Improving the tactical planning process to stabilize the workload

Master Thesis

Industrial Engineering and Management

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Improving the tactical planning process to stabilize the workload

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Preface

This master's graduation project finalizes my master Industrial Engineering and Management at the University of Twente and with that, it also finishes my life as a student. I would like to use this preface as an opportunity to thank the people who helped me during this thesis and my entire studies.

First of all, I would like to thank Mike for giving me the opportunity to conduct my graduation project at Voortman Steel Machinery. I also want to thank him for guiding me through the assignment. I also want to thank my colleagues at Voortman Steel Machinery for being kind and helpful. I would especially thank the colleagues at the Voortman Parts Manufacturing departments for their help during my research.

Moreover, I want to thank Marco Schutten for being my first supervisor at the University of Twente. Due to the feedback from Marco, I had to keep my focus on this research. This has increased the level of my thesis for sure. Furthermore, I would like to thank Martijn Mes for being my second supervisor and for providing feedback in the last phase of my thesis.

Lastly, I want to thank all my friends and family for their support and help. I also want to thank them for the feedback and creative ideas to improve my master thesis.

I hope you enjoy reading my thesis.

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Management summary

Voortman Steel Machinery (VSM) is specialised in the manufacturing of CNC-controlled machinery for steel fabrication. VSM is part of Voortman Steel Group (VSG), a worldwide recognized and leading supplier to the steel construction and manufacturing industry located in Rijssen. VSM is divided into multiple departments, such as the VPM 1, VPM 2, and Assembly department. VSM has grown enormously in the last decade. In order not to hinder this growth, VSM tries to deal with the increasing workload as well as possible.

To spread the workload and to guarantee short delivery times to the customers, VSM uses a rolling forecast (RFC). In the RFC meeting, the management determines which and when machines are expected to be sold. Based on these expectations, the production plan of the machines is updated. Due to the current way of planning, the VPM departments have to deal with a short time horizon. Together with the high variability in the workload per production order, the short time horizon leads to instability in the plan. Since this instability in the plan causes several problems within the VPM departments, VSM wants to know how the workload in the plan can be stabilized. That is why we answer the following research question in this research:

How can the planning process within VSM be organised such that the workload of the VPM 2 department is stabilized?

To organise the planning process within VSM differently such that the workload of the VPM 2 department is stabilized, we first analyse the current planning and production process. The machines of VSM have a modular design. In the Assembly department, the modules are assembled into a machine. Within some of these modules, there are weldments that have to be produced by the VPM 1 and VPM 2 departments. The VPM 1 department also takes care of the production of the roller conveyors and cross transports. The weldments are produced using 6 production steps. In this research, we have chosen to focus only on the plan of the VPM 2 department where 4 of the 6 production steps that could be in a weldment are executed. We define the total workload per week of the VPM 2 department as the sum of the total production time of the production steps planned in a week. The planner of the VPM 2 department first determines the deadline for the VPM 2 department after which he plans the production steps back in time from this deadline. The time horizon the planner of the VPM 2 department has to plan the production steps is approximately 4-6 weeks.

To support the improvement of the plan of VSM, we conduct a literature review. In this literature review, we define our planning problem as a capacity planning problem (CPP) at the tactical level. Such a problem is studied already by multiple researchers. From these studies, we define that our planning problem can be addressed in two different ways. We can approach the planning problem as a time-driven Rough-Cut Capacity Planning (RCCP) problem or as a resource loading problem. Using the mathematical formulations of these problems, we create a MIP model that aims to minimize the maximum workload per week. Besides, we create a constructive heuristic that imitates the current situation, i.e., the CS-heuristic. Afterwards, we improve the plan created by the CS-heuristic using the simulated annealing (SA) algorithm. We use the move (SA-Move) and insert (SA-Insert) operators in the SA algorithm to traverse the full solution space. In the SA algorithm, we aim to minimize the standard deviation of the workload.

Using the solution approaches for the CPP that we come up with, we generate multiple plans. For this, we used input from RFC reports. These reports state which machines are expected to be sold and when these machines are expected to be sold. The plan of the VPM 2 department created by the solution approaches is only valid for a limited time, i.e., for the first 5 weeks after the last included RFC report. We refer to this part of the plan as the relevant plan. We use the relevant plan to base our analyses and experiments on. When comparing the relevant plan created by the MIP model and the heuristics, we conclude that both the MIP model and the SA-Move heuristic perform well. Using 4 predefined datasets, the average standard deviation of the relevant plan decreased from 29.267 in the current situation (CS-heuristic) to 1.857 using the SA-Move heuristic and 0.017 using the MIP model. In addition, the average maximum workload of the relevant plan decreased from 311.2 hours using the CS-heuristic to 259.4 hours using the SA-Move heuristic and 223.33 using the MIP model. Since both the SA-Move heuristic and the MIP model perform well, we decide to perform experiments with these two solution approaches.

We conduct 3 different experiments. In the first experiment, we test how the MIP model and the SA-Move heuristic perform if the maximum allowed inventory value is lowered. From this experiment, we conclude that the MIP model outperforms the SA-Move heuristic until the maximum inventory value drops below €70,000. In addition, we conclude that the results of the SA-Move heuristic hardly change (in contrast to the MIP model) if the maximum inventory value is lowered. The second experiment presents a trade-off between the outsourcing costs and the stability in the plan from which we conclude that the higher the outsourcing costs are, the lower the standard deviation and the maximum workload in the relevant plan are. In the third experiment, we vary the ATW window per weldment. From the results of the analysis of the influence of a varying ATW window on the stability and maximum workload of the relevant plan, we concluded that the workload of the relevant plan can be stabilized the best if the workload per production step and the length of the ATW window are balanced. Table 0-1 shows an overview of the most important results per experiment.

Table 0-1: Overview results per experiment

Experiments	Scenarios	MIP model		SA-Move	
		STDEV	MAX	STDEV	MAX
Experiment 1	Max. inventory value = €350,000	0.015	260.7	1.993	293.3
	Max. inventory value = €66,000	11.971	308.2	2.003	293.3
Experiment 2	Low outsourcing costs	0.015	260.7	1.993	293.3
	High outsourcing costs	0.003	254.2	0.346	291.3
Experiment 3	Current situation	0.015	260.7	1.993	293.3
	New situation	0.015	234.4	0.820	255.4

Based on the analyses and the results of the experiments, we recommend VSM to:

1. Use the SA-Move heuristic to create the plan. From the results of this research, we concluded that this solution approach stabilizes the plan the best and is the most user-friendly.
2. Link the plan of VSM to the (expected) delivery date of a machine. By doing this, the management team gains direct insight into the influence of the production of the machines on the plan of the departments. Based on this updated plan of these departments, the management team can make an informed decision regarding the delivery date of the machine. The plan of the departments within VSM can be better stabilized by varying the delivery date of a machine in this way.

3. Experiment with the outsourcing costs and the fixed lot sizes as we did in the second experiment. Based on the results of this experiment across all weldments and the complete plan (and not across some weldments as we did), VSM can decide for which weldments it is beneficial to have a fixed lot size and for which weldments not.
4. Use the proactive method, i.e., add some slack in the plan to anticipate on causes that can lead to overtime, in combination with the reactive method, i.e., to use a replanning approach which repairs the complete plan, to deal with the uncertainties in the execution of the plan.
5. Focus on the logging of data and the quality of this data to be able to improve processes and to verify these improvements in a data-driven way. Currently, the data is often available but it is difficult to find and not always of high quality.

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Glossary

VSG	Voortman Steel Group
VSM	Voortman Steel Machinery
VPM	Voortman Parts Manufacturing
RFC	Rolling Forecast
MSPM	Management Problem Solving Method
KPI	Key Performance Indicator
BOM	Bill of Materials
ERP	Enterprise Resource Planning
CODP	Customer Order Decoupling Point
MTO	Make-To-Order
ETO	Engineering-To-Order
ATO	Assemble-To-Order
MTS	Make-To-Stock
MPC	Manufacturing Planning and Control
LAP	Largest Activity Part
ICPA	Incremental Capacity Planning Algorithm
SA	Simulated Annealing
TS	Tabu Search
GA	Genetic Algorithm
RCCP	Rough-Cut Capacity Planning
CPP	Capacity Planning Problem
ATW	Allowed-To-Work
MIP	Mixed Integer Programming
LP	Linear Programming
Time of delivery cold start	Within VSM, the term 'time of delivery cold start' refers to the throughput time in weeks of a machine. So, the time of delivery cold start is the total number of weeks that VSM needs to produce a machine.
Production step	We call a job that needs to be planned a 'production step'.
Time horizon	The time a department within VSM gets to finish their production steps, i.e., to deliver their parts for the machines to an external supplier or another department within VSM.
Relevant plan	The plan of the VPM 2 department for the first 5 weeks after the last included RFC report.

1 Introduction

The aim of this research is to improve the planning process within Voortman Steel Machinery (VSM) so that the plan of the Voortman Parts Manufacturing 2 (VPM 2) department is stabilized. This chapter gives an introduction to Voortman Steel Group (VSG) and its departments in Section 1.1. Section 1.2 describes the project. Section 1.3 defines the problem statement and the objective of this research. Section 1.4 discusses the scope of this research. Lastly, Section 1.5 presents the research questions and describes the research design.

1.1 Voortman

Voortman Steel Group (VSG) is a worldwide recognized and leading supplier to the steel construction and manufacturing industry. In 1968, the brothers Voortman founded a mechanization company in Rijssen called H. Voortman & Co. The company started as a business for all kinds of machinery. A few years later, Voortman started designing and building steel structures in addition to the mechanisation operations. As a result, in 1980 Voortman was split into two separate companies; one for machinery (Voortman Steel Machinery) and one for steel structures (Voortman Steel Construction). As of 1995, Voortman Steel Machinery (VSM) concentrated solely on CNC machinery for the steel construction sector. This specialisation has led to the steady growth of the company. To keep up with the global growth over the years, it has been necessary to open several subsidiaries worldwide, for example in Germany, Poland, Russia, England, and the USA (Voortman Steel Group - About, 2020).

Today, VSG still consists of Voortman Steel Machinery (VSM) and Voortman Steel Construction (VSC). VSC designs, produces, and supplies high-quality projects in steel construction. VSM is specialised in the manufacturing of CNC-controlled machinery for steel fabrication. The company consists of multiple departments. Currently, VSM is divided into, among others, Voortman Parts Manufacturing (VPM) and Assembly. At VPM, the parts of the machines are cut and welded. VPM also consists of two departments: Voortman Parts Manufacturing 1 (VPM 1) and Voortman Parts Manufacturing 2 (VPM 2). At VPM 1, all sheet metal parts for VSG are cut. These sheet metal parts are used as semi-finished products for the construction process at VPM 2, and as head and foot plates at VSC. In addition, all cross transports and roller conveyors are also welded and assembled in this department. The cross transports and roller conveyors provide the in- and outfeed of raw materials for the machines. The cut sheet metal is welded at VPM 2. These welded parts are only used as parts for machines of VSM. The welded parts go to external suppliers where they are processed. Afterwards, the parts go to VSM Assembly where they, together with other purchased components, are assembled into a machine. Figure 1-1 provides a schematic overview of the department of VSG.

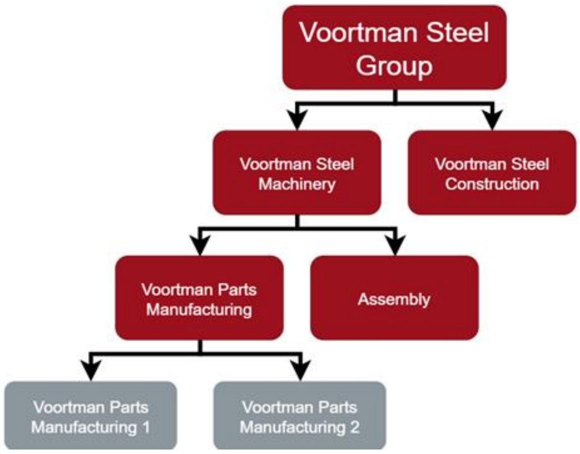

Figure 1-1: Schematic overview departments (relevant for this research) Voortman Steel Group

Figure 1-2 shows the location of the departments of VSG. The VSM Assembly department is in the same building as the VSM department.

Nowadays, VSM is able to produce 23 different machines. All these advanced CNC-controlled machines are used for treating steel. The product range can be divided into four categories:

1. Beam processing
2. Plate processing
3. Flat and angle processing
4. Surface treatment

Figure 1-2: Location of departments of Voortman Steel Group

Most machines are used to saw, drill, cut, or shear the steel. Some examples of the machines of Voortman Steel Machinery are the Voortman V613, the Voortman V310, and the Voortman V550-7. The Voortman V613 is a CNC beam drilling machine that can carry out several processes such as carbide drilling, thread-tapping, countersinking, marking, and centerpoint marking. Figure 1-3 visualizes the Voortman V613. Figure 1-4 displays the Voortman V310, a plasma cutting and drilling machine used for cutting and drilling sheet metal. The Voortman V550-7 CNC flat and angle processing machine, as Figure 1-5 shows, can be used for among others punching, shearing, drilling, and marking strip and angle profiles. These machines are supplied worldwide to customers from various industries such as the oil and gas industry, shipbuilding, and steel construction (Voortman Steel Machinery – Machinery, 2020).

Figure 1-3: Voortman V613

Figure 1-4: Voortman V310

Figure 1-5: Voortman V550-7

1.2 Problem description

VSM has grown enormously in the last decade. For the coming years, even more growth is predicted. In such a growing organisation, it is a challenge to maintain a high performance every day. The work processes will have to continue to grow to keep up with the growth of the company. In order not to hinder this growth, flexibility of the work processes is required. Since some work processes could not cope with the growth, VSM approached these processes differently at a certain point in time. In this way, VSM tried to deal better with the increased workload. In addition, VSM will also have to stay ahead of its competitors to maintain the competitive position, and with this the growth of the organisation. One way in which VSM tries to stay ahead of its competitors is by guaranteeing short delivery times, as more and more customers desire this. To guarantee these short delivery times, the workload must be well distributed.

To spread the workload and to achieve the desired short delivery times, VSM uses a rolling forecast (RFC). An RFC uses historical data and input from sales managers to predict future sales over a certain time period. The sales managers retrieve order information. This information could be freely and continuously revised based on the latest market information provided by customers, with the information coming closer to actual requirements as the moment of ordering approaches (Huang et al., 2011). An RFC differs from a fixed horizon forecast in its dynamic horizon. In the forecast meeting, which takes place about once every 4 weeks, the group leader of the Works Office (who is the Central Planner of VSM), the group leader of Sales, and the management come together to establish the forecast. Based on this forecast, the Central Planner and the group leader of Sales set up the RFC planning. The RFC planning of VSM is a weekly updated plan, in which the planned and expected orders are presented. At the moment, the production of the machines is almost always started based on the forecast. Hardly any machine has a customer when the production starts.

The RFC planning determines when the production of the machines will be started. Since the last step of the production process is the assembly of the components into a machine, the workload of the Assembly department can be directly derived from the RFC planning. To save time and thus reduce the workload, the planners examine if it is possible to cluster assembly work of different machines. As a result, the workload per week can be very different. Currently, the machines to be delivered are planned based on this workload.

Because the components that must be assembled at the Assembly department are made at the VPM 1 and VPM 2 departments, the plan of the Assembly department is decisive for the work that has to be done in these departments. The plan of the VPM departments is therefore actually a plan that is derived from the plan of the machines to be delivered, as shown in simplified form in Figure 1-6. Since this plan of the machines to be delivered is based on the workload of the Assembly department, both VPM departments have a short time horizon to deliver their work.

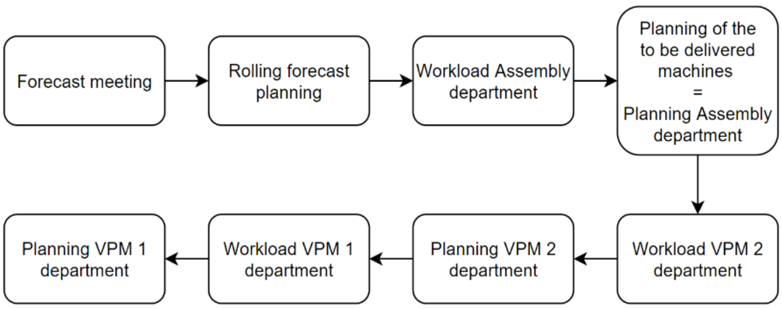

Figure 1-6: Process flowchart of VSM plan

The RFC planning that results from the forecast has thus much influence on the VPM departments. The VPM 1 department has to start immediately producing parts for the forecasted machines after the forecast is established. Only in this way, the machines can be delivered on time. Due to this short time horizon and the preference of the Assembly department to cluster assembly work, the workload of the VPM departments is unstable and shows an erratic pattern.

This erratic pattern in the workload is strengthened by the high variability in the workload per production order. Due to this high variability in the workload per production order, the choice of the mix of machines to be produced (that is made during the forecast meeting) influences the workload of the VPM departments enormously. It becomes, for example, practically impossible for the VPM departments to deliver their parts on time if multiple machines of the same type that have a high workload for the VPM departments need to be produced. Nevertheless, the management currently does not take into account the consequences of the choices made during the forecast meeting. Since the unstable workload causes several problems at the VPM departments, VSM wants to know how this workload can be stabilized.

1.3 Problem statement and research objective

To streamline the research, we follow the Management Problem Solving Method (MPSM). The MPSM is a systematic approach to solve a business problem (Heerkens & Van Winden, 2012). This systematic approach consists of several phases. Using the first phase of the MPSM, we determine the core problem and set an objective for this research.

According to the problem description in Section 1.2, VSM wants to know how the workload at the VPM departments can be stabilized. Due to the current way of planning, the VPM departments have to deal with a short time horizon. In this, the time horizon is defined as the time the VPM departments get to finish their jobs, i.e., to deliver the parts for the machines to the external supplier or Assembly department. In addition to the short time horizon, the high variability in the workload per production order leads to instability in the plan. Therefore, we define the following problem statement:

Due to the short time horizon and the high variability in the workload per production order, the VPM departments have an unstable workload.

To stabilize the workload, we need to investigate the current way of planning and come up with a proposal to plan the workload differently. By investigating the consequences of the choices made during the forecast meeting, VSM can respond more quickly to the variable workload. Besides, this also indirectly extends the time horizon of the VPM departments and creates more flexibility in the plan of these departments. The expectation at VSM is that this more flexible plan contributes to stabilizing the workload for the VPM departments. To find out if this hypothesis is correct or not, we define the following research objective:

Develop a new way of planning that stabilizes the workload of the VPM departments, and a proposal to implement this new way of planning.

1.4 Research scope

In this research, we consider the plan of the VPM departments at Voortman Steel Machinery. We aim to improve the planning process of the VPM departments to stabilize the workload. To reach this goal, we do not try to improve the forecast or come up with alternative forecast methods. A previous study at VSM (Van der Wal & Tholen, 2016) has shown that it is hard to improve the forecast. Therefore, we do not go into detail about the forecast process and the used forecast methods of VSM. The number of machines to be produced that follows from the forecast is not called into question and thus we use it as given information in this research.

Besides, in the plan that we create, we do not consider projects that have a customer when the production starts. We do not consider these projects as they are directly customer-specific made. This means that the machine(s) of this project could contain modules that are not standard modules of the machine(s). Since these modules are not forecasted, and these types of projects hardly occur, we do not consider these projects. It is, however, possible to include these projects in the plan, but we do not do this.

Also, we only try to improve the planning process of the VPM 2 department and not the planning process of other departments since the VPM 2 department has the shortest time horizon and the highest variability in the workload per production order. The improvement of the planning process of the VPM 2 department should, however, not be at the expense of the plan of other departments.

1.5 Research questions

The research objective in Section 1.3 leads to the following main research question:

How can the planning process within VSM be organised such that the workload of the VPM 2 department is stabilized?

To achieve the objective of this research and to answer the main research question, we have created a problem approach. The problem approach is the second phase of the MPSM (Heerkens & Van Winden, 2012). This phase describes in detail how we should approach our research problem. That is why this phase serves as a structure for our research methodology.

We divide the solution process into 5 different phases. For the first phases, we present a research question that we answer using the sub-questions. Next to that, we explain the research design after presenting the research question. For the last phase, we only present a research design.

Phase 1: Current situation

Question 1. What is the current situation at VSM?

a. How is the production process at VSM structured?
b. What does the current planning process of VSM look like?
c. What are the objectives and restrictions for the production plan per department?
d. How is the performance of the plan currently measured?

In the first phase discussed in Chapter 2, we investigate and describe the current situation at VSM. A clear overview of the current production and planning process is essential to improve the planning process. We collect information by conducting informal interviews with employees of different departments of VSM, such as Parts Manufacturing, Works Office, and Sales. Using this information and the information acquired from a data analysis using obtained data, we analyse the production process. The current planning process is described using the same approach. To validate the production and planning process descriptions, we work together with the Central Planner and the group leader of Parts Manufacturing. Next, we also determine per department the objectives and restrictions for the production plan that should be considered. To identify the current performance measures of the plan in terms of Key Performance Indicators (KPIs), an informal interview with the Central Planner is held.

Phase 2: Literature review

Question 2. What relevant knowledge from the literature can be used to support improvement of the planning process of VSM?

a. How is the planning problem of VSM known in literature?
b. What methods are given in the literature to solve the planning problem of VSM?
c. What approaches are described in the literature to cope with uncertainties in the execution of the plan?

In the second phase discussed in Chapter 3, we conduct a literature study. After collecting information about the current situation at VSM, we need information from the literature about several topics. To define the planning problem at VSM, we describe several planning problems including their modelling and solution approach(es) from the literature. We end this phase by describing approaches from the literature that can be used in our model to cope with uncertainties in the execution of the plan.

Phase 3: Solution design

Question 3. How can the planning problem at VSM be improved?

a. How can the planning problem at VSM be modelled?
b. What methods can be used to solve the specific planning problem from VSM?
c. How can the methods be adapted to the planning problem situation at VSM?

In the third phase discussed in Chapter 4, we formulate a model for the planning problem at VSM. We solve this model afterwards using multiple solution approaches. For this, we first select the most relevant methods to solve the planning problem found in our literature study. Afterwards, we adapt the solution approaches to the VSM case.

Phase 4: Analysis of results

Question 4. What is the best solution for the planning problem at VSM?

a. What does the design of the experiments look like?
b. How do the methods perform?

In the fourth phase discussed in Chapter 5, we analyse the alternatives developed in Chapter 4. Before we start with this analysis, we set up an experimental design. Next, using this experimental design, we perform an analysis. In this analysis, we use historical data. We use the performance measures discussed in Chapter 2 to determine the best alternative for VSM. Then, we compare our results with the plan created by the planner. In this, we also take into account how our model reacts to the new workload from the forecast meeting.

Phase 5: Conclusions and recommendations

In the last phase discussed in Chapter 6, we conclude the research. In this chapter, we present instructions about how to implement the designed planning process. Afterwards, we present our recommendations and conclusions for VSM. This chapter ends with a discussion on the results.

2 Current Situation

This chapter describes the current situation at VSM by answering the first research question: "What is the current situation at VSM?". The chapter starts with a description of the production process at VSM in Section 2.1. For this, we first describe the way a production order at VSM is established. Afterwards, we explain the processes at several departments within VSM and give an indication of the production capacity. Section 2.2 discusses the product structure of VSM. Section 2.3 covers the current planning process at VSM. Section 2.4 describes the objectives and restrictions that planners have to deal with. In Section 2.5 we discuss the performance measures used while creating the production plan. Section 2.6 concludes this chapter.

2.1 Production process

Two situations can start the production process of VSM. In the first situation, a customer comes straight to the point during the first meeting with the sales managers and orders a machine. As mentioned in Section 1.2, this situation hardly occurs. In the second situation, which is almost always the case, there is no order for a machine yet, but the machine is already being produced. In this case, the machine will be produced based on a forecast. In the two situations, the production orders are established differently. Therefore, we describe how the production orders are established in both situations in Section 2.1.1.

2.1.1 Production order

A project always starts when a customer shows interest in one of the machines VSM produces. When a customer already knows which machine(s) he wants to buy and so comes straight to the point during the first meeting with the sales managers, a project number is directly assigned to this customer. In this way, the ordered machine(s) can be customized directly from the beginning of the production process. All production orders that follow from the ordered machine(s) are also directly assigned to this customer.

It is also possible, however, that the sales managers first have several conversations with the customer to convince the customer to buy a machine. After each conversation, the sales manager estimates the chance that the customer will buy the machine. This chance of success is afterwards used as input for the forecast meeting. In this forecast meeting, the forecast for approximately 4 weeks in the future (which depends on the throughput time of the machine) is established. Based on this forecast, the Central Planner and the group leader of Sales set up the RFC planning. Using this RFC planning, the sales manager then agrees on a delivery time with the interested customer.

