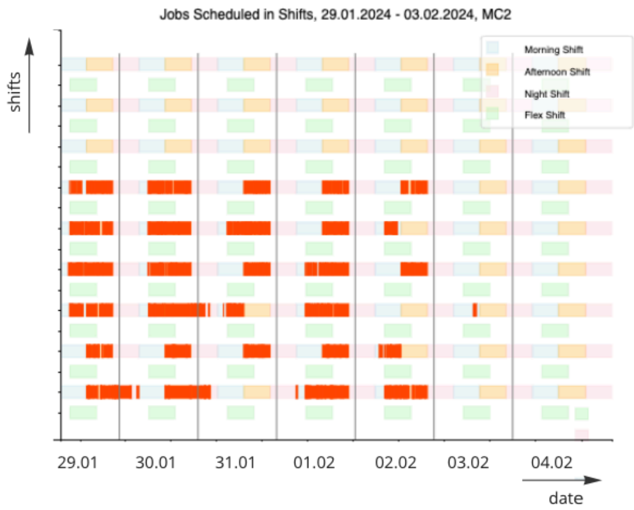

Figure 5.8: Job Schedule shown in Shift Schedule for Changed Cost, Slow Week (29.01.2024 - 03.02.2024)

Table 5.4: Key Performance Indicators for Slow Week (29.01.2024 - 04.02.2024)

Model Config.	KPI	Actual	Model	Unit
1	No. Redundant Hours		76.12	hours
	Cost of Used Shifts		+21.33	%
	No. People Scheduled	32	42	
2	No. Redundant Hours		100.12	hours
	Cost of Used Shifts		+40.77	%
	No. People Scheduled	32	45	

5.5. Result Interpretation

This section contains interpretation of the results, in light of modeling assumptions with respect to reality and optimality gaps. Model results were verified with expert at the DC.

5.5.1. With Respect to Model Performance

When doing the model runs, it was found that not all problem instances were as easily solvable optimally. As seen in the different model runs given in the previous sections, the model was often suboptimal, which resulted in outcomes that did not exceed cost performance by FC itself. The gaps from optimality (an optimal solution being 0.0%) as a result of the different model runs are summarised in Table 5.5.

Table 5.5: Model Performance per Week, by Model Configuration (MC)

MC	Week (scenario)	Mon	Tue	Wed	Thu	Fri	Sat
1	**18.03-24.03** (avg)	0.0%	12.3%	0.0%	0.0%	0.0%	0.0%
	12.02-18.02 (busy)	4.0%	16.1%	0.0%	0.0%	0.0%	0.0%
	29.01-03.02 (slow)	0.0%	8.1%	0.0%	25.8%	0.0%	0.0%
2	**18.03-24.03** (avg)	15.4%	36.9%	9.5%	22.0%	16.3%	0.0%
	12.02-18.02 (busy)	28.1%	20.8%	2.6%	17.3%	26.1%	0.0%
	29.01-03.02 (slow)	14.8%	11.5%	0.0&	13.9%	19.6%	0.0%

As seen in Table 5.5, optimality gaps are structurally larger in the second model configuration than in the first. This is expected to be due to an increase in symmetry in the model's formulation: as two shifts were now cheapest, it makes no difference to schedule in either one, which makes it difficult to weigh off these options (Gent et al., 2006). The gaps between the two model configurations cannot be compared directly, however. As a result of the alterations to shift cost in MC2, the objective bound was lower, resulting in larger gaps in model outcomes.

5.5.2. With Respect to Job Durations

As explained in subsection 4.1.2, the actual time used to complete each order was taken from the data and used for order durations in the model. However, a large shortcoming in this data is that some jobs are portrayed to take longer than they do in reality. An example of this is when they are placed in parking bins, waiting for products that are not yet in stock. To illustrate this, box plots for used order durations of the different weeks are shown in Figure 5.9.

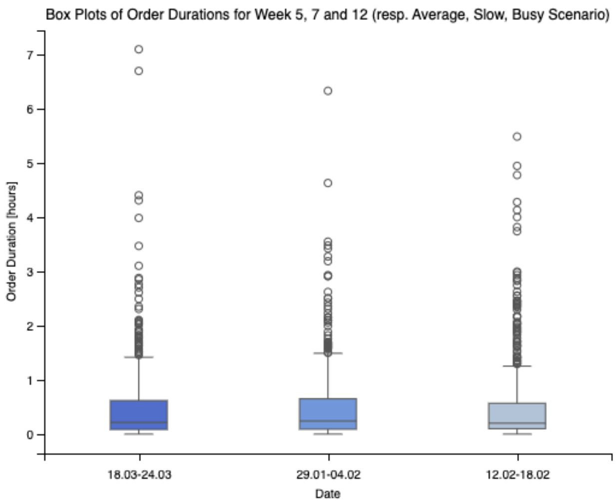

Figure 5.9: Box Plots of Order Durations Taken from Data for the Three Scenarios

As seen in Figure 5.9, the largest part of order durations is less than one hour, which was confirmed by a workflow controller. Another workflow controller stated that picking an order in one and a half hours is also possible, in case of a new picker. Another explanation given is that a picker takes a break and leaves the order he is working on without parking it, making the time spent on this order longer. This was put into perspective by counting the number of jobs for the three scenarios that passed the one-hour, the one and a quarter-hour and the one and a half-hour thresholds, as this is still where a large part of data can be found. These counts are given in Table 5.6

Table 5.6: Counts of Jobs that Pass Duration Thresholds, per Scenario

Week (scenario)	**1 hour**	**1.25 hours**	**1.5 hours**
18.03-24.03 (avg)	82	56	42
12.02-18.02 (busy)	90	65	52
29.01-03.02 (slow)	78	57	41

The effect of these longer jobs in the model is evident from the model formulation. By the definition of shifts as given in Section 4.2, a person represents as shift and cannot work on two orders at once. This avoidance of overlap means that the model may need an extra shift to account for a job that seems to take 5 hours (in an extreme case), even though the actual duration of this order is much shorter.

To deal with this, model outcomes were re-evaluated in light of the lengths these orders realistically had. To this end, the threshold for a logical order picking duration was set to one hour and 15 minutes.

Using this threshold accounts for the differences in picking performance by employees and the cases in which a break is taken without properly parking the order. New order durations for the orders passing the duration threshold were calculated, based on the number of colli they contained and the netto picking norm as calculated by the DC from October 2023 until April 2024. The calculated norm over this time period is given in Appendix F.3.3.

Model outcomes showed in which shifts these orders were scheduled. Combining this with the knowledge of their creation times and deadlines, and the number of redundant hours available in the shifts the jobs were scheduled in, it was evaluated whether a person could be removed from the model outcomes. This was done by calculating the total time difference between the order duration used in the model and the new one calculated using the number of colli in the order, as explained above. This time difference was then divided by eight (for the eight hours of each shift) and rounded down, so that complete shifts were removed. The results of these operations in model outcomes are given in Table 5.7.