If a customer is interested in a machine but does not place an order directly, the management can decide in the forecast meeting to already produce the machine the customer is interested in. This means that the machine will be produced based on the forecast and so without a customer order. A disadvantage of this may be that, due to specific requirements by the customer, adjustments to the machine have to be made later in the production process.

After a production order has been started, the Purchase department purchases the required materials based on the plan of the machines to be produced. These purchases mainly include raw materials that the VPM departments process and components that have to be ordered from suppliers. When the components from the external suppliers are delivered, they are stored in the warehouse waiting for the processed materials from the VPM departments. When all components and materials have been received and processed, the assembly can begin. The production process per department is described in more detail in Section 2.1.2 to Section 2.1.4. To describe the production process per department in more detail, we create a flow chart of the most important steps of a production order. A visualization of the complete flow chart of the production process, including some irrelevant departments, is given in Appendix A.

2.1.2 VPM 1

As stated in Section 1.1, several processes are carried out at the VPM 1 department. Most of these processes are the first steps in the production process at VSM. In total, three different production processes are carried out at the VPM 1 department: (1) Cutting, (2) Drill/Saw, and (3) Handling. Each production process has its input, activities, and output. We discuss the three production processes separately. For this, we use a part of the complete flow chart of the production process. Figure 2-1 shows the part of the complete flow chart related to the production processes at the VPM 1 department.

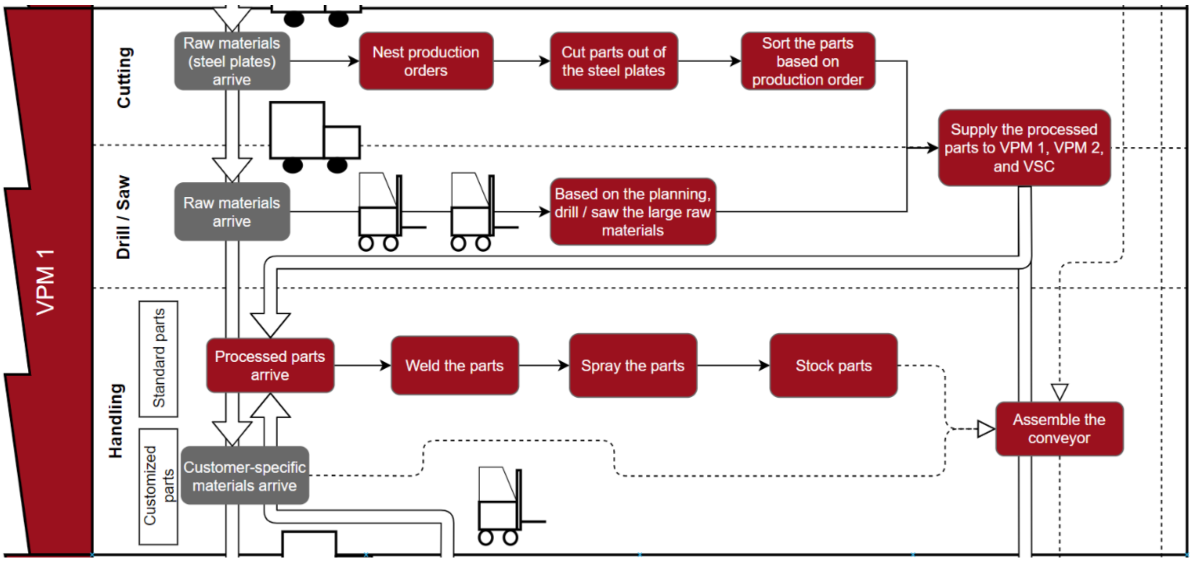

Figure 2-1: Flow chart of the production processes at VPM 1

Cutting

At the production process Cutting, materials for production orders are cut. An external supplier supplies steel plates to the VPM 1 department. Out of these steel plates, parts for machines, cross transports, and/or roller conveyors are cut. In addition, head plates and footplates for VSC are cut out of the steel plates. Because orders may require the same thicknesses of steel plates, several orders are nested. Besides, nesting orders ensure that the total area of the steel plates can be used as efficiently as possible. Once the parts are cut out of the steel plates they are sorted based on the production order number. The cut parts are then supplied, together with the drilled/sawn materials, to the Handling production process at the VPM 1 department, to the VPM 2 department, and/or to VSC. Figure 2-2 and Figure 2-3 show the steel plates that an external supplier delivers and the cut parts from the steel plates, respectively.

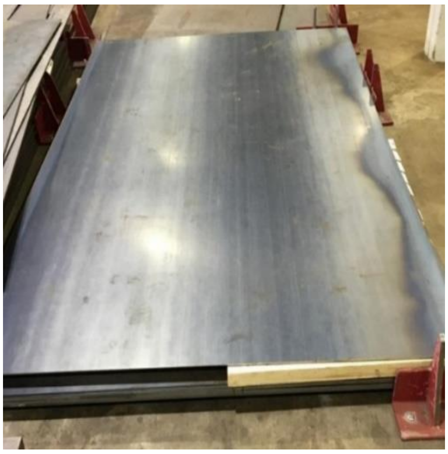
Figure 2-2: Steel plates from external supplier


Figure 2-3: Cut parts out of the steel plates

Drill/Saw

At the production process 'Drill/Saw', mainly UPE 140s (U-profiles with parallel flanges) are drilled/sawn for production orders. An external supplier delivers these UPE 140s to the VPM 1 department. When these materials arrive, employees of VPM 1 drill and/or saw these UPE 140s based on the plan. Only materials larger than 60 by 60 millimetres are drilled/sawn at the VPM 1 department as the installed machines at this department cannot process smaller materials. The materials smaller than 60 by 60 millimetres are drilled/sawn at the VPM 2 department since a machine has been installed here that can process these small materials. When the materials are drilled/sawn at this production process, they will be supplied to the Handling production process at the VPM 1 department or to the VPM 2 department. Figure 2-4 shows some sawn UPE 140s.

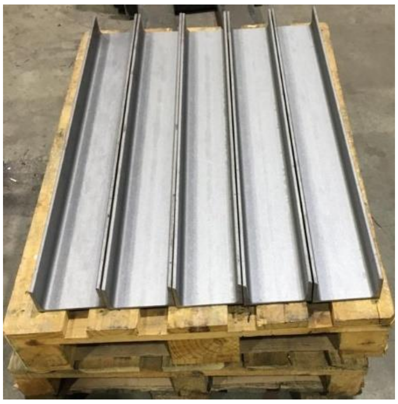
Figure 2-4: Sawn UPE 140s

Handling

The cut, drilled, and sawn materials are delivered to the Handling production process. At this production process, the processed parts are welded and sprayed to semi-finished products that are used for the cross transports and roller conveyors. After the sprayed semi-finished products have dried, they are placed in stock. These products are standard parts of the cross transports and roller conveyors. The customer-specific materials are purchased. These customer-specific materials are used together with the standard parts to assemble the cross transports and roller conveyors. Most of the assembly is done at the Handling production process. Due to transportation reasons, the cross transports and roller conveyors are not completely assembled. Figure 2-5 shows an assembled roller conveyor. Since the Handling production process is important and large in VSM, we consider this line as a separate department in the remainder of the report.

Figure 2-5: Assembled conveyor

2.1.3 VPM 2

When VPM 1 has cut, drilled, and/or sawn all materials, they are brought to the VPM 2 department. In this department, the materials are welded into weldments. This is done in three steps. First, the Preparation of welding step is executed. In this step, employees of VPM 2 post-process the incoming materials, sort the materials, and do some pre-processing work for the welders. After this step, a construction welder welds the materials so that they form a weldment. This construction welder should be able to read a construction drawing. The finalize welder, on the other hand, does not necessarily have to be able to read a construction drawing. Using the construction drawing, the welder can determine how the materials should be merged. The welder merges the materials using welding points. After the materials are merged properly, the finalize welder will complete the weld. When the weld is completed, the weldment is brought to external suppliers. These external suppliers anneal, blast, mill, and/or coat the weldment. The weldment can follow three different paths, as indicated in Figure 2-6. Afterwards, the weldment is brought back and is stored in the warehouse of VSM. Figure 2-7 shows a weldment that is produced at the VPM 2 department before it is taken to the external supplier and Figure 2-6 visualizes a flow chart of the production process at the VPM 2 department.


Figure 2-7: Weldment

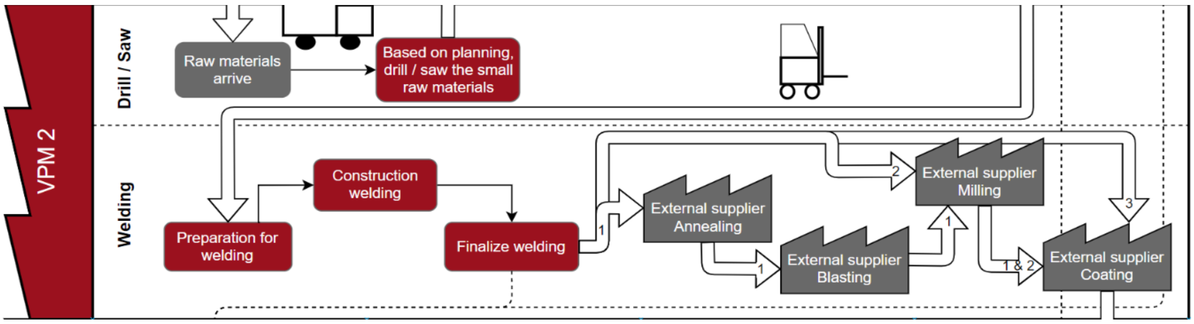

Figure 2-6: Flow chart of the production process at VPM 2

2.1.4 Assembly department

After the production of the weldments, cross transports, and roller conveyors is finished, they are stored in the warehouse of VSM. In this warehouse, the parts are stored until both produced and purchased materials are delivered. Only then the assembly is started. When all parts are merged into one machine, the machine will be tested. If the machine passes this test, it is disassembled into multiple parts (because of transportation reasons). Afterwards, the machine will be shipped to the customer. Here, the machine will be installed and commissioned. Figure 2-8 shows a flow chart of the production process at the Assembly department.

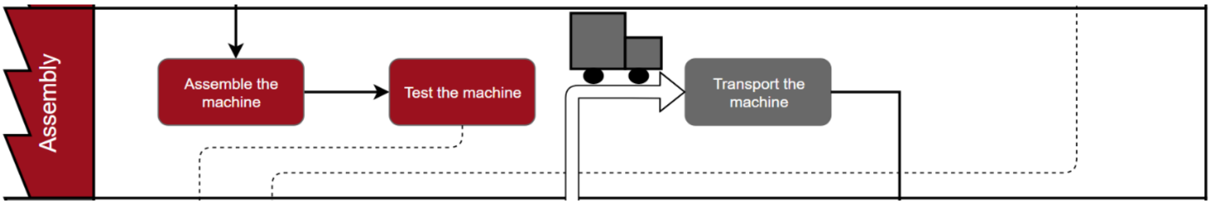

Figure 2-8: Flow chart of the production process at the Assembly department

2.1.5 Capacity

At VSM, the number of employees per department varies every week. This is mainly due to the variable workload. Depending on the workload in a department, employees could be moved to another department. In this way, VSM can better deal with the variable workload without having to hire or fire employees again and again. At the VPM 1 department, there are 7 operators permanently employed. Taking into account the movement of employees, on average, 17 employees are in the welding and assembly shift at the VPM 1 department. These employees are spread over the three production processes. The employees at the Cutting production process work from Monday to Thursday in one of the two shifts of 9 hours and Friday in one of the two shifts of 5 hours. During this shift, the employees can have a break of half an hour in total from Monday to Thursday and 15 minutes on Friday. This means that in total 8.5 hours on Monday to Thursday and 4.75 hours on Friday of production time per employee per day is available. The employees at the Handling department work, depending on the workload, from Monday to Saturday between 38.75 and 53.5 hours a week. The employees have access to 1 drill/saw machine and 4 cutting machines. The time the cutting machines need to cut a steel plate depends on the thickness of the plate and the number of actions the plate needs. For the drill/saw machine, the production capacity also depends on the number of actions required. The total throughput time also depends on activities before and after the production step. The duration of these activities depends on, among others, the weight of the material.

At the VPM 2 department, on average 17 employees saw, drill, or weld from Monday to Friday in a shift of 8.75 hours. The employees at the VPM 2 department have a break of 1 hour in total. So, the total available production time per employee per day is 7.75 hours. There is 1 drilling machine at the VPM 2 department and 2 manual saws. In addition, there are 18 workplaces available for the welders.

Lastly, at the Assembly department, there are about 32 employees available to assemble the machines. These assemblers are also 7.75 hours a day available. We assume that there are sufficient tools available at all departments to run the production.

2.2 Product structure

The machines VSM produces consist of many modules. Some of these modules are standard for a type of machine. For example, there is a 'Weldment sawframe' in all VB1050 machines VSM produces. Besides these standard modules, there are also some modules that the customer could select. These modules are engineered based on the customers' wishes. In this section, we discuss the product structure using the Bill of Materials (BOM).

As stated in Section 1.1, VSM is able to produce 23 different advanced CNC-controlled machines. These machines are built up from modules. These modules contain many materials that are presented in a BOM. Within VSM, this BOM of an order is structured as Figure 2-9 shows. A specific project number is assigned to each machine sold, a so-called '1 million order'. The modules that are in this machine are

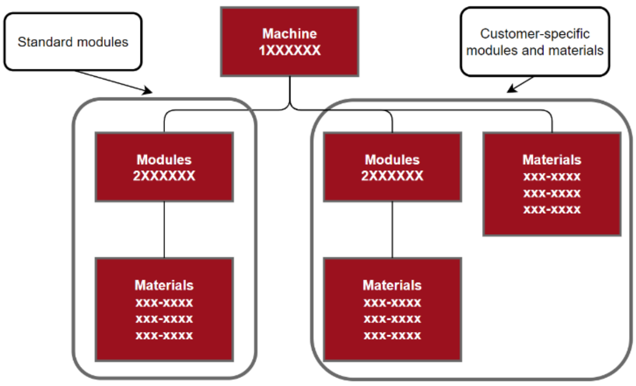

Figure 2-9: Product structure of an order

indicated using a '2 million order' number. Some of these 2 million orders are standard and some of these are customer-specific. When the production of a machine is started based on a forecast, only the standard modules will be made. The 2 million orders consist of materials that in VSM are identified by 'xxx-xxxx'. The purchased materials and components that are not in a specific module are also identified using the 'xxx-xxxx' number. The cross transports and roller conveyors that are part of the machines also have a specific number. These numbers are known as the '3 million orders'. The 3 million orders are, just like the 1 million orders, built up from 2 million orders and purchased components. The BOM of the cross transports and roller conveyors, however, does not completely have the same structure as the BOM visualized in Figure 2-9. The cross transports and roller conveyors are not produced based on the forecast and therefore do not contain standard modules that can be made in advance.

In this research, only the weldments that are in the modules are of interest. Table 2-1 shows for some machines the total number of parts they contain and categorizes all these parts to find the relevant weldments for this research. To reduce the number of weldments, we only consider the weldments that require at least one production step. This means that we consider in total 550 different weldments from 15 different types of machines. A complete list of all relevant machines and corresponding weldments can be found in Table 4-4.

Table 2-1: Number of weldments per machine

		Categorization					
Machine	Parts	Procurement parts	Modules divided into submodules	Modules external production step	Too small parts	Production other departments	Relevant weldments
V807	1314	1177	84	23	2	0	**28**
VB1050	939	726	150	30	3	0	**30**
V2000	477	374	66	16	0	1	**20**
V310	406	365	24	6	1	4	**6**
V613	1133	819	192	54	4	6	**58**

2.3 Planning process

As mentioned in Section 1.2, the Central Planner and the group leader of Sales set up an RFC planning based on the forecast discussed in the forecast meeting. In this forecast meeting, the expected sales for approximately 4 weeks in the future depending on the throughput time of the machine are discussed. So, for example, if the forecast meeting takes place in the second week of the year the expected sales for weeks 17-20 are discussed. As Figure 1-6 already showed, the forecast meeting is leading for the plan of the Assembly, VPM 2, and VPM 1 department. Since most processes at the VPM 1 department are the first step of the production process, this department has the shortest time horizon and so has its workload the most erratic pattern. Figure 2-10 presents an overview of the time period discussed during the forecast meeting and an estimation of the time horizon per department.

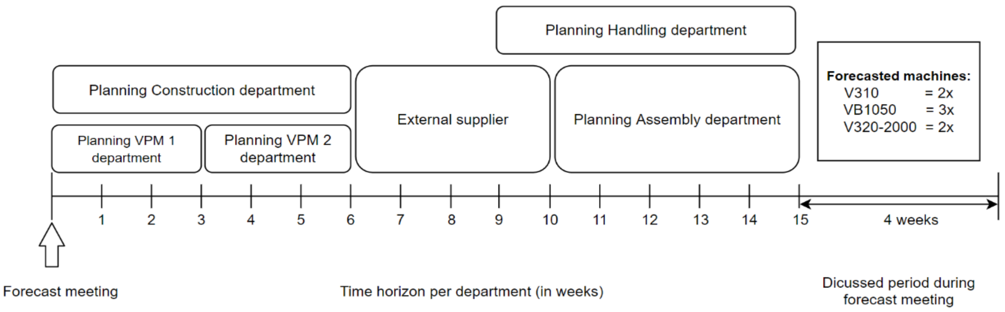

Figure 2-10: Time horizon per department

Note that the presented time horizon per department is an estimation since, in reality, it differs per machine type. The Construction and Handling departments (that are mentioned in the figure) are discussed in Section 2.3.2.

2.3.1 Software

To manage all business activities and to plan all production steps, VSM uses multiple software packages. For this research, only two of them are relevant which are discussed below.

The most important software package used is SAP. SAP is the Enterprise Resource Planning (ERP) system of VSM. Many persons in VSM use SAP to manage business activities and obtain information regarding for example production orders, inventory, (customer-specific) materials, and finance. The planners of VSM use SAP mainly to manage the inventory and to get specific information about their part of the production process.

Next to SAP, the planners use ROB-EX. ROB-EX is the planning software within VSM. The planners plan the different production steps with ROB-EX. For this, each planner has to determine the hours needed to execute a production step. The planners have their own methods for this. These methods are discussed in Section 2.3.2. Using the required hours per production step and the information obtained from SAP, the planners plan the production steps of their department. During this planning process of the production steps in ROB-EX, the available workforce and the current workload is visible. Next to this, the planners see in ROB-EX all tasks they should execute with the corresponding due dates. Figure 2-11 shows an example of a plan made in ROB-EX. Note that in this plan it is possible to expand all rows to get more details about the production steps.

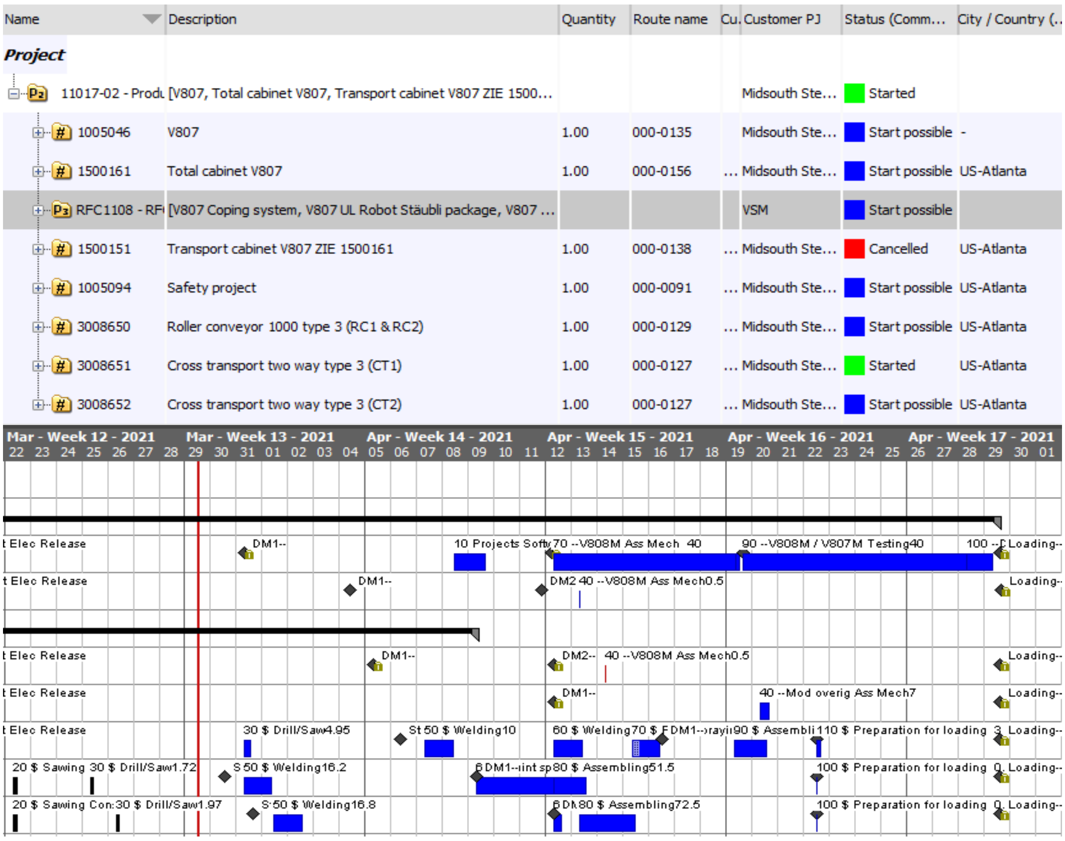

Figure 2-11: Plan in ROB-EX

2.3.2 Workload calculation

After there has been a forecast meeting, the Central Planner updates the RFC planning. Figure 2-12 shows the RFC planning for several machines of which the names are visible on the left in the figure. The RFC planning is updated by colouring cells blue in the planning. These blue cells represent not yet released production slots. When these new production slots are planned depends on the throughput time or so-called 'time of delivery cold start' of the machines. This time of delivery cold start is based on the minimal throughput time that is needed to produce the machine. After the new production slots are created, the materials needed to create the weldments are ordered. When all materials are available, the production will start. The blue cells in the RFC planning will be coloured green. So, these green cells represent the available production slots that are released. These slots are used to start the production of a machine completely based on the forecast. If a customer is then interested in the machine, makes the deal, and transfers the first payment, the green cell is coloured red in the RFC planning. The machine produced in this time slot is then assigned to the customer.

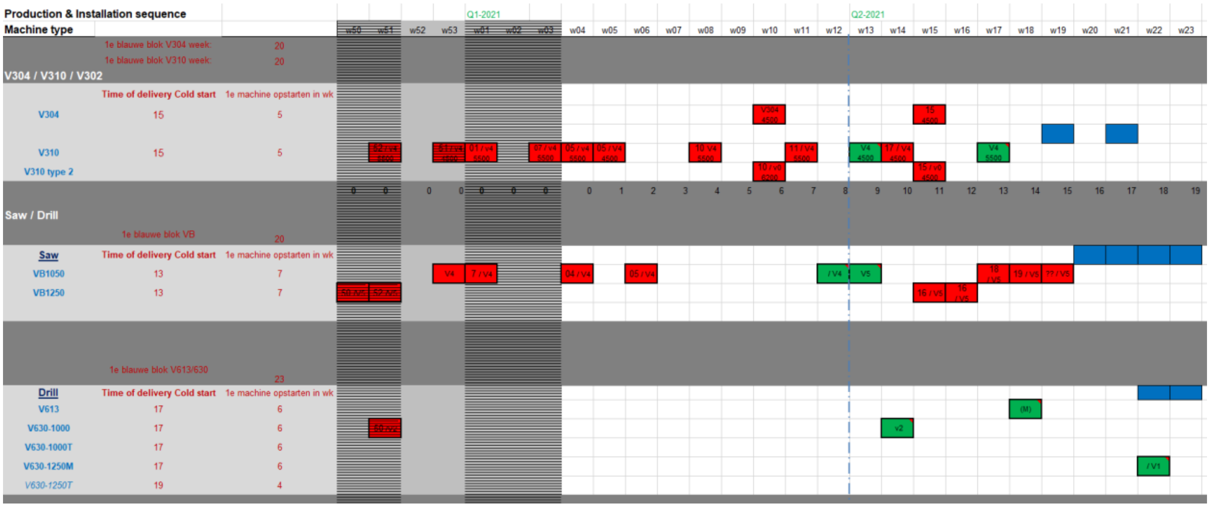

Figure 2-12: Part of the RFC planning

If the RFC planning is updated, the workload for each department can be calculated. The planner of each department has its own method for this. These methods are discussed below.