Table 5.7: Comparison of Cost for Different Weeks after Shift Removal

MC	**Week** (scenario)		**Cost Diff [%]**	**Shifts [#]**	**Red. Hours**
1	**18.03-24.03** (avg)	Actual		45	
		Model	- 18.29 %	42	55.94
		Removed	- 32.09 %	35	
	12.02-18.02 (busy)	Actual		41	
		Model	+ 0.34 %	46	55.19
		Removed	- 18.04 %	37	
	29.01-03.02 (slow)	Actual		32	
		Model	+ 21.33 %	42	76.12
		Removed	+ 4.58 %	36	
2	**18.03-24.03** (avg)	Actual		45	
		Model	- 3.49 %	47	95.94
		Removed	- 18.49 %	40	
	12.02-18.02 (busy)	Actual		41	
		Model	+ 16.69	50	87.19
		Removed	+ 2.25	44	
	29.01-03.02 (slow)	Actual		32	100.12
		Model	+ 40.77 %	45	
		Removed	+ 4.58 %	40	

5.5.3. With Respect to Staffing Trade-Off

When using model outcomes for a staffing trade-off, some observations were made. The first is that in most cases, the model could fit almost all of the workload into flex shifts under the first model configuration. Especially after removing extra shifts based on orders with long durations, as explained in subsection 5.5.2, the model results show large differences in staffing costs for two out of three scenarios for this configuration.

Despite removal of shifts due to job durations in subsection 5.5.2, the model performed worse than the staff schedule in reality in the second model configuration for two of the three scenarios: the average scenario performed better than reality in this case. When considering the optimality gaps for this configuration as observed in subsection 5.5.1, it makes sense that the model could not schedule all jobs in the cheapest shifts. As a result, the redundant hours are generally large in this model configuration. However, the model is able to schedule all orders within the morning and evening shifts in most cases. This means that, despite the suboptimal outcomes, it can be concluded that the workload found at the DC can be absorbed by permanent personnel.

Another observation from modeling outcomes is the difference in workload, and so, necessary shifts, between the days of the week. When considering a new personnel schedule, it is recommended to move around personnel hours to accommodate for this workload variation. This can either be done by changing the permanent personnel norms per day to match workload, or by using flex personnel to account for this difference in workload. The latter is current practice, but in combination with deployment of less permanent personnel can be used for a more efficient personnel schedule.

In the different shift schedules generated by the model, no jobs are scheduled during the afternoon shift on Saturday. This workload is in line with workload perceived by picking personnel during these shifts.

5.5.4. With Respect to the Necessity of the Night Shift

In model outcomes given in the previous sections, it is seen that jobs are scheduled in the (most expensive) night shift. This was expected to be because of the cut off creation times and deadlines, but when examining jobs scheduled in night shifts more closely, it was found that their creation time and deadline both fell during these shifts before they were cut off. When forced to use the night shift anyway, the model added more jobs to fill it up. An example is visualised in Figure 5.10. The figure contains jobs scheduled in the night between 22.03 and 23.03 (taken from the average scenario). The horizontal lines all represent a job; the orange part shows the interval between their cutoff creation time and deadline, and the blue shows their original creation time and deadline.

As seen in the figure, some jobs have a creation time and deadline that both fall in the night shift. When discussing this with a workflow controller, it was confirmed that these orders most likely contained products that had been out of stock when they were originally picked. When considering the duration of orders that actually had to be picked during the night shift, it was found that the total duration generally lie around 4 hours. As the night shift was used about 2 times each weekly scenario and there are redundant hours present in the surrounding shifts, the orders with creation times and deadlines outside the night shift are expected to be compatible to move around the schedule. When possible, it is especially attractive to move them to the following morning shift. Observed in reality as well as in model outcomes, morning shifts have three hours that do not contain orders, as these come in at 09:00. These empty hours can be filled with orders from the day before. As there is a coordinator present during every shift in the current shift schedule, the workload of jobs that need to be done in the night shift is accounted for.

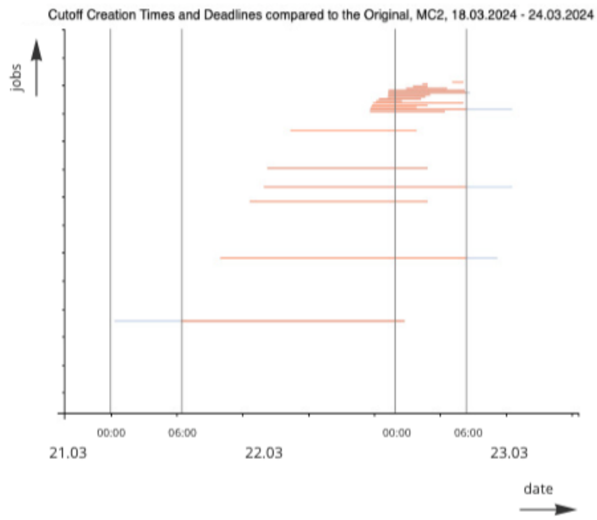

Figure 5.10: Visualisation of Jobs Scheduled in the Night Shift

5.6. Model Verification and Validation

Model verification was done each model run. For all shifts, it was determined that the total time of order durations, with addition of the BAT parameter for each scheduled order, was no larger than shift duration. This verifies 1) that orders were scheduled in shifts between start and end times and 2) that jobs do not overlap within shifts. Outcomes were examined closely and it was determined that jobs were scheduled in the least expensive shifts.

To validate the model, results were discussed with four experts at FC. One of the Team Leads, a Workflow Controller, the Senior Workflow Controller and the CI-specialist at the DC confirmed that model outcomes are likely. However, the numbers of shifts scheduled under high optimality gaps were not considered likely. The high gaps in these cases are expected to be the cause.

5.7. Summary of Model Outcomes

This chapter aimed to answer the fourth sub question: *"How can modeling results be related to the scheduling problem at FC?"* The discussion of model interpretation was given to this end in Section 5.5.

The study goal was twofold. On the one end to make a scheduling trade off between using the flex shift or a combination of the morning and afternoon shift to account for workload. On the other, to determine whether picking during the night shift is necessary. To this end, the model was run for two configurations and three scenarios. The first model configuration, MC 1, uses actual shift cost. In this configuration, flex shifts are least expensive due to absence of shift pay for irregular hours (except for during the weekends, subsection 2.3.1). The second model configuration (MC 2) was run with cost reduction for the morning and afternoon shift. The three scenarios comprised a week containing an average amount of workload, one containing a high amount and one containing a relatively low amount.

It was found that order durations were biased in a relatively high number of cases; model outcomes were modified to account for this effect (subsection 5.5.2). When looking solely at the resulting cost outcomes both before and after this alteration, it can be concluded that using flex shifts to account for workload is least costly. However, only using flex shifts makes the distribution of workload in the model less flexible. As shown in the different shift schedules in the previous pages, the workload often fits into the 09:00-17:00 shifts, with the addition of an afternoon shift here and there. If the workload is accounted for using mostly the morning and afternoon shifts (MC 2), more work can be moved around in a tighter personnel schedule. When observing the cost of MC 2, it is notably higher in more cases than for MC 1. In two out of three scenarios, it performs worse than the shift schedule used in reality. However, when combining this with the knowledge that most of these model runs returned sub optimal results (subsection 5.5.1), these costs will be lower for optimal model runs. Total cost is still expected to be higher when compared to MC1.

The conclusion was drawn that it is not necessary to schedule extra picking personnel during the night shift. This was done by examining jobs that caused scheduling in the night shift closely. It was observed that both their creation times and deadlines fell into the night shift (subsection 5.5.4). This usually happens in case a product was not in stock at the initial time it should have been picked. It was found that the average total durations of these jobs is around 4 hours (which is lower when taking the average over all night shifts, and not just the used ones). Due to the low workload of these jobs, it is expected that the coordinator present at the department can do the picking work, and can leave his less critical tasks for the morning crew. Based on their creation times and deadlines, it is expected that other jobs scheduled during the night shift in the model can be moved to the redundant hours of the shifts preceding the night shift. The preference, though, is to move these jobs into the first three hours of the morning shift.

6 Discussion

The discussion chapter is divided into three sections. Firstly, a discussion with respect to results and modeling assumptions is given in Section 6.1. Secondly, recommendations for further research at FrieslandCampina are found in Section 6.2. The chapter concludes with recommendations for model development and suggestions for different approaches to similar problems in Section 6.3.

6.1. Discussion with respect to Experimental Results and Modeling Assumptions

This study investigated whether orders placed at FrieslandCampina's Distribution Centre in Maasdam could be distributed in a way that avoids manual picking during the night shift to reduce personnel cost. Outcomes support the hypothesis that insight in scheduling deadlines contributes to a more efficient personnel schedule. The model found a significant cost improvement for the average and busy scenario in the first configuration, and for the average scenario in the second model configuration. When examining outputs closely, it was determined that it is not necessary to schedule an extra employee during the night shift. In case some picking needs to be done, (less than) a single employee would be enough to account for workload. This was discussed at FC, and it was estimated that this workload can be absorbed by other personnel present at night. As a result of the night shift being used, other jobs are scheduled here as well. These can be moved either to the previous shift, or into the first three hours of the next morning shift (if their creation time and deadline allow). This outcome supports the gut feeling amongst Workflow Control and Team Leads at FC that the night shift can be avoided.

In a shift trade-off, it is least costly to use flex personnel to account for the workload. However, only using flex shifts leaves less room for the distribution of workload in the model. If workload is absorbed in morning and afternoon shifts (MC 2), the time that can be used for order picking is between 06:00 and 22:00. Comparing this with the model configuration using solely flex personnel, the second model configuration intuitively gives more room to account for unforeseen workload or machine failure.

6.1.1. Order Durations

To avoid the use of norms for order durations, the time it took to complete an order in reality was used in the model. However, as explained in **??**, this duration was biased in a relatively large number of cases. This bias is a result of orders that were started and then placed in parking bins, waiting for stock. The problem with this bias is that one person cannot work on multiple orders in the model, even though this is possible in reality in this case. This rigidity is necessary in the SMPTSP formulation of the model, as a shift represents a person.

The issue was integrated into the results by using picking norms to calculate new order durations when an order exceeds a time threshold, and quite large differences in numbers of shifts used were concluded. As a threshold was used to address these types of orders, it cannot be concluded with certainty that all orders that were placed in a parking bin were caught this way. The threshold was based on the expert opinions of two workflow control employees. However, this encompasses the maximum time a picking order can cost. An order that is shorter than the threshold can still be placed in the parking bin, resulting in an inaccurate order duration.

To avoid this bias in order durations, it is possible to execute the model again for the datasets used with calculated order durations. Netto picking performance (colli/hour) over the desired amount of time can be used for calculations. In this approach, a difference in picking norm should be considered between picking a loose colli and picking a full layer. If, for example, performance is calculated based on loose colli but full layers are picked (which are less time intensive), the pick norm should be changed accordingly. Modeling outcomes for this hypothetical run are expected to result in a lower objective function value, as it is not expected that all parked orders were caught using the threshold method as described above.

6.1.2. Daily Sub Sets

To improve model performance, daily sub sets were created, cutting off jobs based on the algorithm as given in algorithm 1. Through these daily sub sets, less room for job scheduling was available in the model. Doing so did not allow for outcome evaluation of multiple days, which may be useful to determine the absolutely minimal job schedule.

However, it was seen that cut-off jobs are relatively well spread over the considered daily sub sets, so the volumes are expected to be similar per day. By this reasoning, inclusion of orders placed multiple days in advance is not expected to change much in modeling outcomes.

6.1.3. Choice of Shift Cost for the Second Model Configuration

Due to the NP-Hard and symmetric nature of the model, lower cost had to be assigned either to the morning or the afternoon shift in the second model configuration. The cost of the afternoon shift was defined to be lower than cost of the morning shift in the second model configuration, even though it is the other way around in reality. As the morning shift has three unused hours at the start, this was expected to help optimisation performance. In retrospect, model performance is expected to be improved with a less expensive morning than afternoon shift. This is due to A-for-A orders that need to be completed in morning shifts, forcing the model to use either the morning or the flex shift in any case.

6.1.4. Choice for Number of Shifts

In the modeling formulation used for this study, 9 shifts were used for the first configuration and 6 for the second. By reducing the number of shifts even further, a direct trade-off between shift types could be made. In that case, the model would not be able to schedule all jobs in the least expensive shifts.

To improve model performance for the daily runs separately, indications could be made of how many shifts jobs should fit into. These can be used to define a tighter number of shifts to use in the model per daily run.

6.2. Recommendations for Further Research at FrieslandCampina

6.2.1. With Respect to Model Outcomes

Due to optimality gaps in results, cost savings were not always realised in the model and a high number of redundant hours was found in some cases. However, the model does show that job scheduling within the desired shifts is possible, and that job scheduling in the night is due to insufficient stock during daily picking hours.

6.2.2. Shift Schedule

At the moment, FC is evaluating new configurations for their shift schedule. In this process, varying combinations of shift types are assessed. For example, a combination of a two-crew and four-crew schedule is considered to this end. In this schedule, 70% of employees stick to the four-crew schedule and are complemented in the morning and afternoon shifts in a two-crew schedule for remaining employees. Another setup is one in which a one-shift schedule supplements a four-crew schedule during flex shifts. In this case, the flex shifts are filled up with permanent personnel, which results in lower cost of permanent personnel with the removal of surcharge. In both cases, large financial impact is seen for employees on schedules that do not contain night shifts in terms of supplements for irregular hours and break schedules.

When considering the pros and cons of the two scenarios, one of the large drawbacks using the flex shifts is flexibility in moving jobs within the schedule. In a two-crew scenario, there is more room to account for orders that could not be completed before 17:00, as crews are present until 22:00. In case of a one-crew supplementary shift schedule, all jobs need to be finished at 17:00, and more pressure is put on the slimmed-down four crews to finish jobs that are left open.