Assembly department

The planner of the Assembly department calculates the workload of the department using the updated RFC planning. For this, a function in Excel is created. This function looks for a blue cell in the RFC planning. If a blue cell is found, the function looks in a table with the throughput times of the machines how many hours for that machine are required in a week. Table B-1 (see Appendix B) shows the standard hours for each type of machine that are used to calculate a part of the total workload. The total workload in a week for the new forecasted machines is then calculated by taking the sum of the workload for each machine.

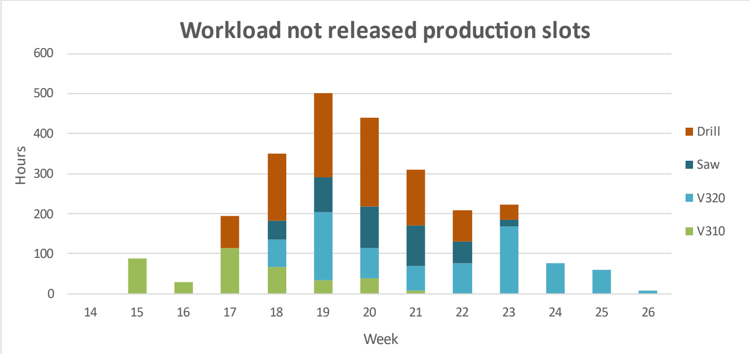

Figure 2-13: Workload not released production slots

Figure 2-13 visualizes an example of the workload for the new production slots that are established at a forecast meeting. This workload is used to determine the total workload for the coming weeks. The total hours of the new production slots are added to the total hours of the production slots that already were released and the total hours of the production slots that contain already sold machines. In this way, the total hours that are needed to produce the machines are calculated. The planner for the Assembly department uses Table B-2 (see Appendix B) to determine the workload for the coming weeks. Using the data in this table, the planner creates a graph to visualize the workload of the Assembly department. Figure 2-14 visualizes an example of such a graph.

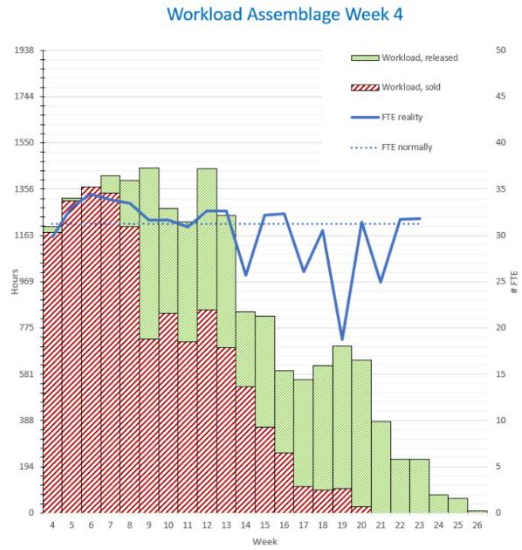

Figure 2-14: Workload Assembly department

The planner of the Assembly department plans this workload using ROB-EX. SAP shows the machines and production steps that have to be planned. For each step of the production process, some precalculated hours need to be planned. These hours are planned using ROB-EX in the time period in which the production step should be executed. The assembly only starts when all required materials are available.

Handling department

The planner of the Handling department calculates the workload of the department using the time frame set by the planner of the Assembly department. In this time frame, all production work should be done. Since the cross transports and roller conveyors are assembled in different parts at the Handling department itself, the plan of the Handling department is not dependent on the plan of the Assembly department. However, the shipping date for the machine is for both departments the same. The planner of the Handling department plans all production steps, like sawing, welding, and spraying, back in time using the end date of the time frame. Before the planner plans all production steps, he first makes a pre-calculation of the number of hours he expects to be needed to produce the cross transports and roller conveyors for this project. For this, the planner uses the ‘sales layout’ of the cross transports and roller conveyors. From this ‘sales layout’, the planner deduces the materials and production hours that are needed. The planner fills these production hours in ROB-EX. Afterwards, the planner can obtain the total workload per week from ROB-EX. The planner uses a similar procedure to determine the workload regarding the cutting tables of the machine. The total workload is found by adding the total required production hours for the roller conveyors and cross transport, the total required production hours for the cutting tables, and the total required production hours for the production process VPM 1 Drill/Saw to each other.

Figure 2-15 visualizes an example of the workload for the Handling department. When the layout of the cross transports, roller conveyors, and cutting tables is finalized, the bill of materials (BOM) is filled. The purchase requests that arise from the BOM consist of materials that need to be purchased. The planned orders from the BOM consist of production orders for cutting plates, sawing activities, weldments, and assembly that the planner of the Handling department plans using ROB-EX. The planner plans a time period for each production step in which the employees can execute the step. Since some of these production orders are standard parts that are put in stock, batches are produced. SAP shows the planner if and when these batches need to be produced. The production orders for weldments can also contain purchase requests for materials.

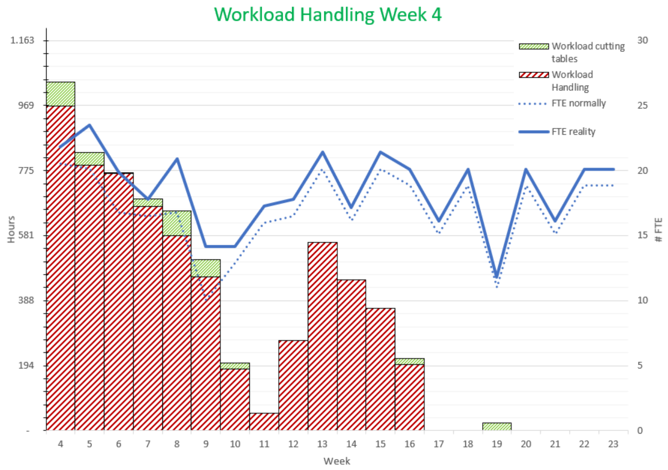

Figure 2-15: Workload Handling department

VPM 2 department

The VPM 2 department, which is also called the Construction department, is the department where all production steps (except for cutting the steel plates and drilling/sawing materials larger than 60 by 60 millimetres) are executed before a weldment goes to an external supplier or the warehouse. Most work that is done in this department is based on the forecast. It is important to note that the workload of the Construction department is based on the number of weldments to be produced. Therefore, the production in this department is not based on the number of forecasted machines but on the number of weldments that must be produced for the forecasted machines.

The planner of the Construction department calculates the workload of the department using the deadlines set by the planner of the Assembly department. Since the planner of the Assembly department determines when and how many weldments for the machines must be delivered to the Assembly department (based on the established number of forecasted machines), this planner also determines the deadline for the production at the Construction department indirectly. Using this deadline, the planner of the Construction department plans all construction work back in time from the deadline. For this, a time period is planned for each production step so that the employees can execute the work somewhere in this time period. For example, for the 'construction welding' step often one

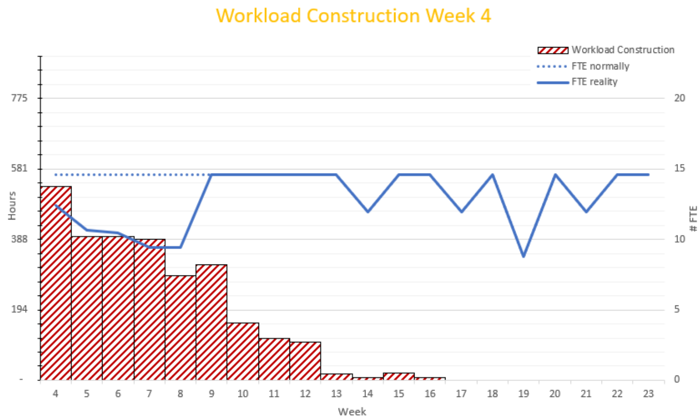

Figure 2-16: Workload Construction department

week is planned, while this step could only take a few hours. The planner makes the plan in ROB-EX. By adding up all production hours in a week in ROB-EX, the total workload in this week is calculated. The exact hours required for a production step per weldment are estimated hours that are on average the same as the production hours from the calculation afterwards. Figure 2-16 visualizes an example of the total workload for the Construction department per week.

2.4 Objectives and restrictions

As indicated in Section 2.1, the production of a machine consists of several steps. These steps are executed at different departments of VSM. Within VSM, there are different objectives. Some of these objectives conflict with each other, which can cause problems. These objectives of a department or employee can also be seen as a restriction for another department or employee. These objectives, restrictions, and problems are discussed in this section.

The most important objective of the management is to sell as many as possible machines. The sales managers at VSM never sell a ‘no’ to a customer. Since the sales managers never know when a customer shows interest in a machine and when this interest becomes so serious that the customer orders a machine, there is a lot of uncertainty in the demand. The current forecasting approach takes some of this uncertainty away but still, some uncertainty remains. This can cause problems, especially in the Construction department. The Central Planner plans the (forecasted) machines assuming an infinite capacity. This means that the Central Planner releases many production slots at the same time if many machines are expected to be sold. As a consequence, the workload at the Construction department becomes extremely high due to its short time horizon.

Another objective of the management is to produce some weldments in small batches (for example per 2 or 4 weldments) as this provides economies of scale in the agreed prices with the suppliers. However, this also stimulates the peaks and troughs in the workload of the Construction department. Because production is done in batches, inventories are created. This means that a weldment that is produced in batches does not always have to be produced, but can also be taken from inventory. On the other hand, this also means that when the weldment does have to be produced, the production order of this weldment also contains relatively much work.

An objective of the sales managers of VSM is to offer as short as possible delivery times to the customers. Using the RFC, VSM tries to achieve these desired short delivery times. If it appears that the customer does not want the machine after all, or that the machine could still be delivered to the customer later, the Central Planner can replan the machine. However, most often the Central Planner only replans the machine after 6 weeks. Since most of the production steps at the Construction department are executed in the first 6 weeks, the Construction department cannot benefit from this replanning process.

In addition to these restrictions for the Construction department, the planner of this department must also take into account some general restrictions when making the plan, such as:

- Production steps must be executed before the due date.
- Production steps must be executed in a specific order.
- The maximum production capacity (machines, workplaces, employees) cannot be exceeded.
- The maximum inventory capacity cannot be exceeded.
- The required materials should be available before production steps are planned.

The planners of the Handling and Assembly department should consider the same general restrictions when making the plan as the planner of the Construction department. These departments, however, are less affected by the aforementioned specific restrictions. This is mainly because the departments have a longer time horizon to plan the production steps. The Assembly department, for example, can benefit from the replanning process of the machine because the production steps at the Assembly department often only start after 6 weeks. Because of this, the planner of the Assembly department can replan the production steps at this department if necessary.

2.5 Performance measures

Currently, the planners of VSM do not measure the performance of the plan. Once a week, all planners come together and discuss the variable workload and how to react to this workload in terms of moving employees between departments. In this meeting, however, the performance of the plan of each department is not discussed.

To measure the performance of the plan we use several Key Performance Indicators (KPIs). Because no KPIs are used yet, we create a KPI tree to come up with indicators to measure the performance of the plan. A KPI tree is a visualization method that allows an organisation's objectives to be broken down into more granular outcomes and relevant KPIs to track those outcomes. KPI trees also visualize complex relationships, conflicts, and interdependencies within an organisation (Smith, 2014). Figure C-1 (see Appendix C) shows the KPI tree. We split up the KPIs in the KPI tree into four categories: quality, variability, costs, and time. We come up with multiple KPIs for each category. In this KPI tree, we only mention the KPIs that are relevant to our research to limit the size of the tree. We select one KPI per category that we use to measure the performance of the plan. These are the following 4 KPIs:

1. **Standard deviation of workload per week**
   To prove that we stabilize the workload of the VPM departments, we measure the standard deviation of the total workload per week. If the measured value for this KPI is less than the measured value for this KPI of the current plan, we have proven to stabilize the workload.
2. **Delivery accuracy**
   Within VSM, agreements have been made when production steps should be executed. In addition, agreements with (external) suppliers have been made regarding the delivery times of purchase and raw materials, and regarding the time they get to process the weldments (annealing, coating, etc.) to finalize them. Normally, the external suppliers get 4-5 weeks to process the weldments. However, if the workload at VSM is high, the external suppliers get less time for this. With this KPI, we measure how often the agreements within VSM and with the external suppliers are met and how often this is not the case. We measure this KPI as a percentage deviation from the agreed time period to get an impression of the delivery accuracy in relative terms.
3. **Outsourcing costs**
   Due to economies of scale, VSM decided to produce multiple weldments simultaneously sometimes. However, producing in batches is one of the reasons for peaks and troughs in the plan. By investigating the impact of batch production on workload variability, we can present a trade-off between the outsourcing costs and the variability in the workload. Using this, we can present VSM at what cost the variability can be reduced. We measure this KPI by calculating the ratio of variability (in terms of standard deviation) to outsourcing costs.

4. **Capacity per production step**
   In VSM, the number of employees per department differs weekly. Next to this, not all employees can execute each production step. This causes that the capacity per production step per week differs extremely. By comparing this KPI in all plans, we can advise VSM about the mix of employees and skills per week that fit the best to the variable product mix.

2.6 Conclusion

The goal of this chapter is to describe all relevant information to provide a clear insight into the current situation at VSM. For this, among others, the production and planning process, the product structure, and some objectives and restrictions are discussed. We answered the first research question: "What is the current situation at VSM?".

VSM produces CNC machinery for the steel construction sector. In most cases, the production of these machines starts based on the forecast. The Central Planner updates the RFC planning based on the number and type of machine established in the forecast meeting. Based on the deadlines that follow from this updated RFC planning, the planner of each department plans the production orders and calculates the workload of his department.

While planning the production orders, the planner of each department has to deal with restrictions. Currently, for example, the planner of the Construction department has to deal with an unstable workload due to its short time horizon. This erratic pattern in the workload arises because many production slots are released simultaneously after a forecast meeting. Another reason for the unstable workload is the batch production of weldments as this provides economies of scale by the external suppliers.

The scope of this research is to create a proof-of-concept planning approach that can be used to create a plan for VSM. The model and heuristics that we used in the planning approach aim to balance the workload for the Construction department ensuring the demand is met. Furthermore, the model and heuristics should consider all restrictions the planners currently have to deal with.

3 Literature Review

This chapter presents a literature review about relevant topics for this research. We answer the second research question: "What relevant knowledge from the literature can be used to support improvement of the planning process of VSM?". The chapter starts with the positioning of the planning problem at VSM in Section 3.1. For this, we first position the customer order decoupling point at VSM. Then, we position the planning problem at VSM using the positioning framework of Hans et al. (2007). Section 3.2 discusses the specific planning problem we encounter at VSM. In addition, we introduce two different ways in which our problem setting can be addressed in this section. Section 3.3 describes some methods found in the literature to approach and solve planning problems. Section 3.4 discusses uncertainties that can occur in the execution of the plan and how to deal with them. Section 3.5 concludes this chapter.

3.1 Planning and Scheduling positioning

As stated in Section 2.1, two situations allow the start of the production process of a VSM machine. Although the production process can be started in different ways, the production process of the two situations differs only slightly. This is because the machines that are produced at VSM contain standard modules called 'weldments'. These weldments can already be made before an order is placed. In this way, short delivery times can be guaranteed. To capture this aspect of the operations strategy, the customer order decoupling point (CODP) is frequently used. The CODP decouples operations in two parts. Upstream the CODP the activities are performed to forecast and downstream they are performed to customer order (Wikner & Rudberg, 2005). Typically, the CODP is approached as a linear concept using four defined CODPs, i.e. engineering-to-order (ETO), make-to-order (MTO), assemble-to-order (ATO), and make-to-stock (MTS). Wikner & Rudberg (2005) show that this linear continuum does not provide a realistic picture of the actual situation many companies face. That is why they come up with a two-dimensional approach. For this, two perspectives are important: the engineering perspective (developing products) and the production perspective (producing parts). Wikner and Rudberg (2005) separate these perspectives so that each perspective has its own CODP. Figure 3-1 shows the two-dimensional CODP space.

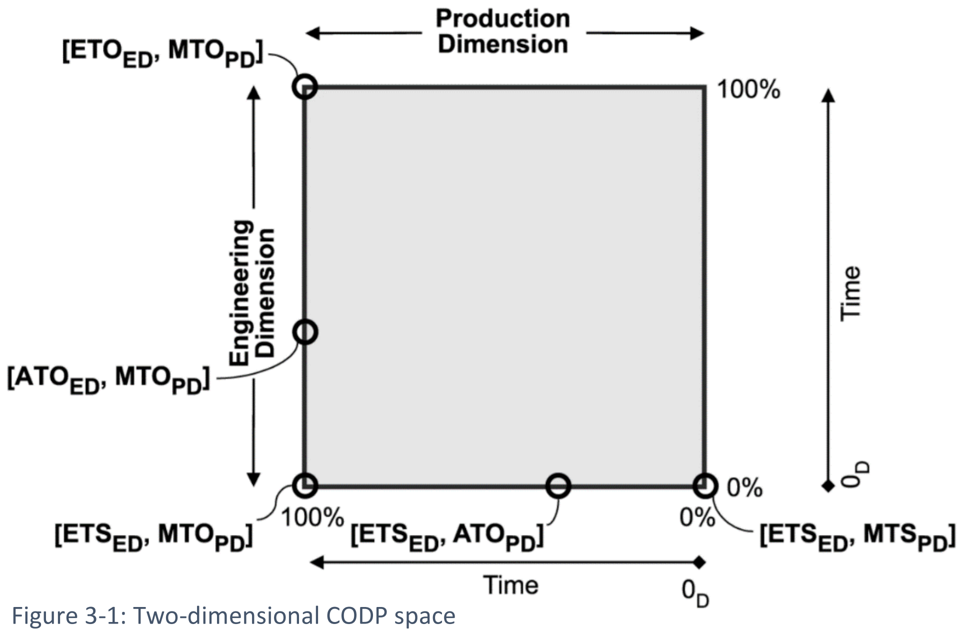

Figure 3-1: Two-dimensional CODP space

Figure 3-1 presents the production dimension (PD) on the x-axis and the engineering dimension (ED) on the y-axis. Wikner & Rudberg (2005) define ATO in the production dimension using the traditional definition assemble-to-order (ATO_{PD}). In the engineering dimension, however, they define ATO as adapt-to-order (ATO_{ED}). Next to this, Wikner & Rudberg (2005) use the definition engineering-to-stock in the engineering dimension (ETS_{ED}) for the situation when a product is designed before the enterprise faces actual customer demand. All other abbreviations Figure 3-1 shows are based on the traditional definitions. The tuples Figure 3-1 presents should be read as the CODP in the engineering dimension followed by the CODP in the production dimension [XXX_{ED}, XXX_{PD}]. The production at VSM is started by an order and modifications are done in the engineering phase. That is why we define the CODP at VSM as adapt-to-order in the engineering dimension and make-to-order in the production dimension [ATO_{ED}, MTO_{PD}].

Because the production process of VSM consists of among others producing standard weldments, which are produced based on the forecast, and adapting the standard machine such that it meets the customer's wishes, it is difficult to create a long-term plan. In addition, there is a lot of uncertainty in the demand for the machines. In literature, often is talked about a manufacturing planning and control (MPC) system to plan and control the manufacturing process, including materials, machines, people, and suppliers (Swamidass, 2000). MPC addresses decisions on the acquisition, utilization, and allocation of production resources to satisfy customer requirements in the most efficient and effective way (Graves, 1999).

To distinguish between different types of project-driven organisations in an MTO environment, many positioning frameworks for MPC are created. Almost all well-known frameworks for MPC organise planning and control functions hierarchically. For this, in many MPC frameworks the hierarchical decomposition into a strategic, tactical, and operational level is used, as Anthony (1965) proposed first. Zijm (2000) defines a basic framework architecture for planning and control in both make-to-stock and make-to-order systems, in which he uses the hierarchical decomposition of Anthony (1965). Next to this, the emphasis in Zijm's framework is on an integration of technological and logistics planning and an integration of capacity planning and materials coordination issues. Hans et al. (2007) use the hierarchical decomposition of Anthony (1965) and the managerial areas of Zijm (2000) to create a hierarchical project planning-and-control framework that serves to position planning methods for multi-project planning under uncertainty. Figure 3-2 visualizes this hierarchical framework from Hans et al. (2007).

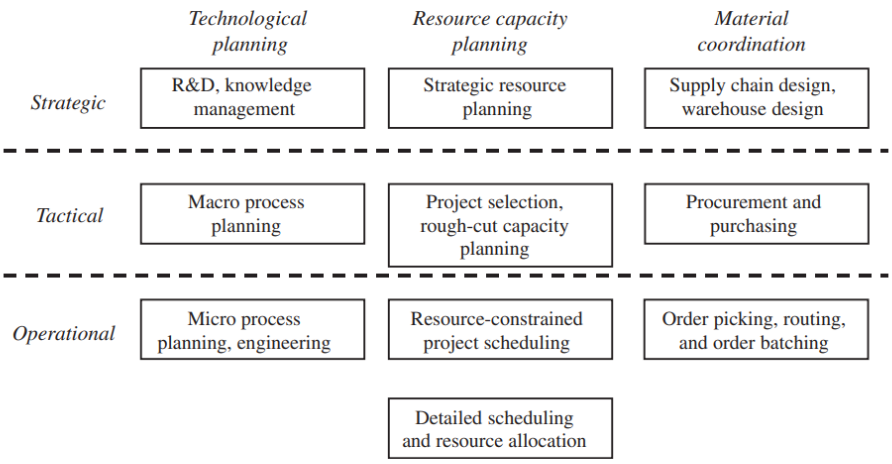

Figure 3-2: Hierarchical framework (Hans et al., 2007)

As this research is restricted to production planning and scheduling, we are interested in existing planning approaches that can help achieve the research objective, i.e. stabilizing the workload. Since the framework of Hans et al. (2007) is meant to aid project management in the choice between various existing planning approaches, we focus on this framework in this research. More specifically, we focus on the resource capacity planning column of the hierarchical framework of Hans et al. (2007).

In the managerial area ‘resource capacity planning’, at each hierarchical level decisions have to be made. At the strategic level, structural decisions for a long planning horizon, like demand forecasting and capacity dimensioning, are made. Next, at the tactical level, mid-term decisions to translate the company goals set to operational management are made. For VSM, these could be decisions about order acceptance, due data quotation, workforce planning, and temporary capacity expansions like overtime or hiring staff. Lastly, the operational level concerns the short-term decision making related to the execution of the production process. There is low flexibility on this planning level since decisions at the higher levels demarcated the scope for the operational level decision making. Detailed decisions such as project scheduling, resource allocation, and responding to uncertainties that appear are made (Hans et al., 2011; Zijm, 2000). In this research, we focus on the decisions made at the tactical level. This means that we can position our planning problem to be a resource capacity planning problem at the tactical level.

3.2 Planning problem

Based on the current situation analysis in Chapter 2 and the positioning of the planning problem at VSM in Section 3.1, we decide to focus on capacity planning problems (CPPs) in the literature to find an appropriate way to solve the planning problem. The term capacity planning is collectively used for all kinds of planning functions that are performed on various production planning levels (Hans, 2001). In the literature, many different definitions for capacity planning can be found. According to Hans (2001), capacity planning comprises the utilization and the expansion or reduction of all capacity, as well as the planning of capacity on all managerial/planning levels. Chen et al. (2009) and Gademann & Schutten (2005) also consider the given demand in their definitions of capacity planning by suggesting that capacity planning determines the resource requirement of an organisation to sustain a given demand over a planning horizon. To specify the specific CPP of VSM, we categorize the problem in Section 3.2.1. Section 3.2.2 introduces afterwards two general models that can be used to model the CPP.

3.2.1 Categorization Capacity Planning Problem

Capacity Planning Problems (CPPs) can be categorized based on several features such as the type of manufacturing process, the planning horizon, the number of projects, and the number of resources. Kerzner (2003) and De Boer (1998) discuss the differences between project-driven and non-project-driven organisations. Kerzner (2003) and De Boer (1998) both argue that all work in a project-driven organisation is characterized through projects and everything centres around these projects, while in non-project-driven organisations projects exist merely to support the product lines. Chen et al. (2009) emphasize the differences between CPPs in MTO and MTS environments. Chen et al. (2009) state that the major difference between MTO and MTS is that using an MTS strategy, standard products are made using a standardized process, which does not exist for MTO at the time of capacity planning. Next to this, an MTS operation usually imposes a freeze period to assure smooth production. In an MTO operation, on the other hand, there is no freezing period imposed. Using the definitions of Kerzner

(2003), De Boer (1998), and Chen et al. (2009), and the positioning of the CODP at VSM as [ATO_{ED}, MTO_{PD}], we position VSM as a project-driven organisation in an MTO environment.

Chen et al. (2009) define three tiers of capacity planning in terms of their planning horizon; (1) long-term, (2) medium-term, and (3) short-term capacity planning. These three categories of planning activities are the same as the ones proposed by Anthony (1965) and used in many positioning frameworks, such as in Hans et al. (2007) and Hans (2001). Using these frameworks, and the definition of medium-term capacity planning by Chen et al. (2009): "The medium-term capacity planning focuses on setting monthly or quarterly resources required for each plant for typically a one-year planning horizon. It decides on workforce level, raw materials, and inventory policy by product group and department. Based on sales forecasts, it generates production capacity plans", we define our CPP to be at the tactical (medium-term) level.

Next, the CPP can also be categorized based on the number of projects to be executed. Platje et al. (1994) discuss that due to the increasing project orientation of organisations, more and more often multiple projects are carried out simultaneously. In these multi-project organisations, the simultaneous management of the throughput times, resource allocations, and costs of the projects is a complex process of balancing the interests of multiple participants. Since the traditional single project-oriented approach cannot be used to manage capacity in a multi-project organisation, Platje et al. (1994) come up with a structure for this and call it project-based management. Such a project-based management structure is also used within VSM. Multiple projects are carried out simultaneously at VSM and that is why we consider a multi-project model for our CPP.

A characteristic of a project is that it consists of a network made up of several interrelated activities. For the execution of these activities, a set of resources is required. Typical resources are labour, machines, equipment, raw materials, and money. De Boer (1998) makes a clear distinction between resources and capacity. According to Hans (2001), resources comprise machines, operators, and tools, while capacity comprises more, e.g., facilities, material handling systems, and factory floor space. In project-driven organisations, multiple projects compete for shared resources. At VSM, this is also the case. Production steps from different projects need most often the same resources. Therefore, they are also competing against each other for these resources. Since these production steps require multiple resources, we also need to consider multiple resources in our CPP model.

3.2.2 Capacity Planning Problem models

From the categorization in Section 3.2.1, we conclude that the specific CPP of VSM can be defined as a multi-resource multi-project medium-term capacity planning problem in an MTO environment. Such a problem is, among others, studied by De Boer (1998), Masmoudi et al. (2012), Gademann & Schutten (2005), and Hans (2001). Multiple different models and methods can be used to approach the problem. Our problem setting can be addressed in two different ways. We can approach the planning problem as a Rough-Cut Capacity Planning (RCCP) problem or as a resource loading problem. Gademann & Schutten (2005) argue that the resource loading problem can be seen as an RCCP problem with simple precedence constraints, where the project network is a chain. Hans (2001) states that the 'analogon' of resource loading (which we discuss in the context of MTO production planning) in project management is known as the RCCP problem. Because of this, the terminology is somewhat different. In the context of project management, we speak of projects subdivided into activities, rather than orders that consist of jobs. In this research, we use the terminologies alternately. The models and corresponding solution approaches of both problems are presented below.

Rough-Cut Capacity Planning problem

At the RCCCP level decisions are made about due dates and milestones of projects, overtime work levels, subcontracting, and so on. The RCCP should be used during the bidding and order acceptance phase of a new project (De Boer, 1998). At the RCCP level, projects are divided into work packages which are clusters of activities. RCCP models determine the order of executing in a set of work packages to minimize the total project duration and/or project cost while respecting precedence relations and resource constraints, and taking into consideration overlapping possibilities (Baydoun et al., 2016).

Hans (2001), Gademann & Schutten (2005), and De Boer (1998) distinguish two variants of the RCCP problem: the *time-driven* and the *resource-driven* variant. In the *time-driven* variant, a desired project delivery time must be met, i.e., it is considered as a deadline. This may imply that nonregular capacity must be used, for example by hiring employees temporarily, subcontracting jobs, and working overtime. The objective of the time-driven RCCP is to minimize the cost of using nonregular capacity (Gademann & Schutten, 2005). In the *resource-driven* RCCP, on the other hand, all (non)regular resource capacity levels are fixed, and the maximum lateness of the projects is tried to minimize, preferably using regular capacity. This variant is applicable in the situation where a customer requests a due date quotation for a project, while the company has to fulfil strict resource constraints (Hans, 2001). In this research, we want to focus on balancing the workload of VSM. For this, we consider deadlines that must be achieved using regular and nonregular capacity. That is why we use the *time-driven* RCCP problem to represent the planning problem.

De Boer (1998) argues that there is no suitable way to transform the time-driven RCCP directly into a linear programming (LP) problem. This is due to the precedence constraints. Relaxing the precedence constraints, however, leads to an LP formulation. The LP problem in which all precedence constraints are ignored can be formulated as follows (Gademann & Schutten, 2005; De Boer, 1998):

Indices	**Description**	
j	jobs;	$j \in \{J_1 \, J_2, \dots, J_n\}$
k	resources;	$k \in \{R_1 \, R_2, \dots, R_K\}$
t	time buckets (weeks)	$t \in \{0,1, \dots, T\}$

Parameters	**Description**
Q_{kt}	regular capacity of resource R_k in week t (hours)
q_{jk}	number of hours job J_j requires of resource R_k
p_j	minimum duration in weeks of job J_j
r_j	release date of job J_j
d_j	deadline of job J_j
c_{kt}	cost of using nonregular capacity of resource R_k in week t

Decision variables	**Description**
x_{jt}	the fraction of job J_j that is performed in week t
U_{kt}	nonregular capacity of resource R_k in week t (hours)
	$= \max\{0, \sum_{j=1}^{n} q_{jk} x_{jt} - Q_{kt}\}$

Mathematical model:

$$\min \ \sum_{t=1}^{T}\sum_{k=1}^{K} c_{kt}U_{kt} \qquad (0)$$

subject to

$$\sum_{t=r_j}^{d_j} x_{jt} = 1 \qquad \forall\, j \qquad (1)$$

$$x_{jt} \leq {}^{1}/_{p_j} \qquad \forall\, j,t \qquad (2)$$

$$U_{kt} \geq \sum_{j=1}^{n} q_{jk}x_{jt} - Q_{kt} \qquad \forall\, k,t \qquad (3)$$

$$x_{jt},\ U_{kt} \geq 0 \qquad \forall\, j,k,t \qquad (4)$$

The objective (0) in this model is to minimize the total cost of required nonregular capacity. For this, some constraints need to be considered. Constraint (1) ensures that each job is performed completely within its time window. Constraint (2) ensures that no more than ${}^{1}/_{p_j}$ of a job can be done in a week and constraint (3) guarantees the required amount of nonregular capacity. Constraint (4) expresses the domain restrictions, i.e. the variables are nonnegative.

Solving this LP problem will, in general, lead to a violation of one or more precedence relations, and thus to an infeasible solution (Gademann & Schutten, 2005). The solution found can be seen as a lower bound for the time-driven RCCP problem with precedence constraints (De Boer, 1998).

To control feasibility, Gademann & Schutten (2005) introduce an Allowed To Work (ATW) window for every job. An ATW window [S_j, C_j] for job J_j specifies the weeks in which we are allowed to work on job J_j. This means that it is not allowed to work on job J_j before week S_j and also not later than week C_j. By replacing constraint (2) with $x_{jt} \leq {}^{s_{jt}}/_{p_j}\ \forall\, j,t$ where parameter s_{jt} (= 1 if $S_j \leq t \leq C_j$, 0 otherwise) indicates whether processing of job J_j is allowed in week t. An ATW window [S_j, C_j] for job J_j is feasible if (1) $S_j \geq r_j$ and $C_j \leq d_j$ and (2) $C_j - S_j \geq p_j - 1$. A set of ATW windows is feasible if every ATW window in this set is feasible. Besides, S_j must be greater than C_i if there exists a precedence relation between jobs J_i and J_j.

De Boer (1998) develops a heuristic that uses LP iteratively, repairing precedence relations if necessary. If a precedence relation is broken after solving the LP problem as mentioned above, it is restored by narrowing the time windows of two jobs J_i and J_j using one of the three ratios that De Boer (1998) suggests. Next, the LP problem is solved with this new deadline and release date. This procedure is repeated until all precedence relations are obeyed.

Masmoudi et al. (2012) use the integer linear programming (ILP) model of Hans (2001) and modify it in such a way that uncertainty regarding the workloads is incorporated. Hans (2001) and Masmoudi et al. (2012) both use the concept of order plans to create a feasible model. The order plans incorporate the time windows and the precedence constraints. An order plan $a_{j\pi} \in \Pi_j$ for project j is a vector of 0-1 values $a_{bjt\pi}$ $(b \in N_j; t = 1, \ldots, T)$, where $a_{bjt\pi} = 1$ if task (b, j) is allowed to be performed in time period t, 0 otherwise. Binary variable $X_{j\pi}$ is 1 if project plan $a_{j\pi}$ is selected for project j, 0 otherwise.

Resource loading problem

Hans (2001) and Hans et al. (2002) discuss the resource loading problem. The resource loading problem originates from the cellular manufacturing concept where each cell or group corresponds to a group of resources. Usually, these are a group of machines and tools, controlled by a group of operators.

Instead of planning every single resource, the management regularly assigns work to the manufacturing cells. The loading of the cells is called resource loading (Hans, 2001).

The resource loading problem is a tactical CPP that concerns the loading of a set of customer orders into a production system with various resources. Resource loading supports customer order processing by determining reliable due dates and the required regular and nonregular resource capacity levels for a set of known customer orders. It can also be used to determine the required resource capacity levels for the underlying scheduling problem (Hans et al., 2002). Besides this, resource loading can be used in the customer order processing phase as an instrument to analyse the trade-off between lead time and due date performance on the one hand, and nonregular capacity levels on the other hand (Hans, 2001).

The resource loading problem can be formulated as a mixed integer linear programming (MILP) model (Hans, 2001; Hans et al., 2002). This MILP model, including the corresponding notations and explanations, can be found in Appendix D. The resource loading model aims to find a feasible loading that minimizes the total costs that result from short-term capacity expansions and the penalties incurred by tardy orders. The capacity restrictions in the MILP model can easily be modelled with linear constraints and continuous variables. Modelling the precedence relations, on the other hand, is much less straightforward and requires the introduction of integer variables (Hans, 2001). In the model Appendix D presents, the time-driven and the resource-driven approach are adopted simultaneously.

3.3 Solution approaches

In Section 3.2, we introduced the CPP and mentioned several ways to model the problem. To solve the problem, we present some approaches in this section. Computational experiments show that the RCCP problem can be solved to optimality for smaller instances, but for larger instances, it becomes too difficult (Gademann & Schutten, 2005). Besides, Kis (2005) proves that the resource loading problem is NP-hard in the strong sense. For this, he first shows that the resource loading problem contains the pre-emptive flow shop scheduling problem as a special case. The pre-emptive flow shop scheduling problem is proven to be NP-hard in the strong sense by Gonzalez & Sahni (1978). Because of this, the resource loading problem is NP-hard in the strong sense as well.

Because the RCCP problem cannot be solved to optimality for larger instances and the resource loading problem is proven to be NP-hard, it is unlikely that the problems can be solved by a polynomial time algorithm. An algorithm is said to be a polynomial time algorithm when its running time is bounded from above by a polynomial function (Hans, 2001). Since the CPP of VSM most likely cannot be solved in polynomial time, we distinguish the solution approaches in three classes, as Wullink (2005) and Gademann & Schutten (2005) did:

- Class 1: straightforward constructive heuristics
- Class 2: LP based heuristics
- Class 3: improvement heuristics

3.3.1 Class 1: straightforward constructive heuristics

Class 1 comprises approximation algorithms that construct a feasible solution. They typically use a priority rule to plan activities or parts of activities. Algorithms in Class 1 do not use mathematical programming techniques (Wullink, 2005). We propose several algorithms and heuristics below.

Basic primal heuristics

Two basic heuristics that can be used for both RCCP and resource loading problem are the H_{basic} and H_{CPM} heuristics as Gademann & Schutten (2005) propose. These heuristics are used to generate feasible ATW windows (order plans) for more advanced heuristics. Both heuristics do not consider capacity restrictions. H_{basic} generates a feasible set of ATW windows by setting the starting time of job j S_j equal to the release date of job j r_j and setting the completing time of job j C_j as large as possible: $C_j = \min\{d_j, \min_{k|J_j \to J_k}(r_k - 1)\}$. H_{CPM} generates a feasible set of ATW windows by first determining the critical path of the instance. Subsequently, H_{CPM} proportionally divides the slack of the activities over the activities of the critical path (Gademann & Schutten, 2005; Wullink, 2005).

Incremental Capacity Planning Algorithm

The Incremental Capacity Planning Algorithm (ICPA) is proposed by De Boer (1998). After sorting the activities in order of nondecreasing deadlines, the ICPA heuristic plans each job in at most two phases. In the first phase, a maximum part of the job j is planned in its time window, without using nonregular capacity and taking into account the release date, deadline, and precedence relations. If the job is not planned totally, capacity is increased in the second phase such that the remaining part of the job fits in its time window. We now present a compact version of the algorithm. For a more detailed version, we refer to De Boer (1998). Note that in our version of the algorithm, the first phase is executed in step 3 and the second phase is executed in step 5. The algorithm stops if all jobs are planned.

Incremental Capacity Planning Algorithm
based on De Boer (1998)

1. Initialise variables U_{kt} and x_{jt} to 0.
2. Rearrange the jobs in order of nondecreasing deadlines.
3. Plan as much and as early as possible of job J_j with the smallest deadline
    a. Earliest start time:
       Job J_j cannot start earlier than its earliest start time ES_j.
       $$ES_j = \max\left\{r_j, \max_{J_h \epsilon P_j}(C_h + 1)\right\}$$
    b. As much as possible:
       Calculate the fraction of job J_j that is allowed to plan in its time window x_{jt}.
       $$x_{jt} = \min\left\{\frac{1}{p_j}, \frac{\min_k (Q_{kt} + U_{kt} - \sum_{i \neq j} q_{ik} x_{it})}{q_{jk}}, 1 - \sum_{\tau = ES_j}^{t-1} x_{j\tau}\right\}$$
4. If this job fits within its time window ($\sum_{\tau=ES_j}^{t-1} x_{j\tau} = 1$), then go to Step 3.
5. If this job does not fit within its time window ($\sum_{\tau=ES_j}^{d_j} x_{j\tau} < 1$), increase nonregular capacity (until complete job J_j is planned).
    a. Still to be planned of job J_j λ_j:
       $$\lambda_j = 1 - \sum_{\tau=ES_j}^{d_j} x_{j\tau}$$
    b. 'Strive value' ξ_j:
       The fraction that would be planned if job J_j would be planned evenly across its time window.
       $\xi_j = \frac{1}{d_j - ES_j + 1}$ (note that $\xi_j \leq \frac{1}{p_j}$, using the assumption that the release dates and due dates of the jobs comply with each other)

c. The fraction that is planned x'_{jt}:
$$x'_{jt} = \max\{x_{jt}, \min(\xi_j, \lambda_j + x_{jt})\}$$

d. Keep track of variables:
$$\lambda_j = \lambda_j - x'_{jt} + x_{jt}$$
$$U_{kt} = \max\{0, \textstyle\sum_{i \neq j} x_{it} q_{ik} + x'_{jt} q_{jk} - Q_{kt}\}$$

6. Go to Step 3.

Largest Activity Part

The Largest Activity Part (LAP) heuristic plans the activities in 4 phases. In phase 1, LAP plans all 'trivial' activities. These are activities that have a minimum duration that is equal to the size of the time window. In phase 2, LAP plans activities using only regular capacity. In phase 3, LAP also uses the nonregular capacity to plan activities. The activity, however, must be at least partly planned in regular capacity. In phase 4, the remaining work content is planned in nonregular capacity (Wullink, 2005).

3.3.2 Class 2: LP based heuristics

Class 2 comprises LP based heuristics. We discuss techniques that generate a (possible infeasible) starting solution by LP that is made feasible with a repair procedure. With the corresponding feasible ATW windows (order plans), a base model can be solved to obtain a production planning. Note that we define a base model to be a model that does not consider the precedence relations.

LP based heuristics

Van Krieken (2001) proposes to use adaptive search in combination with linear programming. The adaptive search algorithm is first proposed by Kolisch & Drexl (1996) and combines a priority rule heuristic with a random search heuristic. Van Krieken (2001) tests three different priority rules: Earliest Due Date (EDD), Minimum Slack (MS), and Minimum Resource Usage (MRU). For these three rules, Van Krieken (2001) calculates the priority of all activities. Then the activities are sorted in order of nondecreasing priority. Van Krieken (2001) calculates a biased probability, using a regret factor, which she uses to select an activity. Next, the selected activity is planned in exactly the same way as using ICPA. If all activities are planned, the algorithm stops, and one iteration of the adaptive search algorithm is finished. Note that in each iteration of the adaptive search algorithm a new solution is created due to the randomness of the selection.

Van Krieken (2001) proposes two ways of incorporating the base model in the algorithms. The first approach is to solve the base model to find a solution for the constructed feasible ATW windows in each adaptive search pass. The second approach is to stop building a production plan when the costs up to that point are higher than the total costs of the current solution. These costs are calculated by summing up all nonregular capacity that is used to that point. Only the ATW windows of completed production plans are used to find the optimal production plans (Wullink, 2005).

H_{enum} heuristic

Gademann & Schutten (2005) suggest an approach based on repairing violated precedence relations one by one. For each pair of jobs with a violated precedence relation, a week T_{ij} is specified to repair the relation. T_{ij} is the time period before which job J_i must be completed and job J_j can start in. To determine T_{ij}, first, the precedence relation that is violated and has the minimum slack S_{ij} is found. S_{ij} is defined as $S_{ij} = d_j – r_i – (p_j + p_i)$. The idea of Gademann & Schutten (2005) is that the little freedom in specifying a T_{ij} to repair the precedence relation should be used as well as possible. Therefore, Gademann & Schutten (2005) suggest the evaluation of all possible values of T_{ij}, that is, $r_j \leq T_{ij} \leq d_i + 1$, and keep the best one. We denote this heuristic by H_{enum}.

3.3.3 Class 3: improvement heuristics

As we described in Section 3.3, it is unlikely that our CPP can be solved by a polynomial time algorithm. Therefore, to improve our initial solution, we use local search heuristics. The idea of a local search algorithm is to start with some initial solution and move from neighbour to neighbour as long as possible while decreasing the objective value (Crama et al., 1995). In this research, the local search heuristics start with an initial feasible solution that is generated by for example a straightforward constructive heuristic from Class 1. The ATW windows resulting from this initial feasible solution are used to solve the base model. Next, to steer improvement iteratively, we can use one of the approaches below.

Shadow price heuristic

Improving a current feasible solution can be achieved by changing the ATW windows for the jobs. Gademann & Schutten (2005) change these ATW windows by increasing and decreasing the start time S_j and completion time C_j by one. For a job J_j, this gives four possible changes. For a feasible set of ATW windows, Gademann & Schutten define the neighbours of this set as all feasible sets of ATW windows that can be obtained from one of the four possible changes to an ATW window in the current set (Gademann & Schutten, 2005). Note that the resulting search space is connected. Connectivity is an important condition to be able to reach the global optimum (Lewis & Thompson, 2015). Using the described neighbourhood, we can apply local search to look for improvements to the current solution. In the shadow price heuristic, Gademann & Schutten (2005) generate an initial feasible set of ATW windows by heuristic H_{basic} or H_{CPM}. Next, the base model is solved and the heuristic retrieves the shadow prices. Shadow prices are used in the sensitivity analysis of the parameters of an LP problem. They show the amount by which the optimal objective function value is improved in case a parameter of the i-th constraint is increased (Winston & Goldberg, 2004). In the shadow price heuristic, the shadow prices are used as an estimate for the expected yield of all possible changes to the time window of each job. Afterwards, the shadow price heuristic evaluates the yields of the possible changes. Starting with the highest yield, it accepts the first yield that results in an improvement (Wullink, 2005). Then, the local search is continued for the neighbours of the new current set of ATW windows. The heuristic stops when no more improvement is found. Since the shadow price heuristic only accepts improvements, the search space is limited significantly. That is why Gademann & Schutten (2005) use both H_{basic} or H_{CPM} to create a starting solution. In this way, the influence of the starting solution on the final solution is tested.

Metaheuristics

A metaheuristic is formally defined as an iterative generation process that guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space, in which learning strategies are used to structure information to find near-optimal solutions efficiently (Osman & Laporte, 1996). Many metaheuristic ideas were proposed to improve local search heuristics to find better solutions. Some examples of these metaheuristics are simulated annealing (SA), tabu search (TS), genetic algorithms (GA), and variable neighbourhood search (VNS). We discuss some of these metaheuristics below.

Simulated annealing

Simulated annealing (SA) was proposed as a framework for the solution of combinatorial optimization problems by Kirkpatrick et al. (1983) and Černý (1985). SA is a metaheuristic that extends basic local search by allowing moves to inferior solutions. Simulated annealing is used to escape from local optima by allowing hill-climbing moves. These are movements that worsen the objective function. The simulated annealing algorithm starts with an initial solution (created by for example a straightforward constructive heuristic from Class 1), including a starting temperature T and a cooling factor α. Next, at each iteration, a neighbour solution is generated. The neighbour solution is generated by using some operator that makes a small change in the current solution. Some examples of operators are 'swap', 'move', and 'insert'. Next, the current solution (CS) and the neighbour solution (NS) are compared. Improving solutions are always accepted, while a fraction of the (inferior) solutions that deteriorate the objective function value are accepted in the hope of escaping local optima in search of global optima. The probability of accepting solutions that deteriorate the objective function value depends on a temperature parameter T, which is typically non-increasing with each iteration of the algorithm (due to the cooling factor α) (Henderson et al., 2003). This type of probabilities is based on a Boltzmann probability distribution, i.e. $e^{(CS-NS)/T}$. After M (the chosen Markov Chain Length) neighbour solutions are evaluated, the temperature parameter T is decreased with the cooling factor α. Figure 3-3 represents a description of the simulated annealing algorithm.

```
Temp          := StartTemp;
Solution      := ConstructInitialSolution;
CurrentBest   := Solution;

while not stopping_criteria do
begin
      for m := 1 to MarkovChainLength loop
      begin
            NeighborSolution := FindNeighborSolution(Solution);
            if NeighborSolution < Solution then
            begin
                  if NeighborSolution < CurrentBest then
                        CurrentBest := NeighborSolution;
                  Solution := NeighborSolution;
            end
            else
            begin
                  if RandomNumber ≤ e^((Solution-NeighborSolution)/Temp) then
                        Solution := NeighborSolution
            end;
      end;
      Temp := α * Temp
end;
Result := CurrentBest;
```

Figure 3-3: Pseudo code simulated annealing (Leeftink, 2020)

Tabu Search

Another metaheuristic that is based on a local search heuristic is Tabu Search (TS). The TS algorithm was proposed by Glover (1989). TS accepts non-improving solutions to escape from local optima when all neighbours are non-improving solutions. Usually, the whole neighbourhood is explored in a deterministic manner, whereas in SA a random neighbour is selected. If the best neighbour that is found is better than the current solution, it replaces the current solution. When a local optimum is reached, the search carries on by selecting a candidate worse than the current solution. The best solution in the neighbourhood is selected as the new current solution even if it is not improving the current solution (Talbi, 2009). TS uses a so-called tabu list to memorize the recent search trajectory. TS needs a list for this to ensure cycles are avoided, i.e., to ensure previously visited solutions are not selected again. TS avoids these cycles by discarding the neighbours that have been previously visited. In this way, the tabu list constitutes the short-term memory. At each iteration of TS, the short-term memory is updated. Preventing formerly visited solutions from being accepted again speeds up the attainment of the optimum solution (Fazel Zarandi et al., 2018). Some disadvantages of TS are that the use of long term memory (which is highly recommended for high quality solutions) complicates the basic algorithm, whether the global optimum is found depends strongly on the parameter settings, and TS is less promising for large solution spaces with many dimensions.