In the current configurations for new crew schedules, the number of people on the schedule are identical on each day except for Saturday, on which there is no night shift. It is recommended to use senior days, as explained in Section 2.3, to account for differences in workload observed between days.

As shown in the consideration of numbers and durations of jobs in Section 5.2, the number of orders differs for different weekdays in the considered weekly scenarios. For each scenario, it is seen that the number of orders on Wednesday and Friday is smaller than that on other weekdays. It is recommended to evaluate whether this is a coincidence or a pattern by analysing volume data over a longer period of time. Using these outcomes, FC can reflect on the number of people that is necessary daily.

6.2.3. Other Recommendations

This study reveals that orders can be moved around the schedule to ensure a more efficient personnel schedule. Picking waves are used at the DC to determine when orders need to be picked, which are assigned using the given client loadtimes. These are often inaccurate, as shown in subsection 2.5.1. A more efficient schedule is expected when more insight is gained in the necessary moments orders need to be completed. As explained in Section 2.5, SL has an expected transport schedule to their disposal, which they update regularly. If the DC could use these expected transport times and link them to the client orders they receive, jobs can be put into more accurate picking waves from the start. By doing so, orders can be left to the next shift with the knowledge that it can be completed then. As a result, a more efficient personnel schedule can be made.

The recommendation to this end is twofold. The more vital but distant one is to find a way to upload SL's transport schedule into FC's system, EWM, so that relatively accurate transport times can be added to orders straight away. To this end, a link must be found between the transport numbers and orders. The performance of picking wave determination can then be evaluated and the personnel schedule can be changed to match. The less vital but more logical first step, is to assign expected volumes to the expected transport times SL has in their schedule. By doing so, estimates can be made about when these volumes should be completed and how FC's personnel schedule should be changed to match.

6.3. Recommendations for Model Development

6.3.1. The Model in Practice

For this study's goal, the model was used deterministically. This allowed to compare minimal shift schedules, asses the necessity of the night shift and determine whether insight in picking deadlines can contribute to an improved job and personnel schedule. The model formulation could also be used to schedule jobs real-time, but this would require some alterations to improve model performance. Two directions to this end are given below.

Symmetry in Model Formulation

Optimisation difficulty is expected to be due to symmetry which is inherently present in the formulation. Symmetry is found in an optimisation model when a search for an optimum can revisit the same solution without finding an optimum (Gent et al., 2006). Through the addition of the symmetry-breaking set of constraints ensuring that no combination of jobs could be scheduled in a shift, some of that symmetry was caught. However, symmetry is also found in the order jobs are scheduled in: one can be scheduled before the other and the other before the one. This formulation was chosen so that the model does not deviate from reality too much.

It is expected that this symmetry can be handled by assigning weights to different jobs, to enforce which job is scheduled before which (Van Kessel et al., 2023).

Another solution to symmetry in the model is to add a decision variable denoting whether job j is a direct neighbour of job k. As the current formulation uses b_{jk} for any two jobs scheduled in the same shift, it adds constraints that may not be necessary, as the only start time that should constrain a job's end time is the one that succeeds it directly. However, the constraints defining the values of b_{jk} and b_{kj} are only active when these jobs are scheduled in the same shift. To this respect, the described method to improve model performance may not make a large difference in this problem scope. It could be used in another problem definition that uses larger shifts.

Number of Binary Decision Variables

The model formulation uses a large number of binary decision variables, which hinders optimisation speed. This was a direct result of the non-overlapping constraints. To avoid the need of these constraints, the model could be reformulated using the number of colli contained in an order, for example. In this formulation, picking performance could be used to determine how many orders can be completed within a shift. In this formulation, creation times and deadlines could be altered to completely fit into a shift, missing some accuracy.

6.3.2. Other Modeling Approaches to Similar Problems

A simulation study would have allowed for more flexible (and just more) scenario testing. This may be formulated as a queueing model in the form of a discrete event simulation, in which picking personnel is each seen as a server with a certain picking capacity (which can be varied to account for reality) and jobs come in at a certain rate. More historical data analysis would need to be done to determine those rates.

7 Conclusion and Recommendations

This study aimed to contribute to decision making at FrieslandCampina's Distribution Centre in two directions, both in context of the (manual) Colli Picking department. The first study outcome is in light of a staffing trade-off between accounting for workload using either a combination of the morning and afternoon shift, or using the flex shift. The second regards the necessity of using the night shift to account for workload at the picking department. Intrinsic in both study goals lies the question is of whether improved insight in definitive picking deadlines can contribute to a more efficient personnel schedule. To this end, the main research question is repeated below:

How can full insight in picking deadlines contribute to a more efficient shift schedule on the manual picking department at FrieslandCampina's Distribution Centre, taking into account the cost of these different shifts and regarding different scenarios for workload deviations?

The main question was supported by sub questions, repeated and answered below. The answer to the main research question is given in Section 7.1.

1. Which opportunities can be identified in the current job scheduling method at FC?

Through the system analysis in Chapter 2, the largest opportunities in the current job scheduling method and picking system were identified. The first is insight in job deadlines. Picking jobs are put into waves based on the deadline they receive with the client order, which is often found to be incorrect. Due to this uncertainty, jobs are completed quickly after their initialisation. This is done both to account for unforeseen circumstances and to fill up time picking personnel is present anyway. Insight in job deadlines is expected to contribute to a more efficient schedule by postponing tasks with confidence. The second opportunity is found in an efficient personnel schedule to match workload deviations. This can be done by using flexible personnel to account for high workload or by using senior days cleverly to account for low workload.

2. How can the practical job scheduling problem at FC be represented in a mathematical formulation?

A MILP model was used to minimise the shift schedule. The Shift Minimisation Personnel Task Scheduling Problem (SMPTSP) as formulated by Krishnamoorthy et al. (2012) was used to define shifts and the objective function minimises cost per shift over all used shifts. As the most expensive shift at the DC is the night shift, it is inherently avoided by the model. One crucial element missing from the SMPTSP is job scheduling. Using the start time as a decision variable in the model, jobs could be scheduled between the start and end time of each shift (Rieck et al., 2012). To avoid overlap, the three-dimensional Bin-Packing Problem (BPP) as defined by Paquay et al. (2014) was reformulated.

To make the model practically applicable, the weekly scenarios were divided into daily sub sets. An extra set of constraints was added, increasing steps solver optimisation. The time between jobs in the model (BAT) was used to improve optimisation performance.

3. How can mathematical results be related to the scheduling problem at FC?

The model was run for two model configurations and three scenarios, using the commercial solver Gurobi. Model Configuration (MC) 1 used actual shift cost calculated using surcharge for irregular hours. MC 2 was run with morning and afternoon shifts that were much cheaper than the flex and night shift. Under both configurations, three scenarios were tested. A week with an average amount of workload, one with a high amount of workload and one with a low amount of workload. Modeling outcomes were biased due to order durations taken from the data. This was altered in the outcomes by recalculating order durations. The model found cost savings under MC1 for two out of three scenarios. Under MC2, the model performed worse than the shift schedule in reality for two out of three scenarios, both before and after removal of hours for biased job durations. Noticeable under MC2 were high optimality gaps; the cost of these solutions is expected to be lower in reality.