Genetic Algorithm

A Genetic Algorithm (GA) is, just like SA and TS, a metaheuristic. GAs have been developed to understand the adaptive processes of natural systems (Holland, 1975). GAs attempt to simulate the phenomenon of natural evolution. GAs encode the decision variables of a search problem into finite-length strings of alphabets of certain cardinality. The strings, which represent candidate solutions to the search problem, are referred to as chromosomes, the alphabets are referred to as genes and the values of genes are called alleles (Talbi, 2009). In contrast to traditional optimization techniques, GAs work with the coding of parameters, rather than the parameters themselves. Encoding the parameters in a chromosome can be very difficult in some cases. The strings are evolving in time according to the rule of survival of the fittest by using a randomized yet structured information exchange. Thus, in every generation, a new set of strings is created, using parts of the fittest members of the old set. When an initial population is generated, a set of operators is used to take this initial population to generate successive populations, which hopefully improve with time. A GA usually applies a crossover, reproduction, and/or mutation operator for this (Roetzel et al., 2019). Another important concept of GAs is the notion of population. Unlike traditional search methods, genetic algorithms rely on a population of candidate solutions. The population size, which is usually a user-specified parameter, is one of the important factors affecting the scalability and performance of GAs (Sastry et al., 2005). Relying on a population of candidate solutions can be seen as a strength of GA since it ensures a wide range of solutions. On the other hand, it can also be seen as a weakness, since it can be difficult to determine the best parameters for the population size.

3.4 Uncertainties

The planning and utilization of production capacity are two of the most important managerial responsibilities for managers in manufacturing. Such decisions have to be made in the face of uncertainty in several important parameters (Escudero et al., 1993). Hans et al. (2007) emphasize that all real-life projects are faced with uncertainty. These uncertainties in the multi-project-driven organisation are caused since detailed information about the required activities becomes available only gradually and due to operational uncertainties on the shop floor. Herroelen & Leus (2005) argue that this uncertainty may stem from a number of possible resources: activities may take more or less time than originally estimated, resources may become unavailable, materials may arrive behind schedule, release dates and due dates may have to be changed, etcetera. De Meyer et al. (2002) categorize these uncertainties in four categories: variation (e.g., variability of customers demand), foreseen uncertainty (e.g., productivity loss due to breakdown of equipment), unforeseen uncertainty (e.g., working with technologies that are rapidly evolving), and chaos (e.g., a natural disaster). Although Herroelen & Leus (2005) stress that uncertainties are gradually resolved during project execution, the validity of the deterministic scheduling has been questioned. Herroelen & Leus (2005) review five different approaches for scheduling under uncertainty: reactive scheduling, stochastic scheduling, scheduling under fuzziness, proactive (robust) scheduling, and sensitivity analysis. We describe the reactive scheduling, proactive scheduling, and stochastic scheduling approaches in more detail. The scheduling under fuzziness and sensitivity analysis approaches are both difficult to implement at VSM. That is why we do not describe these approaches in more detail.

The reactive approach does not try to cope with uncertainty in creating the baseline schedule but revises or re-optimizes the baseline schedule when an unexpected event occurs (Herroelen & Leus, 2005). This revision can be done by, e.g., a replanning approach, which re-optimizes or repairs the complete plan after an unexpected event occurs. Reactive approaches are particularly useful if disturbances cannot be completely foreseen or when they have too much impact to be absorbed by the slack in a plan (Hans et al., 2007).

The proactive method, on the other hand, develops a baseline schedule that incorporates a degree of anticipation of variability during project execution. In this way, the consequences of uncertainties are alleviated prior to the start of the project. The variability considered in the plan usually takes the form of slack in time or slack in capacity (Hans et al., 2007).

The stochastic scheduling approach can be applied to the CPP of VSM as follows. The number of jobs is fixed and known in advance. The processing time of a job is not known in advance, but it is known to be a random draw from a given probability distribution. Different jobs may have different processing time distributions. The release dates and deadlines may also be random variables from known distributions. In stochastic optimization problems, the decision maker has to determine the policy that minimizes the objective in some stochastic sense (Y-T. Leung & Anderson, 2004). By including stochasticity in the model, we model a scenario that fits better to reality.

Masmoudi et al. (2012) use another approach to integrate uncertainty into RCCP. They focus on the expectation and variance of the work content (processing time of job J_j). This means that each task's work content is considered to be a random variable. The choice of an appropriate distribution for these random variables is not trivial since Masmoudi et al. (2012) propose a distribution independent procedure that only uses expectation and variance. In this way, Masmoudi et al. (2012) aim for the development of robust plans, which are, up to a certain degree, protected from variability in the parameters.

3.5 Conclusion

The goal of this chapter is to present a literature review about relevant topics for this research. For this, we positioned the CODP at VSM using Wikner & Rudberg (2005), positioned the capacity planning problem using the positioning framework of Hans et al. (2007), discussed two different ways to address our problem setting based on, among others, Hans (2001) and Gademann & Schutten (2005), described multiple methods from existing literature to approach and solve the capacity planning problem, and discussed uncertainties that can occur in the plan and ways to deal with them using, among others, Hans et al. (2007), Herroelen & Leus (2005), and Masmoudi et al. (2012). We answered the second research question: "What relevant knowledge from the literature can be used to support improvement of the planning process of VSM?".

We positioned our planning problem to be a (resource) capacity planning problem at the tactical level. For this, we used the hierarchical project planning-and-control framework of Hans et al. (2007). Afterwards, we categorized the specific CPP of VSM based on several features such as the type of manufacturing process (Kerzner, 2003; Chen et al., 2009), the planning horizon (Chen et al., 2009), the number of projects (Platje et al., 1994), and the number of resources (Hans, 2001). Using this categorization we defined the CPP of VSM as a multi-resource multi-project medium-term capacity planning problem in an MTO environment.

To address this problem setting, we described two problems from the literature. The first problem we described is the time-driven Rough-Cut Capacity Planning problem (Gademann & Schutten, 2005; De Boer, 1998). The second problem we described is the resource loading problem (Hans, 2001; Hans et al., 2002). To solve these problems, we distinguish solution approaches into three classes: straightforward constructive heuristics (Gademann & Schutten, 2005; Wullink, 2005; De Boer, 1998), LP based heuristics (Gademann & Schutten, 2005; Van Krieken, 2001), and improvement heuristics (Wullink, 2005; Henderson et al., 2003). Since all real-life projects are faced with uncertainty (Hans et al., 2007), we discussed uncertainties that can occur and approaches to deal with these uncertainties (Herroelen & Leus, 2005; Hans et al., 2007; Masmoudi et al., 2012).

Based on the literature review, we conclude that we can combine the RCCP model and the resource loading model to address our problem setting. To solve our problem, we can use an exact approach or an approximation approach. In the exact approach, we can use the model formulations of the RCCP and the resource loading problem. In the approximation approach, we can use constructive heuristics or LP based heuristics to create a feasible solution. This feasible solution can afterwards be improved using improvement heuristics.

4 Solution Design

In Chapter 3, we presented a literature review concerning the planning problem at VSM. In this chapter, we use the information found in the literature to create a planning algorithm. By this, we answer the third research question: "How can the planning problem at VSM be improved?". The chapter starts with a brief contextual description of the planning problem that we intend to solve in Section 4.1. Section 4.2 describes the way we generate instances for the model and the heuristics. Section 4.3 presents the model for the planning problem and shows the solution of a test set of the problem. Section 4.4 discusses the choice for the constructive and improvement heuristic, and their implementation and parameter selection. Section 4.5 explains how VSM can deal with the uncertainties that can occur in the execution of the plan. Section 4.6 concludes this chapter.

4.1 Problem to solve

Recall from Section 2.3.2 that we divide VSM in this research into 3 different departments: the VPM 1 department, the VPM 2 department, and the Assembly department. These departments visualize their workload per week using a workload graph. Figure 2-14 shows such a workload graph. The workload per week per department is made up of the total production time of the production steps that are executed at that department. Table 4-1 gives an overview of the production steps that are executed per department.

Table 4-1: Production steps per department

VPM 1 department	VPM 2 department	Assembly department
Cutting	Sawing construction	Assembly
Drill / Saw	Preparation for welding	Testing
Cutting tables	Construction welding	Disassembly
Cross transports & Roller conveyors	Finalize welding	Loading / Shipping

The workload graph of the VPM 2 and Assembly department shows the total production time of the production steps that Table 4-1 presents. For the VPM 1 department, however, the workload graph does not show the production time for the Cutting production step. Within VSM, the Cutting production step is considered as an individual process and has no workload graph. This choice was made within VSM since for the Cutting production step it is actually only known until the last moment what the actual workload is, as production orders are clustered based on plate thickness. As a result, no conclusions could be drawn from a workload graph showing the total production time of all production orders for a week for the Cutting production step. Recall from Section 1.4 that we only focus on the plan of the VPM 2 department in this research since this department has the shortest time horizon and the highest variability in the workload per production order.

Recalling from Chapter 2, we describe the planning problem of VSM as follows. Once every 4 weeks, there is a forecast meeting. After the forecast meeting, the production of approximately 10 new machines is started. This forecasted demand results in production that must be completed. Each machine contains several weldments and each weldment contains a number of production steps. The production steps (1) Cutting, (2) Drill / Saw, (3) Sawing construction, (4) Preparation for welding, (5) Construction welding, and (6) Finalize welding are variable per weldment. Table 4-2 shows some weldments including their production steps and times. After the productions steps from the weldments have been executed, the weldments go to one (or multiple) external supplier(s) where they are post-processed, annealed and/or coated. Afterwards, the weldments are delivered back to VSM. Once all weldments and purchased materials have been delivered, they are assembled into a machine. We do not include the production steps Cutting tables and Cross transports & Roller conveyors in this research since we focus on the planning process of the VPM 2 department in this research and not on the planning process of the VPM 1 department where these production steps are executed.

Table 4-2: Weldments including production steps & time

Weldment	Weldment description	Production step	Processing time [h]
005-3692	Weldment Base frame	Cutting	1.033
		Drill / Saw	0.750
		Sawing construction	0.250
		Preparation for welding	0.750
		Construction welding	9.000
		Finalize welding	5.500
001-6885	Weldment clamb unit	Cutting	0.302
		Preparation for welding	0.500
		Construction welding	3.500
007-2207	Weldment frame	Preparation for welding	0.160
		Construction welding	0.250

Figure 4-1 visualizes the throughput time of a V613-1000M machine. As can be seen, the throughput time (within VSM also called the time of delivery cold start) of this machine is 17 weeks. This throughput time differs per machine type.

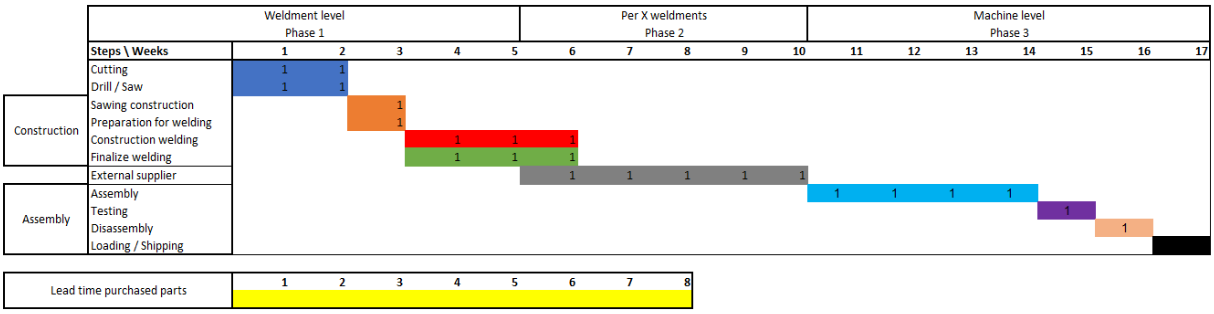

Figure 4-1: Throughput time V613-1000M

When planning the production steps for the VPM 2 department, the aim is to stabilize the total workload per week. Stabilizing the workload should be done while taking into account some constraints. Next to these constraints, we make some assumptions to limit the number of variables in the planning problem. Below we give these constraints and assumptions.

Constraints

- All production steps are executed completely and on time (i.e., before the internal due date).
- Precedence relations between the production steps must be considered (i.e., if a preceding production step has not yet been completed, the next production step cannot be started).
- Inventory levels may both not be negative and not higher than specified capacity limits.
- Production is only allowed in the predefined time windows.
- The production of an order does not start earlier than the delivery date minus the throughput time of the machine, or the first week after the RFC week. In Section 4.2.2, we explain this in more detail.
- The fixed lot sizes of the weldments must be considered. We explain this in more detail in Section 4.2.3.

Assumptions

- Tools and (raw) materials are always available on time and do not constrain the plan.
- Each project is broken down into some weldments that are again broken down into several work packages, which we call production steps.
- The required time per production step is available and deterministic. The hours that we plan per production step are also the actual number of hours the employees have to execute the production step.
- Demand is forecasted and known. The number of machines to be produced that follows from the forecast is used as input.
- The time horizon is divided into T buckets of one week.
- Each production step j must be performed in a time window [r_j, d_j]. These time windows are large enough to execute the production step.
- Costs for materials, tools or employees do not constrain the plan.

4.2 Problem instances

In the planning problem, we try to plan production steps with a specific production time to a certain week such that the total workload per week is stabilized. For this, we need input parameters. Some of these input parameters are easy to obtain, some other parameters have to be calculated first. In this section, we explain how we generate the instances for our planning problem. For this, we explain some pre-processing steps, how we obtain input parameters, and we define which part of the plan we base our analyses on.

4.2.1 Production steps

First, we need to determine how we generate the production steps. Recall from Section 4.1 that the VSM machines consist of several weldments and that each weldment consists of a number of production steps. Figure 4-2 visualizes the structure from an order to the production steps that we have to plan.

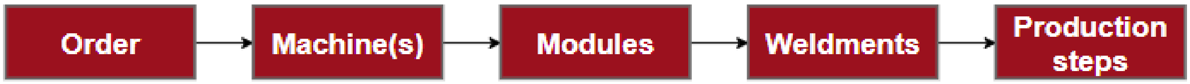

Figure 4-2: Structure from order to production steps

To plan the production steps, we need customer orders for machines. We choose not to determine per machine which production steps must be planned in advance because this can be variable per machine. Even if the same machine type is sold, the number of production steps to be planned can be variable as the customer needs to select which modules are added to the machine. To include this variable number of modules in our solution approaches, we let the solver of the model and the heuristics calculate which production steps must be planned and which not. This makes the model and heuristics more complicated than just giving a set of production steps to be planned to them but makes adding orders to the model/heuristics easier. Table 4-3 gives an example order list we could use in the model and heuristics.

Table 4-3: Order list for test set

Customer number	Machine	Deadline (week)	Deadline Year	RFC week	Deadline	Time of delivery Cold start	Release date (week)	Release Year	Release date	Weeks available for production
RFC1065	V325-3000	7	2021	40	19-2-2021	20	40	2020	28-9-2020	20
RFC1066	V325-3000	12	2021	40	26-3-2021	20	45	2020	2-11-2020	20
RFC1067	V310	2	2021	40	15-1-2021	15	40	2020	28-9-2020	15
RFC1068	V310	4	2021	40	29-1-2021	15	42	2020	12-10-2020	15
RFC1069	V320-3000	6	2021	40	12-2-2021	16	43	2020	19-10-2020	16
RFC1070	V320-2000	10	2021	40	12-3-2021	16	47	2020	16-11-2020	16
RFC1071	V631-1050T	6	2021	40	12-2-2021	18	41	2020	5-10-2020	18
RFC1072	V807M	4	2021	40	29-1-2021	14	43	2020	19-10-2020	14
RFC1073	V807M	5	2021	40	5-2-2021	14	44	2020	26-10-2020	14
RFC1074	V807M	6	2021	40	12-2-2021	14	45	2020	2-11-2020	14
RFC1075	VSB1500-4/15	8	2021	43	26-2-2021	15	46	2020	9-11-2020	15
RFC1077	V310	7	2021	44	19-2-2021	15	45	2020	2-11-2020	15
RFC1078	V310	8	2021	44	26-2-2021	15	46	2020	9-11-2020	15
RFC1079	V310	9	2021	44	5-3-2021	15	47	2020	16-11-2020	15
RFC1080	V550-7	12	2021	44	26-3-2021	19	46	2020	9-11-2020	19
RFC1081	VB1050	5	2021	44	5-2-2021	13	45	2020	2-11-2020	13
RFC1082	VB1050	7	2021	44	19-2-2021	13	47	2020	16-11-2020	13
RFC1083	VB1250	8	2021	44	26-2-2021	13	48	2020	23-11-2020	13
RFC1084	V631-1050M	9	2021	44	5-3-2021	18	44	2020	26-10-2020	18
RFC1085	V807M	7	2021	44	19-2-2021	14	46	2020	9-11-2020	14
RFC1086	V807M	8	2021	44	26-2-2021	14	47	2020	16-11-2020	14
RFC1087	V807M	9	2021	44	5-3-2021	14	48	2020	23-11-2020	14
RFC1091	V310	11	2021	48	19-3-2021	15	49	2020	30-11-2020	15
RFC1092	V310	12	2021	48	26-3-2021	15	50	2020	7-12-2020	15
RFC1093	VB1050	11	2021	48	19-3-2021	13	51	2020	14-12-2020	13
RFC1094	VB1050	12	2021	48	26-3-2021	13	52	2020	21-12-2020	13
RFC1095	V807M	7	2021	48	19-2-2021	14	48	2020	23-11-2020	12
RFC1096	V807M	8	2021	48	26-2-2021	14	48	2020	23-11-2020	13
RFC1097	V807M	9	2021	48	5-3-2021	14	48	2020	23-11-2020	14
RFC1098	VSB1500-4/15	11	2021	48	19-3-2021	15	49	2020	30-11-2020	15

As can be seen in the order list, VSM sells many different machines. Since it is too much work to analyse all machines, we reduce the total number of machine types. For this, we grouped some machines based on the family names of the machines. We use the family names of the machines to group some machines as this gives us the best estimation of the number of production hours that a machine requires. By grouping some machines, we reduce the total number of machines to only 15 different types of machines. Table 4-4 presents all machine types, the machine types we include, and the relevant weldments that we consider in this research.

Table 4-4: Machines included in the research

Included machines and modules				
Machine	Family names	Machine included	Parts	Relevant weldments
V807M	V8xx	V807M	1314	**28**
V808M				
VB1050	VB1x50	VB1050	939	**30**
VB1250				
V2000-400	V2000	V2000-400	477	**20**
V2000-200				
V310	V310	V310	406	**6**
V613-1000M	V613/V630	V613-1000M	1133	**58**
V613-1000T				
V630-1000M				
V630-1000T				
V630-1250M				
V630-1250T				
V325-3000	V325-3000	V325-3000	1813	**71**
V600	V600	V600	818	**19**

V631-1050M V631-1050T V631-1250M V631-1250T	V631-1x50x	V631-1050M	1342	**40**
V633-1050T V633-1050M	V633	V633-1050T	530	**31**
V200	V200	V200	1053	**31**
V303 V304	V303/V304	V303	291	**6**
V320-2000 V320-3000	V320-x000	V320-2000	1208	**60**
V550-7	V550-7	V550-7	1401	**62**
VSB1500-4/15 VSB1500-6/15 VSB2500-6/15	VSBx500-x/15	VSB1500-4/15	1562	**101**
VP1500 VP2500	VPx500-4	VP1500	831	**19**

4.2.2 Allowed To Work (ATW)-heuristic

Using the customer orders from the order list, we can determine, among others, the start and end date of a particular order. This date can be used by VSM. In the model and heuristics, we do not use dates but we express the time in buckets of 1 week (1, …, T).

In the order list, we define the release week as

$$\text{release week} = \max\left(\text{deadline week} - \text{throughput time}, \text{RFC week}\right).$$

This means that we assume that the production of a machine will not start earlier than needed, i.e., in the week that is equal to the deadline week minus the throughput time of the machine. If the production of a machine is started too late (deadline week – RFC week < throughput time), the release week will be the current week, i.e., the RFC week. It is important to note that there will be no production of the released machine in the release week itself. The production of a released machine will therefore always start in the first week after the release week. We decide not to start the production of a released machine until the first week after its release week since most often the RFC meeting takes place at the end of the week. In addition, we decide that an order must be finished at the end of the deadline week and therefore the deadline week itself can be used as a production week. So, for example, if the RFC week is the 50^{th} week, the deadline week the 66^{th} week, and the throughput time of the machine is 15 weeks, the production of the machine will start in week 52 (since the release week will be week 51; 66 – 15) and not in week 51 (first week after RFC week), and the production of the machine should be finished at the end of the 66^{th} week.

Then, we use a heuristic to determine in which weeks it is allowed to execute a production step. We will refer to this heuristic as the '**ATW-heuristic**'. To determine in which weeks it is allowed to execute a production step, we use the precedence relations between the production steps and the throughput time of the machines such as Figure 4-1 visualizes, and the release date of an order. For each order, we check which machine is ordered, which modules are in this machine, which weldments need to be produced, and which production steps are in each of these weldments. Then, we look for the release date of the order and add the weeks in which the production steps are allowed to be produced to the release date. So, for example, if a customer orders a V550-7 machine in week 10, the ATW windows are as Table 4-5 shows. Note that we just show two weldments and not all of them.

Table 4-5: ATW windows example

Customer name	Machine	Weldment	Production step	ATW window
RFC0001	V550-7	007-5198	Cutting	[11, 12]
RFC0001	V550-7	007-5198	Preparation for welding	[13]
RFC0001	V550-7	007-5198	Construction welding	[14, 15, 16]
RFC0001	V550-7	005-4636	Cutting	[11, 12]
RFC0001	V550-7	005-4636	Drill / Saw	[11, 12]
RFC0001	V550-7	005-4636	Sawing construction	[13]
RFC0001	V550-7	005-4636	Preparation for welding	[13]
RFC0001	V550-7	005-4636	Construction welding	[14, 15, 16]
RFC0001	V550-7	005-4636	Finalize welding	[14, 15, 16]

4.2.3 Fixed lot sizes

VSM machines have a modular design. Each module has its characteristics such as the number of times it is in a machine, its fixed lot size, its current stock, its value, its number of production steps, and the required time per production step that is in the module. In the solution approaches, we consider these characteristics.

The number of weldments to be produced after a machine is ordered is not always the same. This is due to the fixed lot size that some weldments have. Due to the fixed lot sizes, stocks are created. The stock, lot size, demand, and the number of times the weldment is in the machine determine how many weldments must be produced for a machine. Table 4-6 presents an example of the number of weldments to be produced per week. Note that the inventory position given in the table is the inventory position at the beginning of the week. The rows in the bold square in the table are variable per week. As Table 4-6 shows, in the first week, there is a demand for 4 weldments. The fixed lot size of this weldment is 8, while the weldment is only twice in the machine. Since the inventory position at the beginning of the week is 0, $\max\left(\left\lceil\frac{4-0}{8}\right\rceil * 8, 0\right) = 8$ weldments have to be produced. The inventory position at the end of week 1 (beginning of week 2) will then be 0 + 8 – 4 = 4. This procedure is repeated for all weeks.

Table 4-6: Number of weldments to be produced

	Weeks			
	1	**2**	**3**	**4**
# weldments in machine	2	2	2	2
Fixed lot size	8	8	8	8
Demand	4	2	14	2
Inventory position	0	4	2	4
To be produced weldments	8	0	16	0

To visualize the different number of weldments that can be produced in a week for a module, we show a module from a V807M machine. Figure 4-3 shows this module, called a V807M-clamp. In this module are in total 19 weldments. Figure 4-4 visualizes these 19 weldments. 11 of the 19 weldments have a fixed lot size that can cause stocks. This means that for these weldments, the fixed lot size is not equal to the number of times the weldment is in the machine and so do not always have to be produced when there is demand for them. When all these 11 weldments are in stock, only the remaining 8 weldments need to be produced. These weldments have a fixed lot size that is 1 or that is equal to the number of times the weldment is in the machine and so have to be produced always. Figure 4-5 shows the 8 weldments that always need to be produced.