7.1. Answer to the Main Question and Recommendations to FC

Answering the main question, this study's results are translated into the following findings. In making a trade-off between different shift types to account for the workload present at the DC, the least costly solution is to schedule as many jobs as possible in the flex shifts. However, using a combination of the morning and afternoon shift will result in increased scheduling flexibility for workload, as not all orders need to be finished at 17:00 in that case. To this end, it is recommended to use the morning and afternoon shifts to account for workload.

In evaluation of the night shift, the coordinator or an employee from another department is expected to be sufficient to account for the workload. The volume of jobs that have both their creation time and deadline during the night have an average total duration of four hours. Considering that this volume is not found in every night shift, the average volume is even lower. Based on their creation times and deadlines, remaining jobs scheduled in this shift can either be completed during the redundant hours of the shift before, or during the first three hours of the morning shift in the next day.

To be able to fully use these study outcomes, however, it is necessary for FC to link definitive order deadlines early on in the process. As explained in Section 2.5, large differences identified between the deadlines put through in client orders and the definitive deadlines. When these deadlines are known, orders can be postponed in the schedule to spread workload over a minimal number of shifts.

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A
Scientific Paper

Examining Strategies for Shift Scheduling at FrieslandCampina

Quirine de Zeeuw

Abstract—In their Distribution Centre in Maasdam, FrieslandCampina uses a four-crew shift schedule to prepare all necessary orders for their clients, 24 hours of each Monday to Saturday. Their large automated warehouse is home to 10 000 pallet places, containing fresh dairy products. From here, orders are either prepared as full pallets, machine-picked layers or hand-picked "colli". In the last department especially, personnel cost is high relative to the throughput. Definitive picking deadlines are often ambiguous, posing challenges in job and personnel scheduling. The study goal is twofold. Firstly, to find out whether full knowledge of picking deadlines can contribute to a more efficient job, and so, shift schedule. Secondly, to offer insight for a trade-off between shift types to absorb workload. To reach this study goal, a Shift Minimisation Personnel Task Scheduling Problem (Krishnamoorthy et al., 2012) and a Bin Packing Problem (Paquay et al., 2014) were combined and tailored to fit the scheduling problem at FC's DC. In three weekly scenarios, the Mixed Integer Linear Programming (MILP) model scheduled picking jobs in the least expensive shifts through a cost minimisation function. Two model configurations were used, one to prefer the shift between 09:00 and 17:00 (flex), and one to prefer either one of the 06:00-14:00 (morning) or the 14:00-22:00 (afternoon) shifts. Both model configurations inherently avoided the most expensive 22:00-06:00 (night) shift. Main findings include the possibility to absorb workload using the morning and afternoon shift and to avoid the night shift. Additionally, it was confirmed that insight in picking deadlines can contribute to an efficient personnel schedule a great deal.

Index Terms—Distribution Centre – Optimization – Shift Minimisation Personnel Task Scheduling – Bin Packing Problem

I. INTRODUCTION

COLOCATED with their factory in Maasdam, FrieslandCampina's (FC) Distribution Centre (DC) is the centre of fresh dairy product distribution throughout the Netherlands. Their fully automated warehouse is home to 10 000 pallet places, from where customer orders are prepared to be shipped Business-to-Business (B2B). A large number of logistic processes underlie the successful distribution of these products to their clients, starting with the preparation or orders. This is done either as full pallets, picked mechanically using a layer picker or picked by hand. Though undesirable due to the relatively high cost of manpower, the last category is inevitable as a result of client order or physical product specifications. In manual order picking, the cost of manpower is a direct result of shift pay for irregular hours, as the DC operates 24 hours from Monday to Saturday.

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A. Context Description

In four crews, the DC operates in three shifts per day, supplemented by "flex" shifts. The times these shifts operate is shown in Table 1. The last table column contains the relative cost of different shifts. As the percentage difference varies for week and weekend days, this cost was portrayed as "+", in which more pluses mean higher cost.

Table 1: Shifts and their Relative Cost

Shift Name	Time	Relative Cost
Morning	06:00 - 14:00	++
Afternoon	14:00 - 22:00	+++
Night	22:00 - 06:00	+++++
Flex	09:00 - 17:00	+

Currently, morning, afternoon and night shifts are staffed using permanent crews and flex shifts using flexible personnel. However, shift types can in theory be manned through use of either personnel type.

B. Problem Description

In the current scheduling process, orders are placed in picking waves based on the deadlines contained in client orders. However, as shown in Figure 1, these deadlines often differ from the definitive deadlines. This makes it difficult to determine when picking needs to be executed in order to spread workload effectively, resulting in risk-averse scheduling choices. Both to avoid effects of unforeseen circumstances and due to personnel presence, activities are often done as quickly as possible.

C. Study Goal

This study's goal is to find out whether, and to what extent, improved insight in picking deadlines can contribute to a more efficient personnel schedule. By doing so, it aims to contribute to a trade-off between permanent shifts and flex shifts and to offer handles to assess the necessity of the night shift. To this end, the main research question was formulated:

"How can full insight in picking deadlines contribute to a more efficient shift schedule on the manual picking department at FC's DC, taking into account the cost of these different shifts and regarding different scenarios for workload deviations?"

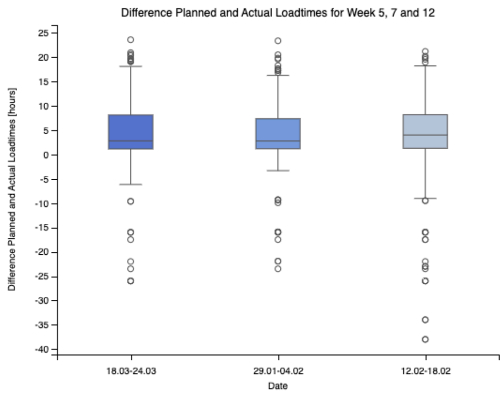

Fig. 1: Box Plot for Difference between Actual and Planned Loadtimes for Week 5, 7 and 12

D. Methodology

To compare minimal shift schedules and make a scheduling trade off to this respect, the problem was formulated as a Shift Minimisation Personnel Task Scheduling Problem, using constraints from the Bin-Packing Problem (BPP) to avoid overlap between jobs scheduled in the same shift.

E. Paper Structure

This paper is structured as follows: it starts with a literature review, given in section II. The problem is formulated in line with literature in this section. The mathematical model is then presented in section III. section IV contains the experimental setup and results, followed by a discussion in section V. The study is concluded in section VI, which includes recommendations with respect to FrieslandCampina and further research.

II. LITERATURE REVIEW

A great deal of research is done in job scheduling, workload balancing and shift cost minimisation, many of which use Mixed Integer Linear Programming (MILP) formulations with objectives that minimise the difference between minimum and maximum workloads (e.g. Ouazène et al. (2016). Other formulations include cost minimisation (Golpîra and Tirkolaee, 2019) and minimisation of the maximal planned load over all used resources (Vanheusden et al., 2020).

In the aircraft industry, BPP is used for task scheduling by Witteman et al. (2021), who used this method for maintenance scheduling taking into account different ability levels of mechanics. A fictitious bin was used to schedule tasks that did not fit into the formulation. Their objective function contains a cost minimisation. In their study conducted in 1978, Coffman et al. used a Bin Packing formulation for multiprocessor task allocation.

Shift allocation of work force must meet requirements of the workforce. This shift allocation problem is seen as trivial to solve, but too rigid in the case workforce demand fluctuates too much during a shift (Baker, 1976). This shift scheduling problem requires a predetermined workforce demand, which would mean that personnel scheduling could be done more efficiently based on current workload. Smet et al. (2014) formulated a new method to solve the Shift Minimisation Personnel Task Scheduling Problem (SMPTSP), in which they use an extra binary variable that indicates whether an employee has a task during a shift.

Based on the SMPTSP as defined by Krishnamoorthy et al. (2012), the model objective is to minimise shift related cost, using a weighted objective function.

The model formulation by Krishnamoorthy et al. (2012) differs from the model needed in this study on a critical aspect: job scheduling. In their model, jobs have set start and end times, based on which jobs are placed in "cliques" of jobs that overlap. Using these cliques, a minimal shift schedule is devised. However, the start and end times of jobs in the model required in this study are not set, meaning a separate job scheduling addition needs to be made.

A continuous time horizon was used as these models generally have a smaller problem size (e.g. Stefansson et al., 2011). With this horizon, jobs can be scheduled both between their creation time and deadline and between the start and end time of a shift. However, when multiple jobs are scheduled in one shift, they are not allowed to overlap as one person cannot work on multiple orders. To this end, non-overlapping constraints are found in the BPP approach as formulated in 3D by Paquay et al. (2014). As the temporal dimension is the only one this study requires, these overlapping constraints can be reformulated into 1D constraints. In their BPP approach to a job scheduling problem, Witteman et al. (2021) created a fictitious bin in which jobs can be placed if they cannot be planned in the given bins in the model. In this vein, more shifts than necessary are defined in the model to leave room for jobs that do not fit into the desired shifts.

III. MATHEMATICAL MODEL

This section starts with a problem formulation in subsection III-A. Model requirements and assumptions are given in subsection III-B. Sets and Parameters can be found in subsection III-D and Decision Variables in subsection III-E. The mathematical model is given in subsection III-F.

A. Problem Formulation

As described in section II, the model is formulated as a SMPTSP with the addition of job scheduling. BPP constraints are used to avoid overlap between jobs in the model. Shift representation in the model is based on the SMPTSP and shown in Figure 2. In the figure, three shift instances are portrayed. A shift instance is defined as the number of people that jobs can be scheduled in between start and end time of a shift

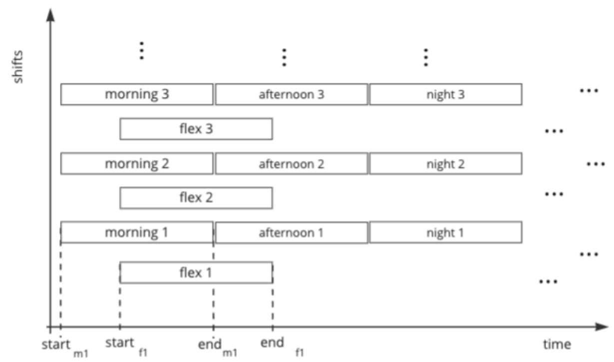

Fig. 2: Conceptual Representation of Shifts in the Model

B. Requirements

An overview of the model requirements are given below.

- An order must be completed within one shift;
- An order must be completed between its creation time and deadline;
- No job preemption is allowed;
- All jobs must be completed;
- No overlap is allowed between jobs assigned to the same shift;
- A time gap is added between the end of one job and the start of the next to account for processing time between orders.

C. Assumptions

The model assumptions are listed below.

- There are no skill requirements to complete jobs;
- The model uses a continuous time frame;
- In real life, orders contain different picking tasks. These picking tasks are contained in an order and an order is indicated using the word "job";
- Jobs are finished in one go;
- Building on the previous assumption, the shifts are not paired to a person. This means the model does not take into account time between workers' shifts as defined in the Collective Labour Agreement;
- The model is focused only on picking jobs, and not on any other tasks employees must perform in this department;
- The model does not contain a break schedule.

D. Sets and Parameters

This section contains the sets, parameters and decision variables used in the mathematical model. Table 2 contains the used sets, Table 3 its parameters and Table 4 shows the decision variables in the model.

Shown in Table 2, two sets are used in the model. J denotes the set of picking jobs, and S denotes the set of shifts. Parameters are found in Table 3.

DL_j and CT_j respectively denote a job's creation time and deadline. A job's duration is given by D_j. Shift cost is denoted by C_s, and its start and end times by ST_s and ET_s. The time reserved in the model for time between activities is given by the BAT parameter, and a large temporal value V is used in the constraints.

Table 2: Sets used for the mathematical formulation

Set	Definition
J	Set of picking jobs
S	Set of shifts

Table 3: Parameters

Parameter	Definition	Unit
DL_j	Deadline of job j	[seconds]
CT_j	Creation time of job j	[seconds]
D_j	Duration of job j	[seconds]
C_s	Cost of shift s	[€]
ST_s	Start time of shift s	[seconds]
ET_s	End time of shift s	[seconds]
BAT	Between-activity time	[seconds]
V	Large temporal value	[seconds]

E. Decision Variables

Decision variables used in the model are given in Table 4. The binary decision variable x_{js} indicates whether job j is scheduled in shift s. The binary decision variable u_s indicates whether shift s is in use. The start time of job j is denoted by $start_j$. b_{jk} indicates whether job j is scheduled before job k.

Table 4: Decision Variables for the Mathematical Model

Variable	Definition	Sets
x_{js}	Binary variable indicating whether job j is assigned to shift s	$j \in J, s \in S$
u_s	Binary variable indicating whether shift $s \in S$ is used	$s \in S$
$start_j$	Continuous time variable indicating the start time of task j	$j \in J$
b_{jk}	Binary variable indicating whether task j is scheduled before task k	$j \neq k \in J$

F. Objective and Constraints

1) Objective: Following from the problem formulation, the objective function minimises the sum of used shifts in Equation 1.

$$min: \sum_{s \in S} C_s * u_s \tag{1}$$

2) Task Scheduling and Shift Capacity Constraints:

$$\sum_{s \in S} x_{js} = 1 \qquad \forall j \in J \tag{2}$$

$$x_{js} \leq u_s \qquad \forall\ s \in S, j \in J \tag{3}$$

$$\sum_{j \in J} x_{js} * D_j + \sum_{j \in J} x_{js} * BAT \leq ET_s - ST_s \qquad \forall s \in S \tag{4}$$