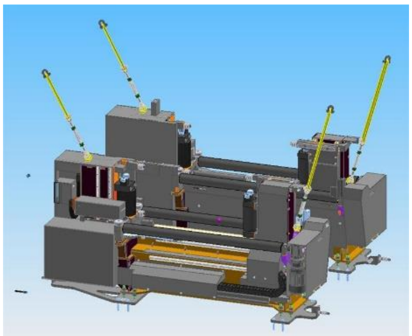

Figure 4-3: V807M-clamp

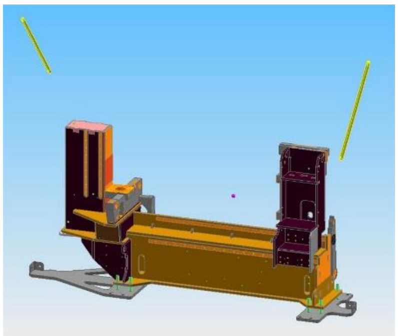

Figure 4-4: All weldments in module

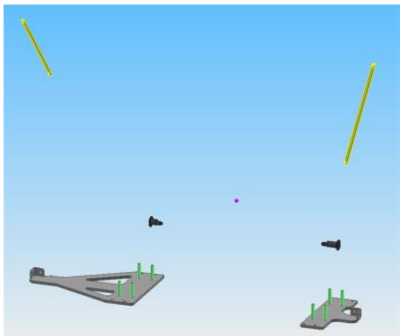

Figure 4-5: Always to be produced

4.2.4 Relevant plan

During the research, we collected many RFC reports. These reports state which machines are expected to be sold and when these machines are expected to be sold. Using these RFC reports, we can make order lists such as Table 4-3 shows. These order lists are used as input datasets for the analysis of the solution approaches and the experiments. We perform these analyses and experiments in Chapter 5. Due to the short time horizon the VPM 2 department has, the plan that follows from the results of the mathematical model and the heuristics is only valid for a limited time, i.e., for the first 5 weeks after the last included RFC report. This is the plan that is relevant for the VPM 2 department directly and so we base the results of our analyses and experiments in Chapter 5 on this part of the plan. To make it clear that we base the results only on this part of the plan, we define the following term:

*The **relevant plan** is the plan of the VPM 2 department for the first 5 weeks after the last included RFC report.*

We only use the first 5 weeks after the last included RFC report of the plan to analyse the results of the solution approaches and the experiments because the plan can still change a lot after these weeks, for example due to new input. This means that the plan must be updated at least every 5 weeks. In the remainder of this study, we use the term relevant plan to refer to the plan for the first 5 weeks after the last included RFC report.

4.3 Mathematical model

In Section 3.2.1, we defined the planning problem of VSM as a capacity planning problem (CPP) in an MTO environment. Multiple different models and methods can be used to approach the problem. Our problem setting as discussed in Section 4.1 can be addressed in two different ways. We can approach the planning problem as a Rough-Cut Capacity Planning (RCCP) problem (Gademann & Schutten, 2005; De Boer, 1998) or as a resource loading problem (Hans, 2001; Hans et al. 2002). Based on the mathematical formulations of the time-driven RCCP (Gademann & Schutten, 2005; De Boer, 1998) and the resource loading problem (Hans, 2001; Hans et al., 2002), we create a MIP model. We define the following indices, parameters, variables, objective function, and constraints for our MIP model.

Indices	Description	
o	orders;	$o \in \{1,2, \dots, O\}$
m	machines;	$m \in \{1,2, \dots, M\}$
w	weldments;	$w \in \{1,2, \dots, W\}$
j	production steps;	$j \in \{1,2, \dots, J\}$
t	time buckets (weeks);	$t \in \{1,2 \ \dots, T\}$

Parameters	Description
N_{wm}	number of times weldment w is in machine m
FL_w	fixed lot size per weldment w
V_w	value of weldment w
II_w	initial inventory of weldment w
PS_{wj}	$\begin{cases} 1 \text{ if production step j is in weldment w} \\ 0 \text{ otherwise} \end{cases}$
PT_{wj}	production time of production step j in weldment w
ATW_{omwjt}	$\begin{cases} 1 & \text{if production step j of weldment w in machine m} \\ & \text{for order o is allowed to be executed in week t} \\ 0 & \text{otherwise} \end{cases}$
DW_{omwjt}	$\begin{cases} 1 & \text{if week t is the last ATW week for production} \\ & \text{step j of weldment w in machine m for order o} \\ 0 & \text{otherwise} \end{cases}$
D_{wjt}	number of weldments w that is demanded per production step j in week t $= \sum_{o=1}^{O} \sum_{m=1}^{M} DW_{omwjt} * N_{wm} \qquad \forall\, w, j, t$
InvValue	the maximum allowed inventory value $= €350{,}000$
MaxCapCutting	the maximum number of hours per week the production step Cutting is allowed to be executed $= 77.5$
MaxCapDrillSaw	the maximum number of hours per week the production step Drill / Saw is allowed to be executed $= 25$
BigM	a large number (i.e. 500) that is higher than the highest number of times a production step can be executed (but is not too high)

Decision variables	Description
I_{wjt}	inventory position of production step j for weldment w in week t
P_{wjt}	number of times production step j is executed to produce weldment w in week t
TP_{wjt}	total number of times production step j is executed to produce weldment w in weeks 1 … t $= \sum_{tt=1}^{t} P_{w,j,tt} \qquad \forall\, w, j, tt < t$
Y_{wjt}	$\begin{cases} 1 \text{ if production step j for weldment w is executed in week t} \\ 0 \text{ otherwise} \end{cases}$
Z_{wjt}	number of times the fixed lot size of weldment w per production step j is executed in week t

W_{jt}	workload per production step j in week t	
	$= \sum_{w=1}^{W} P_{wjt} * PT_{wj}$	$\forall$ j, t
TW_t	the total workload in week t	
	$= \sum_{j=3}^{J} W_{jt}$	$\forall$ t
BalanceWorkload	maximum workload per week	

Objective function

The objective function aims to minimize the maximum workload per week. This aim is reflected by the following objective function (0).

$$\min z = \text{BalanceWorkload} \tag{0}$$

Constraints

Constraint (1) ensures that the maximum workload is at least as high as the total workload in week t. By using the variable BalanceWorkload to minimize the maximum workload we linearize the model. Note that we define the total workload as the sum of the third, fourth, fifth, and sixth production step (i.e., the production steps Sawing construction, Preparation for welding, Construction welding, and Finalize welding) since these production steps are executed at the VPM 2 department. The first two production steps, Cutting and Drill / Saw, are included in the model but we do not try to minimize the maximum workload of these production steps. Constraint (2) and constraint (3) ensure that the maximum production capacity of these two production steps is not exceeded. The maximum production capacities are determined by the group leader of Parts Manufacturing.

$$\text{BalanceWorkload} \geq TW_t \qquad \forall\, t \tag{1}$$
$$W_{1t} \leq \text{MaxCapCutting} \qquad \forall\, t \tag{2}$$
$$W_{2t} \leq \text{MaxCapDrillSaw} \qquad \forall\, t \tag{3}$$

Constraints (4) – (11) are all required to ensure that production step j is executed an allowable number of times, i.e., considering the ATW windows, demand, inventory position, and fixed lot size. Constraint (4) ensures that in the first week no production steps are executed. Since the first week in the model is the release week of the first order, no production is allowed in that week as explained in Section 4.2.2. Constraint (5) ensures that production steps are only executed in their ATW windows.

$$P_{wj1} = 0 \qquad \forall\, w,\ j \tag{4}$$
$$P_{wjt} \leq \sum_{o=1}^{O} \sum_{m=1}^{M} ATW_{omwjt} * \text{BigM} \qquad \forall\, w,\ j,\ t > 1 \tag{5}$$

Constraint (6) guarantees that a weldment is not produced when there is either no demand for the weldment or the initial inventory of the weldment is higher than the total demand for the weldment. In this way, we ensure that only the weldments that are demanded are made, to avoid unnecessary stock at the end of the model's last week. Constraint (7) ensures that, for each weldment with a fixed lot size of 1 and a demand higher than its initial inventory, the total number of produced weldments is equal to the difference between the total demand and the initial inventory. In this way, we ensure that exactly enough weldments are produced in addition to the weldments that we take from stock. Constraint (8) guarantees that, when a weldment has a fixed lot size of at least 2 and the demand is higher than its initial inventory, the total number of weldments to be produced is at most the total demand minus the initial inventory plus the fixed lot size of the weldment. Note that constraints (6) – (8) together make up the complete set of weldments w. Each restriction covers a specific subset.

$$\sum_{t=1}^{T} P_{wjt} = 0 \qquad \forall\, w \mid \frac{\sum_{t=1}^{T}\sum_{j=1}^{J} D_{wjt}}{\sum_{j=1}^{J} PS_{wj}} \leq II_w,\ j \tag{6}$$

$$\sum_{t=1}^{T} P_{wjt} = \sum_{t=1}^{T} D_{wjt} - II_w \qquad \forall\, w \mid \frac{\sum_{t=1}^{T}\sum_{j=1}^{J} D_{wjt}}{\sum_{j=1}^{J} PS_{wj}} > II_w\ \&\ FL_w = 1,\ j \mid PS_{wj} = 1 \tag{7}$$

$$\sum_{t=1}^{T} P_{wjt} \leq \sum_{t=1}^{T} D_{wjt} - II_w + FL_w \qquad \forall\, w \mid \frac{\sum_{t=1}^{T}\sum_{j=1}^{J} D_{wjt}}{\sum_{j=1}^{J} PS_{wj}} > II_w\ \&\ FL_w > 1,\ j \mid PS_{wj} = 1 \tag{8}$$

Constraint (9) ensures that the variable Y_{wjt} becomes 1 if production step j for weldment w is executed in week t. To guarantee that at least this fixed lot size is produced for these weldments, we use constraint (10). To ensure that the fixed lot size is considered in the model, we set in constraint (11) the ratio P_{wjt}/FL_w equal to Z_{wjt} in which Z_{wjt} is an integer.

$$P_{wjt} \leq Y_{wjt} * BigM \qquad \forall\, w,\ j,\ t > 1 \tag{9}$$
$$FL_w - P_{wjt} \leq (1 - Y_{wjt}) * BigM \qquad \forall\, w,\ j,\ t > 1 \tag{10}$$
$$P_{wjt}/FL_w = Z_{wjt} \qquad \forall\, w, j, t \tag{11}$$

Constraints (12) – (14) are required to control the inventory in the model. Constraint (12) ensures the inventory at the end of the first week in the model is balanced. In general, the inventory levels may both not be negative and not higher than specified capacity limits. Constraint (13) guarantees that the inventory levels at all weeks, except the first week, are balanced. Constraint (14) ensures that the total inventory value is not higher than the total allowed maximum. In Chapter 5 we perform experiments regarding the level of this inventory value.

$$I_{wj1} = II_w + P_{wj1} - D_{wj1} \qquad \forall\, w,\ j \mid PS_{wj} = 1 \tag{12}$$
$$I_{wjt} = I_{wjt-1} + P_{wjt} - D_{wjt} \qquad \forall\, w,\ j \mid PS_{wj} = 1,\ t > 1 \tag{13}$$
$$\sum_{w=1}^{W} \left(\frac{\sum_{j=1}^{J} I_{wjt}}{\sum_{j=1}^{J} PS_{wj}} \right) * V_w \leq InvValue \qquad \forall\, t \tag{14}$$

Constraint (15) guarantees that no more production steps of a weldment are executed than its previous production step. This is necessary to ensure the precedence relations are met. So, for example, we ensure with this restriction that no more weldments are welded (production step ‘Construction welding’) than are cut (production step Cutting). Constraint (16) ensures that the inventory position in the last week is equal for all production steps.

$$TP_{wjt} \leq TP_{w,jj,t} \qquad \forall\, w,\ j \,\middle|\, PS_{wj} = 1\ \&\ j > 1, jj \,\middle|\, PS_{wjj} = 1\ \&\ jj < j, t \tag{15}$$
$$I_{wjT} = I_{w,jj,T} \qquad \forall\, w,\ j \,\middle|\, PS_{wj} = 1\ \&\ j > 1, jj \,\middle|\, PS_{wjj} = 1\ \&\ jj < j \tag{16}$$

The last constraints, constraints (17A) – (17C), are the domain restrictions of the variables. These constraints ensure that the variables are nonnegative, integer, or binary.

$$I_{wjt}, P_{wjt}, TP_{wjt}, W_{jt}, TW_t \geq 0 \qquad \forall\, w, j, t \tag{17A}$$
$$Y_{wjt} \in \{0, 1\} \qquad \forall\, w, j, t \tag{17B}$$
$$Z_{wjt} \geq 0 \text{ and integer} \qquad \forall\, w, j, t \tag{17C}$$

4.3.1 Solving a test problem

In order to solve the mathematical model, we use the CPLEX solver of AIMMS. IBM ILOG CPLEX Optimization Studio is a prescriptive analytics solver that enables the rapid development and deployment of decision optimization models using mathematical and constraint programming (ILOG CPLEX Optimization Studio - Overview, 2021). To check whether both the model works correctly and whether it can be solved optimally in a reasonable time, we run the model with the instance as Table 4-7 describes.

Table 4-7: Instance size

Name (description)	Indices / Parameters	Size
Orders	O	30
Machines	M	8
Weldments	W	381
Production steps	J	6
Time buckets (weeks)	T	26
Weeks in which there is demand	$t \mid \sum_W \sum_J D_{wjt} > 0$	16
Total production steps to be planned	$\sum_W \sum_J \sum_T Z_{wjt}$	4854

Just like the RCCP problem and the resource loading problem, it is not possible to solve the MIP model for the planning problem by a polynomial time algorithm. Note, however, that we use the ATW windows as input in our model and that the model for the time-driven RCCP problem (Gademann & Schutten, 2005) calculates the windows themselves. If the model of Gademann & Schutten (2005) for the time-driven RCCP problem would get the ATW windows as input, the model can, on the other hand, be solved optimally. For the problem instance that Table 4-7 describes, our model can be solved close to the optimum using a branch and bound algorithm. When running the CPLEX solver for 900 seconds, the optimality gap (which we define as the difference between the discrete problem solution and the continuous problem solution) is less than 0.01%. Despite the solver does not stop automatically running the model, the solution found by the solver is close to the best possible solution. That is why we use the results of the MIP model as a benchmark for the results of our heuristic. Figure 4-6 visualizes the total workload per week for the VPM 2 department. The part of the workload graph in the red square is the relevant plan for the VPM 2 department.

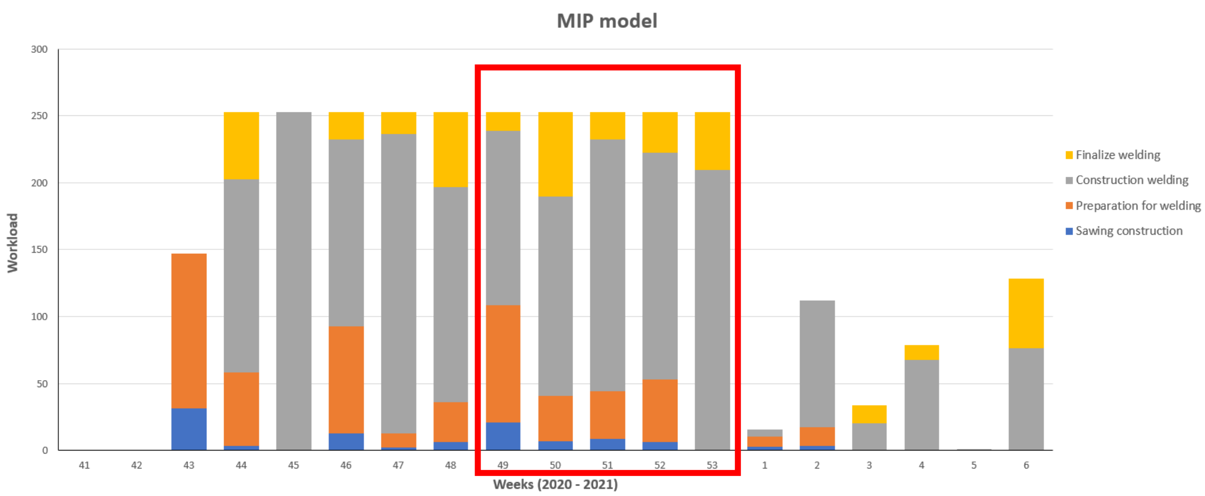

Figure 4-6: Workload graph test problem

4.4 Approximation methods

In this section, we propose a constructive and improvement heuristic to solve the CPP. As described in Section 4.3.1, the solution of the MIP model found by the CPLEX solver is close to the best possible solution for the given problem instance. That is why we use the results of the MIP model first as validation for our heuristic and later as a benchmark for the results of our heuristic. We decide to also propose a heuristic for the CPP based on an analysis of the results of the MIP model. The MIP model stabilizes the plan almost optimally. However, the disadvantage of the result of the MIP model is that many parts of the weldments are kept in stock for a long time. At the moment it is not desirable at VSM to keep many parts of weldments in stock, as VSM has no warehouse where they can store these parts. To keep the internal stocks to a minimum, all production steps of a weldment are currently executed within a few weeks. To show the difference between a stable plan with high inventories (MIP model results) and a more unstable plan with low inventories (current situation), we first propose a constructive heuristic that imitates the way the planner currently creates the plan. Afterwards, we improve this plan using an improvement heuristic. In Section 4.4.1, we elaborate on our choice for the constructive and improvement heuristic. Afterwards, in Section 4.4.2, we discuss the implementation and parameter selection of both heuristics.

4.4.1 Constructive and improvement heuristic

As explained in Section 4.1, in the planning problem we try to plan production steps with a specific production time to a certain week such that the total workload per week is stabilized. We initially plan these production steps in the same way as the planner currently does to compare the results of the MIP model with the results of the current plan. Section 4.4.2 describes in more detail how we imitate the plan the planner currently creates and the implementation of the algorithm.

To both maintain the current planning methodology and to propose an improvement to the current plan, we improve the current plan using an improvement heuristic. Since we want to adapt the current plan iteratively to construct a final plan, we choose to use a local search. To not get stuck in a local optimum, we choose a metaheuristic that balances between intensification (exploiting the best solutions found) and diversification (exploring the search space) (Talbi, 2009). Based on the literature review, we decide to use Simulated Annealing (SA) to improve the current plan. We choose SA as it has the advantage that is easy to implement because only a few parameters need to be defined. In Section 4.4.2, we discuss and set these parameters. In contrast to SA, the Genetic Algorithm (GA) required many parameters to be defined. Since it can be hard to determine the best value for all these parameters, we choose to not implement this metaheuristic for this planning problem. Besides, SA requires less computational time compared to Tabu Search (TS) for example. TS requires an evaluation of the entire neighbourhood. Since the production steps to be planned in the planning problem can run into the thousands, the planning problem has a relatively large neighbourhood. This will cause a high computational time for TS. Therefore, we do not implement this metaheuristic for this planning problem.

4.4.2 Implementation and parameter selection

To create a feasible plan for the planning problem, we plan the production steps in the same way as the planner currently does. For this, we use a heuristic. This heuristic plans the production steps over time and we will refer to it as the Current Situation-heuristic, or in short the '**CS-heuristic**'. Then, to improve the feasible plan, we use the SA algorithm. We explain how the heuristic and the algorithm are implemented below.

CS-heuristic

At the moment, the planner receives a list with all weldments that need to be produced in the coming weeks. Using this list, the planner makes another list that contains all production steps that are in the weldments that he has to plan over the weeks. To ensure that the heuristic knows which production steps have to be planned as soon as the production of a machine is started, tables are created stating which weldments must be produced and which production steps must be executed for that machine. Using these tables, we create an initial plan completing the following steps:

1. Select the first order from the order list. This order list is not sorted as the planner does not do this at the moment. So, by not sorting the order list the current situation is simulated the best.
2. Look up in the tables which and how many weldments need to be produced per ordered machine
3. Select the first weldment that needs to be produced
4. Look up in the tables which production steps are required for that weldment
5. Select the first production step
6. Determine in which weeks the production step is allowed to be planned using the ATW-heuristic
7. Select the week in which the total workload is the lowest at that moment
8. Plan the production step in the selected week
9. Go to the next production step. If there is no next production step in the weldment:
10. Go to the next weldment. If there is no next weldment:
11. Go to the next order. If there is no next order:
12. All production steps are planned, i.e., the heuristic is finished

By planning the production steps always in their ATW windows, we ensure that production steps are never executed too late in the plan. However, in this plan, we did not yet consider the capacity or inventory value violations as defined in the model (see constraints (2), (3), and (14)). To consider these capacity and inventory value violations, we check the inventory value per week and the total workload for the Cutting and Drill / Saw production steps after we selected the week in which the total workload is the lowest. If one of the capacity constraints is violated, we plan the production step to the week with the lowest workload in its ATW window (but another week than the current week), if possible. If this is not possible or one of the constraints is still violated, we plan the production step in the first week after its ATW window. If the solution is still not feasible yet, we plan the production step again a week later. We repeat this until the solution is feasible.

Using the same test set we used for the MIP model, we obtain the workload graph as shown in Figure 4-7. This workload graph is the result of the initial plan that is created using the CS-heuristic. Together with the planner of the VPM 2 department, we verify this initial plan. The planner plans a comparable number of production steps of the same weldments. Afterwards, we compare the results of both plans. From these results, we conclude that the initial plan that is created using the CS-heuristic indeed imitates the current situation well. The relevant plan is shown in the red square in Figure 4-7.

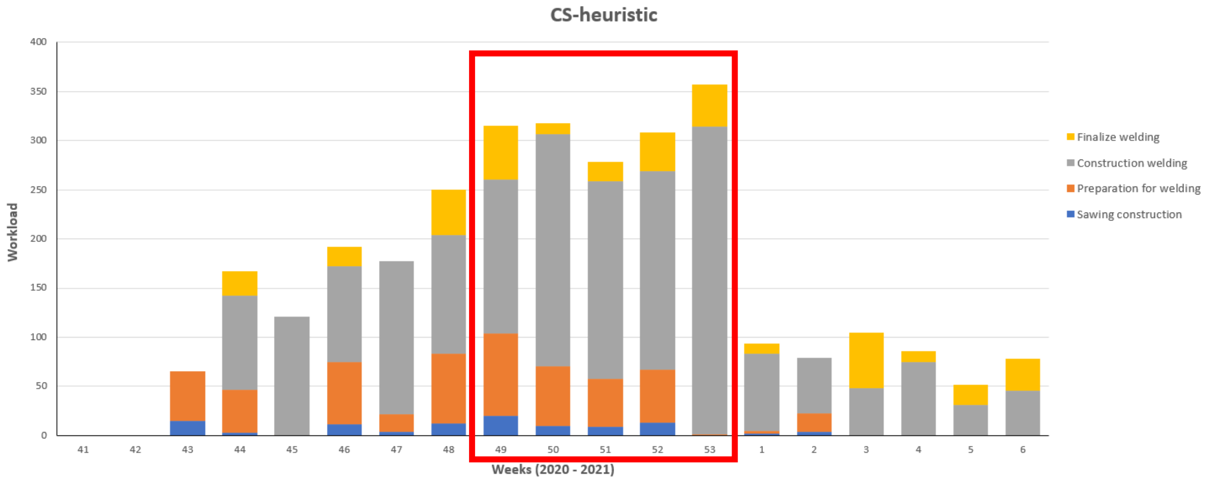

Figure 4-7: Workload graph CS-heuristic

Simulated Annealing

Once we created the heuristics that imitate the current way the planner plans the production steps, we can initiate the SA algorithm. The current plan is set as the initial plan in the SA algorithm. Next, we set the objective function and all parameters and settings that we need in the SA algorithm. We use the following objective function, parameters, and settings:

Objective function

As indicated in Section 1.3, we want to stabilize the workload per week. In the model we describe in Section 4.3, we try to achieve this objective by minimizing the maximum workload per week. To not only minimize the maximum workload per week but also stabilize the workload in the weeks the workload is not that high, we minimize the total standard deviation of the workload in the SA algorithm. Despite that VSM also prefers low inventories, we do not try to minimize the inventory in the objective function. We explain this in Section 5.3.2. Because the CPLEX solver cannot efficiently solve nonlinear models, we cannot minimize the total standard deviation in the MIP model. To linearize the MIP model, we minimize the maximum workload. Since this is not needed in the SA algorithm, the objective function in this algorithm is $\min z = \sqrt{\sum_t((\sum_{j=3}^{6} \text{Workload}_{jt} - \text{AvgWorkload})^2) / T}$, in which Workload_{jt} is the workload per production step j in week t, AvgWorkload is the average workload of the first 4 production steps of the data set, and T is the total number of weeks in which there is workload. Recall from Section 4.1 that there are in total 6 production steps that are variable per weldment and that at the VPM 2 department only 4 of these production steps are executed.

Neighbourhood structure

Within the SA algorithm, we evaluate two different strategies to create a neighbourhood. First, we use the 'move' principle as a neighbourhood operator. For this, we select randomly a weldment and its production steps. Then we look for the predefined ATW windows of the production steps and select randomly a production week per production step from the ATW windows. If the ATW window consists of only one week, the production step will be executed in the same week as it is currently executed. No production step may be moved. In that case, we first try another 9 times to select randomly a week per production step from the ATW windows. If still no production step is moved, we select a different weldment. We refer to this strategy as **SA-Move**. Figure 4-8 illustrates how the move operator works.

Note that the Cutting step for this weldment takes 1.5 hours, the Sawing construction step 1 hour, the Preparation for welding step 5 hours, the Construction welding step 10 hours, and the Finalize welding step also 10 hours.