3) Start Time Scheduling Constraints:

$$CT_j \leq start_j \qquad \forall\ j \in J \tag{5}$$

$$start_j + D_j + BAT \leq DL_j \qquad \forall\ j \in J \tag{6}$$

$$start_j \geq ST_s - (1 - x_{js}) * V \qquad \forall\ j \in J, s \in S \tag{7}$$

$$start_j + D_j + BAT \leq ET_s + (1 - x_{js}) * V \qquad \forall\ j \in J, s \in S \tag{8}$$

4) Overlapping Constraints:

$$b_{jk} + b_{kj} \geq (x_{js} + x_{ks}) - 1 \qquad \forall\ j \neq k \in J, s \in S \tag{9}$$

$$start_j + D_j + BAT < start_k + (1 - b_{jk})V \qquad \forall\ j \neq k \in J \tag{10}$$

The constraints in Equation 2 ensure that all jobs are scheduled in exactly one shift. A shift is marked as used in Equation 3. Equation 4 impose that the total duration of jobs scheduled in a shift, with the addition of BAT, does not exceed shift duration. Equation 5 denotes that a job's start time must be larger than its creation time, and Equation 6 prevents a job from exceeding its deadline, using its duration. The large temporal value V was used to schedule a job between the start and end time of a shift, respectively in Equations 7 and 8.

Through the constraints in Equations 9 and 10, overlap between jobs is avoided. If two jobs j and k are scheduled in the same shift s, Equation 9 forces one of the two jobs to be scheduled before the other. If job j is scheduled before job k (i.e. $b_{jk} = 1$), the start time of job j (with the addition of its duration and the BAT parameter) is constrained by the start time of job k.

IV. EXPERIMENTAL SETUP AND RESULTS

A. Experimental Setup

The model was run for three scenarios under two cost configurations. The model configurations are explained below.

1) Model Configuration 1 (MC1): The first model configuration contains the cost of shifts as calculated from the shift charge for irregular hours. In this configuration

2) Model Configuration 2 (MC2): The second model configuration comprises low cost for both the morning and afternoon shift.

As actual cost is sensitive, relative shift cost is used. This is summarised for both model configurations in Table 5.

Three weeks containing historical order data were used as scenarios. The average week (18.03.2024-24.03-2024) contained 577 orders, the busy week (12.02.2024-18.02.2024) 628 orders and the slow week (29.01.2024-04.02.2024) 504.

Table 5: Relative Cost of Shifts under MC1 and MC2

Shift Name	Time	Cost MC1	Cost MC2
Morning	06:00 - 14:00	++	++
Afternoon	14:00 - 22:00	+++	+
Night	22:00 - 06:00	+++++	+++++
Flex	09:00 - 17:00	+	++++

B. Model Inputs

To solve the model within acceptable time, some alterations to input data and parameters were made. These alterations are described below.

1) Daily Sub Set Creation: Through the creation of daily sub sets, the problem size was reduced. To do so, jobs were cut off at their creation time or deadline at 06:00 each day. This was done in cooperation with the company; 06:00 was seen as a logical cut-off time in between the night and morning shift. An example of cut off jobs for three days is shown in Figure 3.

Fig. 3: Visualisation of Job Creation Time and Deadline Cutoffs, for Jobs between 11.03.2024 06:00 and 14.03.2024 14:00

2) BAT Parameter: Test runs indicated that the BAT parameter influenced optimisation performance. Through a sensitivity analysis, this effect was confirmed. The model was run for 81, 109, 115, 124 and 142 jobs with BAT values of 0, 30, 60, 120 and 240 seconds. When the parameter was set to 120, an optimum was found for all numbers of jobs except for the subset with 124 tasks. To this end, a BAT of 120 was used for experimental runs.

3) Definition of Number of Shifts: When testing the model, it was found that the number of shifts impedes optimisation a great deal. This was especially the case for larger problem instances. To deal with this, 9 shift instances were used to run MC1. As the morning and afternoon shifts were expected to accommodate most jobs during the day, MC2 was run using 6 shift instances.

C. Experimental Results

Experimental Results are given in this section. They are first summarised and related to job durations in subsubsection IV-C1, and then put into perspective of model performance in subsubsection IV-C2.

1) Model Outcomes with respect to Job Durations: When results were generated, a bias was found as a result of using actual order durations in the data. A box plot of these durations is shown in Figure 4. Large spread was observed in order durations. When discussing this with two employees at FC, it was confirmed that an order should take no more than one to one-and-a-half hour. The conclusion was drawn that stock most likely did not suffice for these orders, so they had to be parked. This time in the parking bin is added in order data, causing the bias in durations. Using a theshold of 1 hour and 15 minutes to determine which orders were biased, new durations were calculated based on picking performance between the months October and April. This information is sensitive but calculations can be requested with the author. New order durations were subtracted from the originals to determine how much time an order had spent in a parking bin, and shifts were subtracted from model outcomes accordingly. The comparison of model outcomes is given in Table 6.

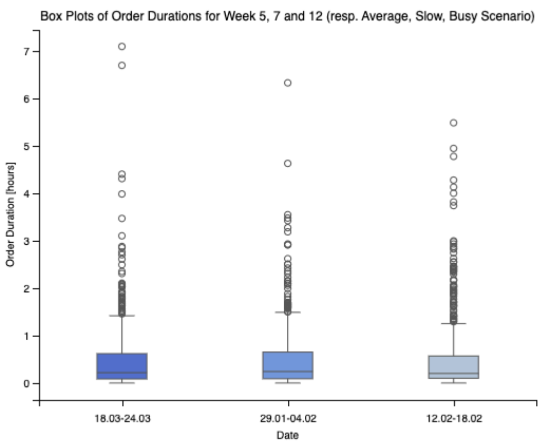

Fig. 4: Box Plot of Order Durations of the Three Scenarios

2) Model Performance: Model performance per week-day and per weekly scenario is summarised in Table 7. The optimality gap found under MC2 is quite large in many cases. The gaps between the two model configurations cannot be compared directly, however. As a result of the alterations to shift cost in MC2, the objective bound was lower, resulting in larger gaps in optimality.

3) Aggregated Results: When looking solely at the resulting cost outcomes both before and after the alteration to order durations in subsubsection IV-C1, it can be concluded that using flex shifts to account for workload is least costly: when observing the cost of MC 2, it is notably higher in more cases than for MC 1 in Table 6. In two out of three scenarios, results from MC2 perform worse than the shift schedule used in reality.

However, when combining this with the knowledge that most of the model runs for MC2 returned sub optimal results (subsubsection IV-C2), these costs will be lower for optimal model runs. Total cost is still expected to be higher when compared to MC1.

In model outputs, some jobs were still scheduled in the night shift. These instances were examined closely, which revealed that both the creation time and deadline of a partition of these jobs fell in the night shift. Creation times and deadlines may both be found during the night shift when stock does not suffice for picking earlier on. The workload induced by these jobs lie around four hours. When taking into account that not all night shifts

Table 6: Comparison of Cost for Different Weeks before and after Shift Removal

MC	Week (scenario)		Cost Diff [%]	Shifts [#]	Red. Hours
1	18.03-24.03	Actual		45	
	(avg)	Model	-18.29 %	42	55.94
		Removed	-32.09 %	35	
	12.02-18.02	Actual		41	
	(busy)	Model	+0.34 %	46	55.19
		Removed	-18.04 %	37	
	29.01-03.02	Actual		32	
	(slow)	Model	+21.33 %	42	76.12
		Removed	+4.58 %	36	
2	18.03-24.03	Actual		45	
	(avg)	Model	-3.49 %	47	95.94
		Removed	-18.49 %	40	
	12.02-18.02	Actual		41	
	(busy)	Model	+16.69	50	87.19
		Removed	+2.25	44	
	29.01-03.02	Actual		32	100.12
	(slow)	Model	+40.77 %	45	
		Removed	+4.58 %	40	

Table 7: Model Performance per Week, by Model Configuration (MC)

MC	Week (scenario)	Mon	Tue	Wed	Thu	Fri	Sat
1	18.03-24.03 (avg)	0.0%	12.3%	0.0%	0.0%	0.0%	0.0%
	12.02-18.02 (busy)	4.0%	16.1%	0.0%	0.0%	0.0%	0.0%
	29.01-03.02 (slow)	0.0%	8.1%	0.0%	25.8%	0.0%	0.0%
2	18.03-24.03 (avg)	15.4%	36.9%	9.5%	22.0%	16.3%	0.0%
	12.02-18.02 (busy)	28.1%	20.8%	2.6%	17.3%	26.1%	0.0%
	29.01-03.02 (slow)	14.8%	11.5%	0.0&	13.9%	19.6%	0.0%

contained such jobs, the average number of hours that needs to be spent picking in the night shift is even lower. It is expected that personnel present during the night suffices to absorb this workload, and no extra employee needs to be scheduled to account for it.

V. DISCUSSION

This study investigated whether orders placed at FrieslandCampina's Distribution Centre in Maasdam could be distributed in a way that avoids manual picking during the night shift to reduce total personnel cost. It does so under two model configurations. The first absorbs the necessary workload in the absolute minimal shift schedule (using flex shifts) and the second considers whether workload can be accounted for using a combination of the morning and afternoon shift.

Results support the hypothesis that insight in scheduling deadlines contributes to a more efficient personnel schedule. The model found a significant cost improvement for the average and busy scenario in the first configuration, and for the average scenario in the second model configuration. When examining outputs closely, it was determined that it is not necessary to schedule an extra employee solely for picking during the night shift. In the cases some picking needs to be done during the night, a single employee from another department would be able to account for workload. This expectation was confirmed when discussing the outcomes at FC.

In a shift trade-off, it is least costly to use flex shifts to account for the workload. However, only using flex shifts leaves less room for the distribution of workload in the model. If the workload is accounted for using mostly the morning and afternoon shifts (MC 2), the time that can be used for order picking is between 06:00 and 22:00, which intuitively gives more room to account for unforeseen circumstances than if all jobs need to be finished between 09:00 and 17:00.

Cost reductions were found only after results were altered to account for bias in the input data (subsubsection IV-C1) in some cases. Order durations used from the data sometimes contained the duration an order was parked, waiting for stock. Even though an employee in reality is able to complete other picking tasks in parallel in this event, the non-overlapping constraints in the model do not allow to do so. This means that too much time was scheduled for these jobs with respect to reality, causing the model to schedule extra shifts. This was accounted for in model results by recalculation of order durations based on their contents and average picking performance in the colli picking department. However, it cannot be said with certainty that the chosen threshold encompasses all biased jobs.

To be able to use the model for solutions within acceptable time, daily sub sets were created. The effect in cost outcomes is not expected to be significant, as the volumes that were cut off into different days leveled out. Nonetheless, it is a deviation from reality. To use the model to schedule longer jobs over multiple days, other assumptions would have to be made.

In addition to extra time scheduled due to biased job durations, the model was subject to optimality gaps in most cases under the second model configuration. This means that the cost savings in reality are expected to be larger than generated by the model.

These increased optimality gaps are expected to be a result of symmetry in the model (Gent et al., 2006). An attempt was made to avoid symmetry by choosing a less costly afternoon than morning shift. However, it is expected that the presence of A-for-A orders extinguished that effect. To test this theory, the model could be run again with a less costly morning shift in comparison to the afternoon shift.

1) Other Modeling Approaches to Similar Problems: A simulation study would have allowed for more flexible (and just more) scenario testing. This may be formulated as a queueing model in the form of a discrete event simulation, in which picking personnel is each seen as a server with a certain picking capacity (which can be varied to account for reality) and jobs come in at a certain rate. More historical data analysis would need to be done to determine those rates.

VI. CONCLUSION AND RECOMMENDATIONS

This study aimed to answer the following research question:

”How can full insight in picking deadlines contribute to a more efficient shift schedule on the manual picking department at FC's DC, taking into account the cost of these different shifts and regarding different scenarios for workload deviations?”

The study's results can be translated into the following outcomes. An employee from another department, or a coordinator is expected to be sufficient to account for the workload that is present during the night. Taking into account the average number of redundant hours in a shift and the first three hours during the morning shift that are left unfilled, the jobs that were scheduled during the night shift in the model are expected to be moved out of the night shift in the job schedule.

In making a trade-off between different shift types to account for the workload present at the DC, the least costly solution is to schedule as many jobs as possible into the flex shifts, but it is recommended to keep using flex shifts as a supplement to the morning and afternoon shifts. Even though the model configuration supporting this solution space resulted in overall higher total cost for two of the three scenarios, using the morning and afternoon shifts to account for this workload will result in more flexibility to move jobs around in the schedule when necessary.

Both of these outcomes come together in the necessity of linking expected ordering deadlines to orders. As explained in subsection I-B, large differences are seen between the deadlines put through in client orders and the definitive deadlines. The model shows that this insight can contribute to reduced cost by scheduling in less costly shifts, but knowing when orders must be complete (and so, how much time is actually available for picking) is crucial to be able to put these outcomes to practice.

A. Recommendations for Further Research

A suggestion for further research is to run the model again, using picking performance to calculate all order durations. A critical look should be taken at pick performance to find its deviation from reality.

Despite the difficulty in finding optimal solutions without alterations to input data, the model was suitable for this study. It is not suitable, however, to use for predictive daily job scheduling yet. Neither is it practical for historical analysis over longer periods of time. The largest problem in performance is expected to be symmetry.

A suggestion to remove symmetry from the model, is to use weights that define which job precedes the next (Van Kessel et al., 2023). This way, the model does not have to make that decision. These can be added to orders based on their creation times. If creation times are the exact same, weights can be assigned based on ascending or descending order lengths. Order durations are a component in making the model functional for predictive job scheduling. As these are not known exactly beforehand, they need to be estimated. This can be done using picking performance as described above, or by estimating how long different client orders generally take using historical data.

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