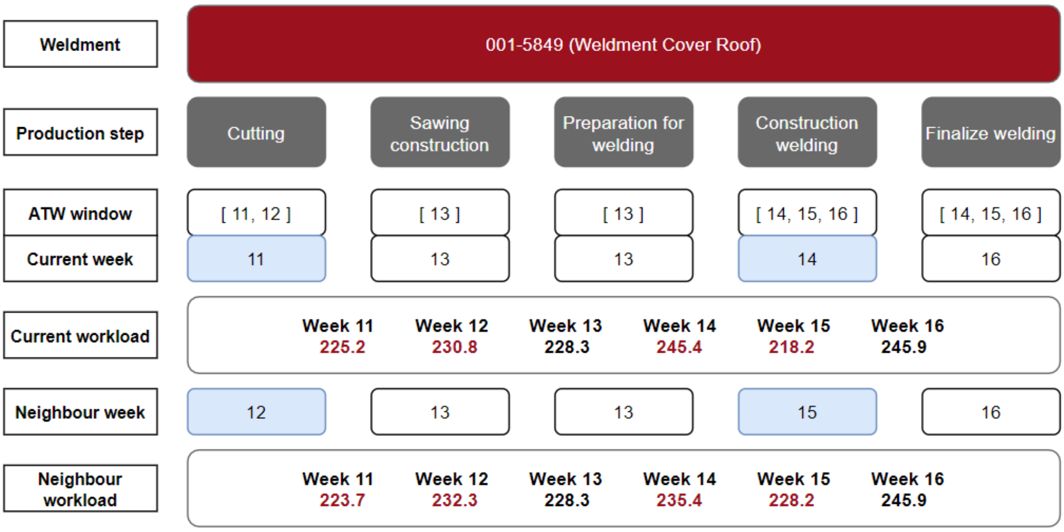

Figure 4-8: Move operator

The second operator we use to create a neighbourhood is the ‘insert’ neighbourhood operator. The insert operator is, just like the move operator, a commonly used neighbourhood operator in SA. In general, it randomly selects a job from the current sequence, removes that job, and reinserts it into a randomly selected new position (Cicirello, 2007). We apply the insert operator slightly differently. Using the insert operator in our SA algorithm, we randomly select a weldment and its production steps from the current plan, remove the production steps one by one, and reinserts the production steps into the week (in its ATW window) in which the workload is the lowest at that moment. We refer to this strategy as **SA-Insert**. Figure 4-9 illustrates how the insert operator works. Note that both operators realize connectivity, i.e., by repeatedly applying one of the two operators, all other solutions can be reached (from every possible solution). Both operators must realize connectivity because in this way, the entire solution space can be explored and the optimal solution can be found.

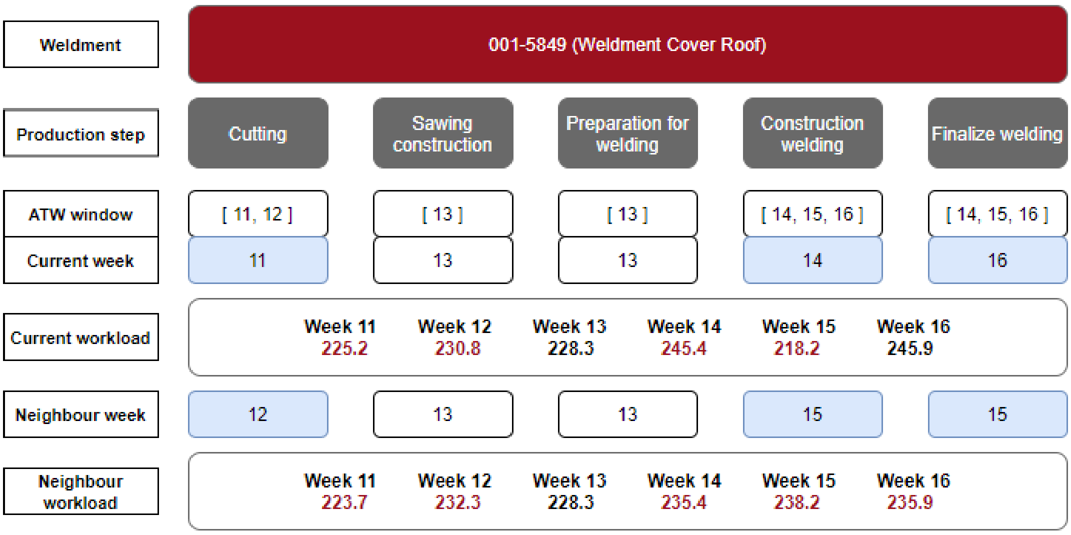

Figure 4-9: Insert operator

Cooling schedule

To run the SA algorithm, we need to determine the cooling schedule. The cooling schedule consists of the length of the Markov Chain, the starting temperature, the cooling down factor, and the stop temperature. Table 4-8 shows an overview of the values we use for the parameters. We determine these values after several experiments, i.e., we establish the values empirically. The results of these experiments can be found in Appendix E.

Table 4-8: SA cooling schedule

Parameter	Value	Explanation
Starting temperature	1	We use a starting temperature of 1 as using this temperature, we achieve an acceptance ratio of approximately 1 in the first Markov Chain.
Stop temperature / stopping criteria	1*10^-5	Using a stop temperature of 1*10^-5, we achieve an acceptance ratio of approximately 0 in the last Markov Chain. Note that the algorithm also can be stopped if the solution has not changed after two Markov Chains. If the solution has not changed after two Markov Chains, the probability that the solution will still change is so small that we stop the heuristic.
Cooling down factor	0.80	We use a cooling down factor α = 0.80 with a cooling scheme $T_{k+1} = \alpha T_k$.
Length Markov Chain	150	We use a Markov chain length of 150. We determine this Markov chain length after some experiments.

Again, using the same test set as we used for the MIP model and using the SA-Move strategy, we obtain the workload graph as Figure 4-10 shows. This workload graph is the result of the improved plan that is created using the SA algorithm. The part of the workload graph in the red square is the relevant plan for the VPM 2 department using the SA-Move strategy. The standard deviation of the relevant plan decreased from 25.114 (using the CS-heuristic) to 0.920 using the SA-Move strategy. In Section 5.2, we analyse the results of the MIP model, the CS-heuristic, and the SA algorithm in more detail.

Figure 4-10: Workload graph SA-Move

4.5 Uncertainties in the execution of the plan

The planning problem that we are trying to solve contains several uncertain factors such as last-minute changes in the forecast, replanning of machines over time (because the customer cannot complete the payment on time for example), deviations in the time it takes an employee to execute a production step, sicknesses, etcetera. In Section 3.4 we discussed four different approaches to deal with scheduling under uncertainty (Herroelen & Leus, 2005; Hans et al., 2007; Masmoudi et al., 2012). An interesting method to apply for VSM is the proactive method.

In the proactive method, we develop a baseline plan that incorporates a degree of anticipation of variability during project execution by using some slack in the plan. By adding some slack in the plan, VSM can anticipate on causes that can lead to overtime. The planned slack is based on the knowledge of the planners. We do not base the planned slack on the results of an analysis of historical data, such as Hans et al. (2008) did for example, as the last annual analysis of the average deviation of the total planned production times from the actual production times has shown that the deviation is very small (0.11%) (Mansveld, 2021). Nevertheless, we advise adding slack in the plan since this slack in time can also tackle other uncertainties, such as sicknesses among employees. This slack can be based on the results of the average deviation analysis.

Next to the proactive method, the planners could also use the stochastic scheduling approach or the approach from Masmoudi et al. (2012). However, we believe that it is not wise to use any of these approaches, as the stochastic scheduling approach requires a probability distribution, and the approach from Masmoudi et al. (2012) requires an expectation and variance of all production steps per employee. Because there are more than 1,900 weldments, it does not seem profitable to determine a probability function and/or expectation and variation for all the production times of the underlying production steps. In addition, the deviation is currently very small and therefore not worth changing or investing much time in. On the other hand, it is always wise to monitor and adjust production times as soon as major differences arise between the planned and actual production times.

There may also be last-minute changes in the plan. To deal with these changes, VSM could combine the proactive approach with the reactive approach to adjust the plan. To reduce the uncertainties in the forecast, we could perform an analysis of the forecast used at VSM. However, this is outside the scope of this research.

4.6 Conclusion

The goal of this chapter is to formulate different solution approaches for the planning problem we defined in Chapter 3. The chapter starts with a description of the planning problem, after which we formulate the different solution approaches. We answered the third research question: "How can the planning problem at VSM be improved?".

To introduce the planning problem, we present a brief contextual description in which we explain the tasks we need to plan, the restrictions we have to consider, and the assumptions we make. After we introduce the model, we explain how we generate the instances that we use as input for the solution approaches. The most important parameter we describe here is the way we generate the ATW windows using the ATW-heuristic. Afterwards, we formulate three different solution approaches in this chapter.

The first solution approach we present in this chapter is a MIP model. The objective of this model is to minimize the maximum workload per week. After we formulate the MIP model, we try to solve an instance of the CPP using the CPLEX solver. It becomes quickly clear that the model could solve the CPP close to optimality. Nevertheless, after analysing the results, we decide to propose a constructive and improvement heuristic for the CPP as well since many parts of weldments are kept in stock in the model, and this is not directly desired at VSM.

Afterwards, we create a heuristic that imitates the current way the planner plans the production steps. In this CS-heuristic, we create an initial plan completing twelve steps. Once we create the heuristics that imitate the current way the planner plans the production steps, we initiate the SA algorithm. The plan that follows from the CS-heuristic is set as the initial plan for the metaheuristic. The objective of the SA algorithm is to minimize the total standard deviation of the workload. In this way, we not only minimize the maximum workload per week but also stabilize the workload in the weeks the workload is not that high. To find neighbour solutions, we use both the move and insert operator. The move operator randomly selects another week in the ATW window in which the production step needs to be planned. The insert operator, on the other hand, looks for the week in the ATW window in which the current workload is the lowest and plans the production step into this week.

Lastly, we discuss how VSM can deal with uncertainties that may arise during the execution of the plan. We advise using the proactive method in combination with the reactive method, i.e., to add some slack in the plan and to revise the plan when an unexpected event occurs. Using this method, VSM can anticipate on causes that can lead to overtime.

5 Analysis

In Chapter 4, we formulated different solution approaches for the CPP. In this chapter, we use the solution approaches to generate plans. The resulting plans are then compared to each other. With this analysis, we answer the fourth research question: "What is the best solution for the planning problem at VSM?". The chapter starts with an explanation of how we collect our data in Section 5.1. Then, in Section 5.2, we analyse the results of the MIP model and the results of the heuristics. Section 5.3 explains the experiments we perform and discusses their results. Section 5.4 concludes this chapter.

5.1 Data collection

Before we can analyse the results of the different solution approaches that we formulate in Chapter 4, we need to define how we collect our data. Using the data, we create datasets that we use to test our solution approaches.

Recall from Section 4.2.4 that we can make order lists using RFC reports since these RFC reports state which machines are expected to be sold and when these machines are expected to be sold. These order lists are used as input datasets for the analysis of the solution approaches and the experiments. We decide to use 4 datasets each containing at least 17 weeks in which there is demand. These datasets are from 2019, 2020 or 2021. Table 5-1 shows per dataset the number of weeks in which there is demand, the total production steps to plan, and the weeks the RFC report are from.

Table 5-1: Datasets for experiments

Dataset	Weeks with demand	Total production steps to plan	RFC reports (week-year)
Dataset 1	27	4,605	51-2019 & 04-2020 & 09-2020
Dataset 2	17	2,802	40-2020 & 44-2020 & 48-2020
Dataset 3	19	3,179	08-2021 & 12-2021 & 15-2021
Dataset 4	23	3,320	15-2021 & 17-2021 & 21-2021

Recall also from Section 4.2.4 that the relevant plan is the plan of the VPM 2 department for the first 5 weeks after the last included RFC report. The relevant plan is the result of the input from one of the datasets using one of the solving approaches. For Dataset 1, for example, this means that the relevant plan only consists of weeks 10-14. Note that we need multiple RFC reports as input for the model and the heuristics, as there is overlap in the production weeks of the machines that are expected to be sold in the RFC meeting. That is why we need at least the RFC reports of the last 7 weeks before the relevant plan to determine the relevant plan. This means that if we want to know the relevant plan from weeks 20-24, for example, we must have at least the RFC reports from weeks 13-19.

5.2 Analysis solution approaches

In this section, we analyse the results of the MIP model, the CS-heuristic, and the SA algorithm. Recall from Section 2.5 that we define 4 KPIs to measure the performance of the plan: (1) Standard deviation of workload per week, (2) Delivery accuracy, (3) Outsourcing costs, and (4) Capacity per production step. KPI (1), (2), and (4) are used in the analysis of the results of the solution approaches in this section. In Section 5.3, we analyse the results of the experiments we conduct. In these analyses, we use, among others, KPI (1) and (3).

As stated in Section 4.2.4, the plan that follows from the results of the model and the heuristics should be updated at least every 5 weeks. If new demand comes in earlier, the plan has to be updated even more often. For this reason, we compare the results of the model and the heuristics for multiple datasets. We use the current inventory level as the initial inventory level for the model and the heuristics. To determine to what extent the results of the SA algorithm depend on the variability caused by the randomness, we replicate both the SA-Move strategy and the SA-Insert strategy 3 times. We choose to replicate the SA algorithms 3 times in this section to make sure we have chosen the correct parameters. If the differences between the results are less than 0.01, we no longer replicate the SA algorithms in the remainder of this study.

Table 5-2 shows the results of the MIP model and the heuristics for all datasets. In the column 'STDEV' and 'MAX', we record the standard deviation of the relevant plan and the maximum workload in hours from the relevant plan, respectively.

Table 5-2: Results of all datasets

Solution approach	Dataset 1		Dataset 2		Dataset 3		Dataset 4	
	STDEV	MAX	STDEV	MAX	STDEV	MAX	STDEV	MAX
MIP model	0.019	205.8	0.009	227.3	0.015	260.7	0.024	199.5
CS-heuristic	27.117	300.1	26.884	328.8	35.605	382.8	27.463	236.1
SA-Move	3.478	244.2	0.179	283.8	1.993	293.3	1.777	216.2
SA-Insert	19.532	272.6	14.979	300.5	24.056	340.2	5.630	220.6

The results show that the SA-Move heuristic creates the best plan based on the standard deviations compared to the CS-heuristic and the SA-Insert heuristic. Both the SA-Move and the SA-Insert heuristics have improved the CS-heuristic in all datasets. The CS-heuristic plans the production steps one by one. In this, the heuristic does not consider the whole dataset. As a result, this heuristic performs less well than the SA heuristics. Besides, the SA-Insert heuristic focuses too much on planning the production steps in the weeks in which the workload is not that high. Because of this, too few new solutions are found to escape the local optimum at the end of the heuristic. The randomness in the selection of the production week from the ATW window per production step in the SA-Move heuristic ensures that new solutions are also found at the end of this heuristic which makes this heuristic performing the best. Figure 5-1 and Figure 5-2 show the differences between the standard deviations and maximum workload for all datasets and solution approaches based on the relevant plan.

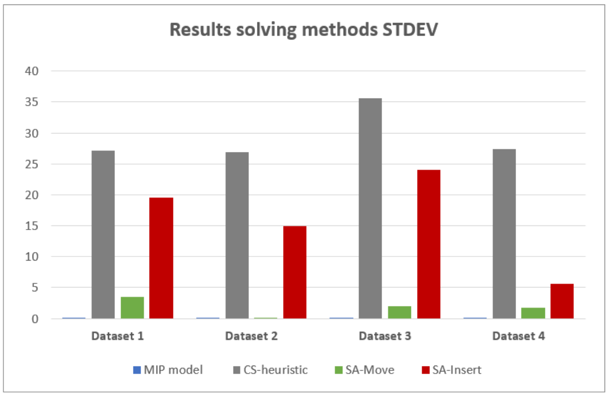

Figure 5-1: Comparison results STDEV

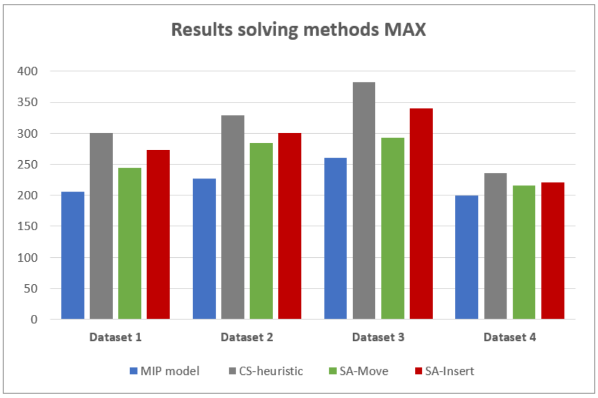

Figure 5-2: Comparison results MAX

As can be seen in the figures, the MIP model performs the best in terms of standard deviation and maximum workload for the relevant plan. The average standard deviation of the MIP model for the 4 datasets is 0.017. This means that there is almost no variability in the plan and therefore that the plan is very stable. The average standard deviations of the CS-heuristic, SA-Insert heuristic, and SA-Move heuristic are 29.267, 16.049, and 1.857, respectively. Figure 5-3 to Figure 5-6 show the relevant plan created using the input from Dataset 3. To keep the report concise, we only present the workload graphs using Dataset 3 in the remainder of this chapter. We use the results from Dataset 3 in this chapter because the results from this dataset show the differences between the solution approaches most clearly.

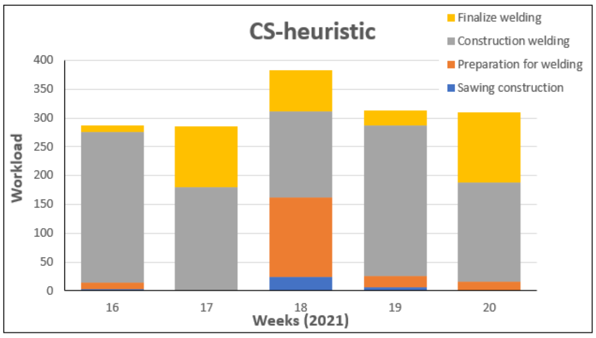

Figure 5-3: Relevant plan Dataset 3 CS-heuristic

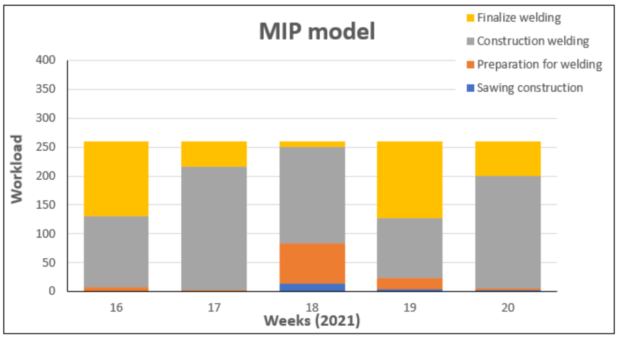

Figure 5-4: Relevant plan Dataset 3 MIP model

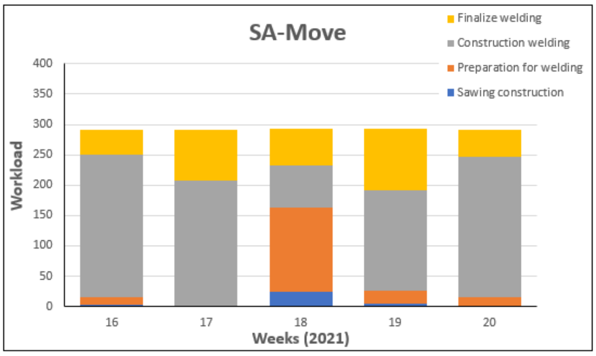

Figure 5-5: Relevant plan Dataset 3 SA-Move

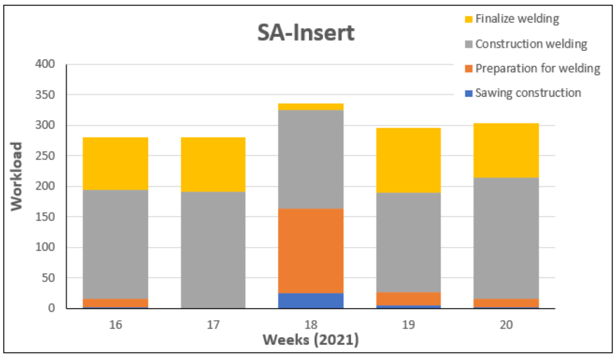

Figure 5-6: Relevant plan Dataset 3 SA-Insert

As the figures show, both the MIP model and the SA-Move heuristic stabilize the relevant plan. The CS-heuristic and the SA-Insert heuristic both have a high peak in week 18 in the relevant plan. Using the CS-heuristic, this peak (382.8 hours) is more than 40 hours higher than using the SA-Insert heuristic (340.2 hours). Besides, we note that the average workload of the MIP model is lower than the average workload of the heuristics. This is mainly because the MIP model plans as much workload as possible as early as possible so that the maximum workload in the relevant plan is low. However, as mentioned in Section 4.4, the results of the MIP model have a major drawback compared to the heuristics. The MIP model puts many parts of the weldments in stock for a long time. Since VSM has no warehouse for these parts at the moment, it is not desirable to put many parts in stock. Figure 5-7 shows the difference between the intermediate inventory value of the MIP model and the heuristics of the complete plan.

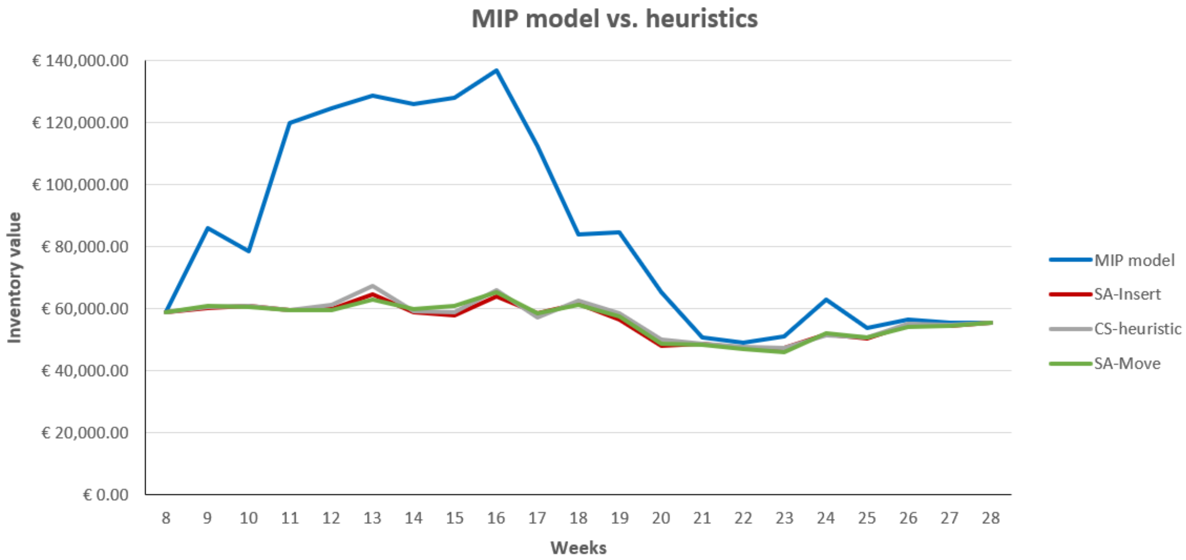

Figure 5-7: Inventory value MIP model vs. heuristics

As we can see in the graph, especially in the first weeks of the complete plan resulting from the MIP model, the inventory value is much higher than the inventory value of the complete plan resulting from the heuristics. In the heuristics, all production steps of a weldment are executed within a few weeks, keeping internal inventory levels low. The results of the MIP model show that the production quantities in the first weeks are higher than the demand, while the production quantities in the heuristics are almost equal to the demand. The CPLEX solver of the MIP model makes the model produce more than is demanded in the first weeks to reduce the average workload. Since the maximum inventory value restriction allows this up to an inventory value of €350,000, the intermediate inventory value increases. Because we do not try to minimize the maximum workload in the heuristics (but the standard deviation), the intermediate inventory value of the heuristics does not increase.

In addition to the intermediate inventory value, we also conclude from the distribution of the capacity per production step that the MIP model keeps many parts of weldments in stock. Figure 5-8 and Figure 5-9 show workload graphs of all production steps of the complete plan resulting from the MIP model and the SA-Move heuristic using Dataset 3. Note that these workload graphs are *not* workload graphs for the VPM 2 department but are workload graphs showing all 6 production steps.

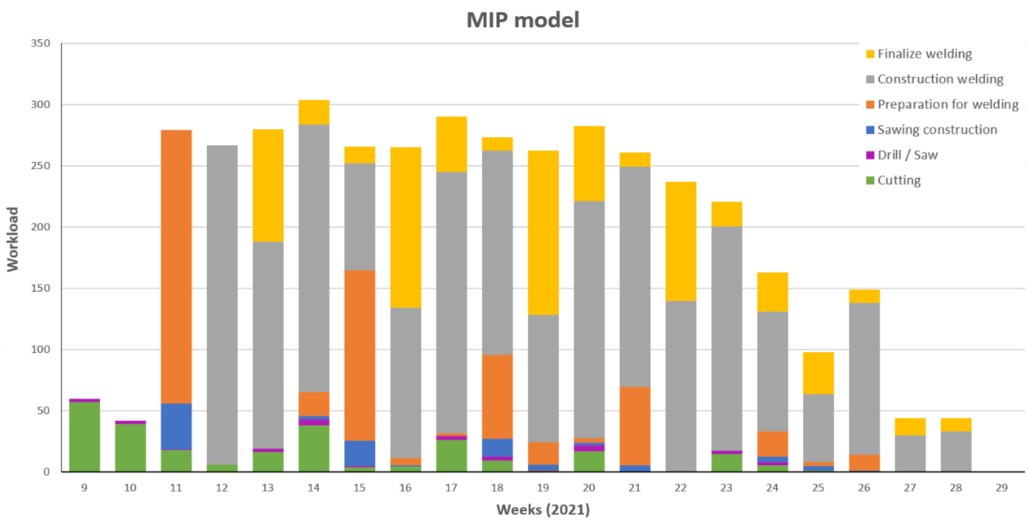

Figure 5-8: Workload all production steps using MIP model

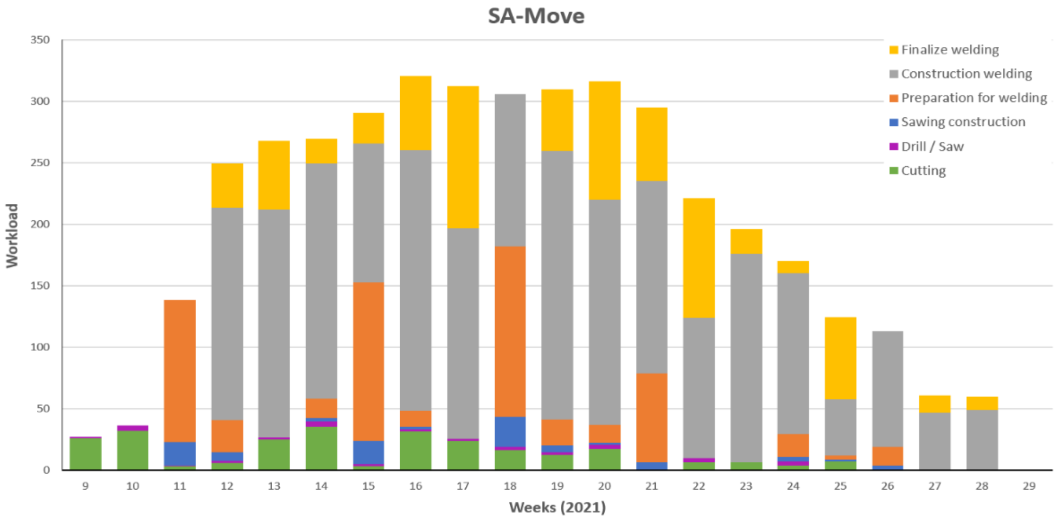

Figure 5-9: Workload all production steps using SA-Move

We present these workload graphs that are showing all 6 production steps to show the distribution of the capacity of all production steps. This is interesting to present as there are precedence relations between the production steps. As we see in the two figures, a large part of the production steps Cutting, Drill / Saw, Sawing construction, and Preparation for welding is executed in the first weeks in the workload graph created with the MIP model. Table 5-3 presents the percentage of the total production time per production step that is executed in the first 5 weeks of the complete plan using the MIP model and the heuristics.

Table 5-3: Percentage of production steps executed in first 5 weeks

Production step	Dataset 3			
	MIP model	CS-heuristic	SA-Insert	SA-Move
Cutting	52.6%	37.2%	37.5%	35.9%
Drill / Saw	27.5%	33.3%	33.7%	28.0%
Sawing construction	38.3%	27.1%	27.1%	27.1%
Preparation for welding	38.4%	24.3%	24.3%	24.3%
Construction welding	18.1%	17.9%	13.9%	15.1%
Finalize welding	12.5%	12.5%	12.5%	12.5%

Since the first 4 production steps take generally not much time, the MIP model plans as many as possible of these steps in the first weeks so that the remaining production steps (which generally take more time) can be spread over the weeks later in the plan. However, this leads to a higher intermediate inventory value since many parts of weldments are put in stock by the MIP model. In Section 5.3, we experiment with the inventory value.

In addition to the standard deviation and the maximum workload of the relevant plan, we measure the performance of the relevant plan created by the solution approaches in terms of delivery accuracy and capacity per production step. We measure the delivery accuracy of the MIP model and the heuristics by dividing the number of times a production step is planned inside its time window by the total number of times a production step is planned. The delivery accuracy of all production steps in both the MIP model and in the heuristics is always 100%. This is because we use the ATW-heuristic. In this heuristic, we determine the time window in which a production step should be executed. We then, generally, plan the production steps in this time window. Recall from Section 4.2.2 and Section 4.4.2 that in some situations, such as when the production capacity is exceeded, production steps are planned outside the time window. However, these situations do not occur using the defined datasets. This means that if at the end of each week in the relevant plan all production steps that have been planned have been executed, delivery will never be late. In practice, however, the relevant plan will probably not be completed every week because of the uncertain factors that are in the plan. Recall from Section 4.5 that we advise VSM to add some slack in the plan and to revise the plan when an unexpected event occurs to anticipate on causes that can lead to overtime.

Lastly, we determine the capacity per production step for VSM based on the input of the datasets and the results of the relevant plan. For each dataset, we calculate the total number of hours per production step that must be executed in the relevant plan. Table 5-4 lists these hours for Dataset 3.

Table 5-4: Total hours to be executed per production step

Production step	MIP model	CS-heuristic	SA-Move	SA-Insert
Cutting	58.8	102.6	102.6	102.6
Drill / Saw	11.6	11.6	11.6	11.6
Sawing construction	22.0	33.9	33.9	33.9
Preparation for welding	99.2	186.7	186.7	186.7
Construction welding	800.0	1,023.6	907.1	894.6
Finalize welding	382.0	333.0	332.0	381.0
Total	**1,373.6**	**1,691.4**	**1,573.8**	**1,610.3**

After we calculated the total number of hours per production step that must be executed in the relevant plan, we calculate the ratio between the hours per production step. The left side of Table 5-5 shows the ratios between the hours per production step and per solution approach for Dataset 3. For the MIP model, for example, 4.28% (which is 58.8 hours divided by 1,373.6 hours) of the total production time in the relevant plan must be spent on the production step Cutting. We execute these calculations for each solution approach and then take the average over the 4 datasets. From the results of these calculations, we conclude that the ratio between the production steps is 6:1:2:13:62:16. This means that for every 100 employees, 6 must be able to execute the production step Cutting, 1 the Drill / Saw, 2 the Sawing construction, 13 the Preparation for welding, 62 the Construction welding, and 16 the production step Finalize welding. Recall from Section 2.1.5 that there are approximately 25 employees at VSM who execute one of these production steps. So, in practice, the ratio between the production steps will be approximately 2:1:1:2:15:4. The right side of Table 5-5 shows the average ratios between the hours per production step and per solution approach over the 4 datasets.

Table 5-5: Ratios per production step

	Dataset 3				Average			
Production step	**MIP model**	**CS-heuristic**	**SA-Move**	**SA-Insert**	**MIP model**	**CS-heuristic**	**SA-Move**	**SA-Insert**
Cutting	4.28%	6.07%	6.52%	6.37%	4.89%	6.05%	6.32%	6.01%
Drill / Saw	0.85%	0.69%	0.74%	0.72%	1.13%	1.02%	1.03%	1.02%
Sawing construction	1.60%	2.00%	2.15%	2.10%	1.82%	2.06%	2.13%	2.08%
Preparation for welding	7.22%	11.04%	11.86%	11.59%	10.23%	13.36%	13.73%	13.45%
Construction welding	58.24%	60.52%	57.63%	55.55%	62.21%	62.63%	61.40%	62.02%
Finalize welding	27.81%	19.69%	21.09%	23.66%	19.72%	14.87%	15.39%	15.41%
Total	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**

From this analysis of the performance of the solution approaches, we conclude that the SA-Move heuristic is the heuristic that performs the best. The standard deviation and the maximum workload of the relevant plan created using the SA-Move heuristic are the lowest compared to the other heuristics. Although the MIP model has a lower maximum workload in the relevant plan, the standard deviations are close to each other. In addition, the SA-Move heuristic keeps fewer parts of weldments in stock. The division between the capacity in the production steps is more evenly distributed in the SA-Move heuristic than in the MIP model. Since the performance of the MIP model and the SA-Move heuristic are close to each other, we decide to conduct experiments using these two solution approaches.

5.3 Analysis experiments

In this section, we discuss the results of the 3 experiments we conduct. First, we describe these 3 experiments. Then, we explain our method per experiment in more detail and analyse the results of the experiments.

5.3.1 Experiments

In this research, we conduct 3 different experiments. In these experiments, we want to test how the MIP model and the SA-Move heuristic react if a constraint is changed, if some input data is changed, and if we vary the ATW windows. Since we saw in the analysis of the solution approaches that the variability due to the randomness in the SA heuristics has only a small influence on the results (the differences between the results are less than 0.01), we decide not to perform replications in the experiments.

In the first experiment, we fluctuate the maximum inventory value (see constraint (14) in the model). Currently, in the model and algorithms, we include an inventory value restriction of €350,000. In this experiment, we fluctuate this maximum inventory value. By fluctuating this value, we want to demonstrate the trade-off between inventory value and stability in the plan.

In the second experiment, we analyse the trade-off between the outsourcing costs due to the fixed lot sizes and the stability in the plan. At the moment, some weldments have a fixed lot size because this has financial advantages. By producing the weldments individually, the outsourcing costs for these weldments would be higher. By excluding these fixed lot sizes and thus giving the MIP model and the SA-Move heuristic the possibility to produce only the weldments that are demanded, we can demonstrate the trade-off between outsourcing costs and stability in the plan.

In the third and last experiment, we analyse the influence of varying time windows on the plan. We do this by generating time windows per weldment in several ways. With this, we want to analyse how much influence a varying time window has on the stability and maximum workload of the relevant plan.

5.3.2 Experiment 1: Inventory value restriction

As stated in Section 5.3.1, in this experiment we fluctuate the maximum inventory value to demonstrate the trade-off between inventory value and stability in the plan. Currently, the maximum inventory value is €350,000. After a brief analysis, we conclude that the inventory value in both the MIP model and the heuristics is always less than €140,000. Since we include only 550 of the 1,952 different weldments in this research and the current maximum inventory value (€350,000) is based on the 1,952 weldments, it makes sense that this maximum inventory value restriction will never be binding. By considerably lowering the maximum inventory value restriction, we can analyse the effect of this restriction on the results of the MIP model and the SA-Move heuristic. Table 5-6 shows the maximum inventory values we use in the experiments and the results of the MIP model and the SA-Move heuristic in terms of standard deviation and maximum workload. Note that we fluctuate the maximum inventory value using Dataset 3.

Table 5-6: Results per maximum inventory value Experiment 1

Max. inventory values (x 1,000 €)	MIP model		SA-Move	
	STDEV	MAX	STDEV	MAX
350	0.015	260.7	1.993	293.3
135	0.013	260.7	1.982	293.3
120	0.006	260.7	1.976	293.3
105	0.007	260.7	1.994	293.3
90	0.003	260.8	1.988	293.3
75	0.004	269.8	2.001	293.3
70	0.024	281.9	1.984	293.3
66	11.971	308.2	2.003	293.3

As can be seen in the table, the standard deviation of the SA-Move heuristic hardly changes. This is because we ensure that the production of a weldment is always finished within several weeks in this heuristic. Because of this, the intermediate inventory value in the SA-Move heuristic is already low. If we lower the maximum inventory value to €70,000, the MIP model still outperforms the SA-Move heuristic. Only when we lower the maximum inventory value to €66,000, the SA-Move heuristic outperforms the MIP model. The SA-Move heuristic outperforms the MIP model if the maximum inventory value is €66,000 because the MIP model can in that case no longer minimize the maximum workload peak in the relevant plan, causing a higher standard deviation. If we lower the maximum inventory value even further to, for example, €50,000, there is no longer a feasible solution. This is because (using Dataset 3) there is a minimum total inventory value of approximately €60,000. Recall from Section 4.2.3 that this minimum inventory value arises due to the fixed lot size of weldments. Figure 5-10 visualizes the evolution of the inventory value per experiment for the MIP model. Figure 5-11 shows the difference in the maximum workload per experiment.

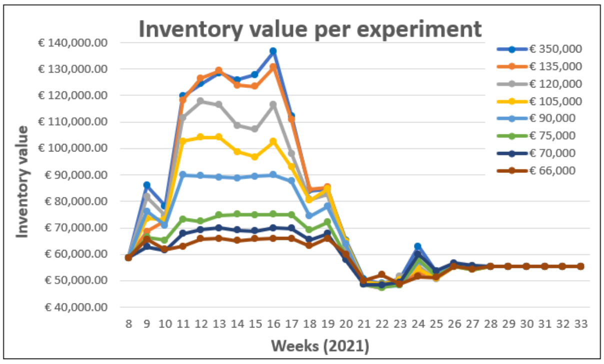

Figure 5-10: Inventory value per experiment

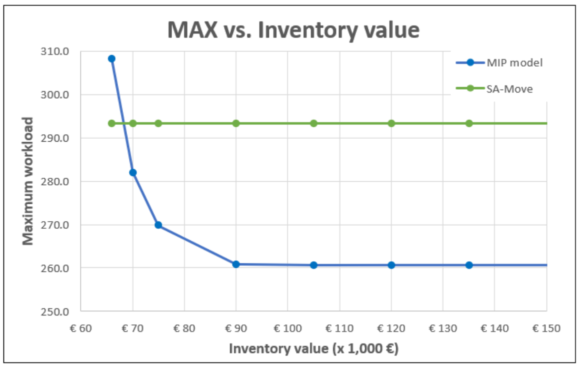

Figure 5-11: Maximum workload vs. inventory value

From these results, we conclude that the MIP model stabilizes the plan better than the SA-Move heuristic even if we lower the maximum allowed inventory value to €70,000. Only from an inventory value lower than €70,000 we see changes in the results of the MIP model in terms of stability and maximum workload of the relevant plan. Using a maximum allowed inventory value of €66,000 limits the MIP model in its solution. In addition, we see that the results of the SA-Move heuristic hardly change due to the decrease in the inventory value. This is because the inventory value of the SA-Move heuristic already only varies between €60,000 and €70,000.

5.3.3 Experiment 2: Outsourcing costs vs. Fixed lot size

As mentioned in Section 5.3.1, some weldments have a fixed lot size because this has financial advantages. For some weldments, external suppliers offer a lower price to VSM if VSM supplies these weldments per batch (2 or 4 for example). Often, the external supplier can process these weldments faster per batch than per piece, making it more beneficial for the supplier to produce these weldments per batch. By analysing the amount of money involved and how much influence this batch production has on the plan, we can present the trade-off between outsourcing costs and stability in the plan to VSM.

To conduct this experiment, we need a list of weldments currently being produced in batches. This list is presented in Appendix F. Next to this, we need to define the scenarios that we use in this experiment. In total, we use 4 different scenarios. In the first scenario, we imitate the current situation, i.e., the MIP model and the heuristic produce the weldments in batches that currently are produced in batches. In the second scenario, we reduce the fixed lot size using two bounds. If the price advantage per weldment is more than €200, we use the fixed lot size as currently used, and if the price advantage per weldments is more than €100 (but less than €200), we use a fixed lot size that is twice as high as the number of weldments that is in the machine. If the price advantage per weldments is less than €100, we do not use a fixed lot size. In the third scenario, we determine the fixed lot size in the same way but we do not use the price advantage per weldment but the total production time per weldment. The bounds in this scenario are 3 hours and 5 hours. If the total production time of a weldment is less than 3 hours, we use the currently used fixed lot size, if it is between 3 and 5 hours, we use a fixed lot size that is twice as high as the number of weldments that is in the machine, and if it is more than 5 hours we do not use a fixed lot size. In the last scenario, we set the fixed lot size equal to the number of times a weldment is in the machine.

Using Dataset 3, we know that the total demand for the weldments from the list in Appendix F is equal to 313 weldments. The total number of weldments that are in stock at the end of the complete plan is for both the MIP model and the SA-Move heuristic for each scenario the same. Table 5-7 gives the number of weldments in stock and the outsourcing costs per scenario. We divide the outsourcing costs into costs for weldments that are demanded and costs for weldments that have been produced (due to the fixed lot size) but are not demanded yet and therefore are put in stock. In the column 'Cost advantage', we present the cost advantage of producing the weldments per batch compared to the costs of producing the weldments per piece. Note that we increase/decrease the cost of producing the weldments in batch proportionally based on the price per weldment and the price per batch. For example, this means for weldment 006-4287 that, given the outsourcing costs of €159.83 for a fixed lot size of 10 and the outsourcing costs of €312.85 per weldment, we determine the outsourcing costs for a fixed lot size of 2 of these weldments to be €295.85 (= €159.83 + ([€312.85 - €159.83]/[10 – 1]) * [10 – 1 – 1]).

Table 5-7: Costs per scenario

Scenarios	Weldments in stock	Total costs	Costs weldments demanded	Costs weldments not demanded	Cost advantage
Scenario 1	39	€219,411	€203,139	€16,272	€70,900
Scenario 2	19	€228,387	€215,050	€13,337	€56,525
Scenario 3	34	€246,425	€236,213	€10,212	€35,304
Scenario 4	0	€266,338	€266,338	€0	€0

We measure the stability in the plan using the standard deviation of the relevant plan. In addition, we measure the maximum workload of the relevant plan. Table 5-8 shows the standard deviation and the maximum workload of the relevant plan. These results follow from the MIP model and the SA-Move heuristic.

Table 5-8: Stability in the relevant plan per scenario Experiment 2

Scenarios	MIP model		SA-Move	
	STDEV	MAX	STDEV	MAX
Scenario 1	0.015	260.7	1.993	293.3
Scenario 2	0.003	259.7	1.126	292.3
Scenario 3	0.014	257.1	0.908	292.6
Scenario 4	0.003	254.2	0.346	291.3

From the results presented in Table 5-7 and Table 5-8, we conclude that the higher the outsourcing costs, the lower the standard deviation in the relevant plan and vice versa. In the results of the MIP model, we see that the created relevant plan is (already) almost completely stable. The standard deviation of the SA-Move is also already low but still decreases smoothly when lowering the fixed lot sizes in the scenarios. In addition, we see that the maximum workload in the relevant plan decreases slightly in both the MIP model and the SA-Move heuristic when fewer weldments from the list in Appendix F need to be produced. Nevertheless, it is difficult to give a clear recommendation which weldments should have and which weldments should not have a fixed lot size. Because we only include a part (550) of the total (1,952) weldments in our research, the differences between the scenarios are small. In our datasets, there are only a few weldments that have a fixed lot size for financial reasons. Figure 5-12 and Figure 5-13 visualize the trade-off between the outsourcing costs and the stability in the relevant plan.

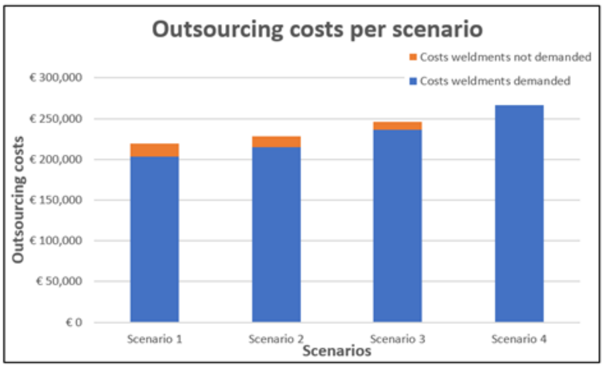

Figure 5-12: Outsourcing costs per scenario

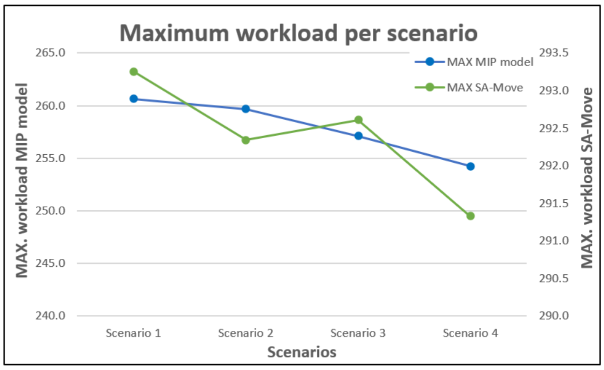

Figure 5-13: Maximum workload per scenario

5.3.4 Experiment 3: Varying time window

As stated in Section 5.3.1, we vary the time window per weldment in this experiment. By varying the time window per weldment, we analyse how much influence a varying time window has on the stability and maximum workload of the relevant plan.

To test different methods to generate the ATW windows, we define 3 scenarios. In scenario 1, we generate the ATW windows using the ATW-heuristic. In scenario 2, we determine in which weeks it is allowed to execute a production step by using the precedence relations between the production steps and the individual production times of the production steps. For this, we first calculate the total number of weeks within which all 6 production steps must be executed. Then, we divide for each production step the production time of the production step by the total production time of the weldment and multiply this by the total number of weeks within which all 6 production steps must be executed. This value is rounded to the closest integer with a minimum of 1. We determine the ATW window of a production step then using the precedence relations, the lengths of the previous ATW windows, and the release date of the order of the weldment. If the total length of all ATW windows is longer than the total number of weeks within which the 6 production steps must be executed, the window with the largest absolute difference between the rounded number and the unrounded number is reduced (unless this window already consists of only 1 week). In scenario 3, we determine the ATW windows per production step based on the total production time of the weldment. If the entire weldment can be produced within 8 hours, we give each production step an ATW window of 1 week. If the weldment can be produced within 40 hours but not in 8 hours, the production step gets an ATW window of 1 or 2 weeks, depending on the individual production time of the production step. If the production step can be executed in less than 4 hours, it gets an ATW window of 1 week, otherwise an ATW window of 2 weeks. If the total production time of a weldment is longer than 40 hours, we use the ATW-heuristic to define the ATW windows per production step. Table 5-9 shows the standard deviation and the maximum workload of the relevant plan using Dataset 3.

Table 5-9: Stability in the relevant plan per scenario Experiment 3

Scenarios	MIP model		SA-Move	
	STDEV	MAX	STDEV	MAX
Scenario 1	0.015	260.7	1.993	293.3
Scenario 2	0.015	234.4	0.820	255.4
Scenario 3	0.004	251.4	11.300	302.4

From the results, we conclude that the workload is stabilized the best in scenario 2. In the heuristic we use in this scenario, we balance the workload per production step and the length of the ATW window. The production steps with the longest production time get the longest window and vice versa. As a result, the MIP model and the SA-Move heuristic have more (allowed) weeks to plan the production steps with much production time and so to spread the workload, reducing the maximum workload of the relevant plan. In scenario 3, the MIP model stabilizes the workload almost optimally for the relevant plan. However, the MIP model puts many parts of weldments in stock for this. The SA-Move heuristic does not put many parts of weldments in stock which causes a less stable workload in the relevant plan made by this heuristic.

5.4 Conclusion

Based on the analysis of the results of all solution approaches, we conclude that the SA-Move heuristic performs the best. The SA-Move heuristic outperforms the CS-heuristic and the SA-Insert heuristic in terms of the standard deviation of the relevant plan and the maximum workload from the datasets. Both the SA-Move and the SA-Insert heuristics have improved the CS-heuristic in all datasets. Although the MIP model performs better than the SA-Move heuristic, the MIP model has a drawback compared to the heuristic. The MIP model puts many parts of the weldments in stock for a long time, which is currently not desired at VSM. Since the performance of the MIP model and the SA-Move heuristic are close to each other, we decided to conduct experiments using these two solution approaches.

In the first experiment, we fluctuate the maximum inventory value. We decreased the maximum allowed inventory value from €350,000 to €66,000. From the results of this experiment, we concluded that the MIP model stabilizes the relevant plan better than the SA-Move heuristic even if we lower the maximum allowed inventory value to €70,000. We also concluded that the results of the SA-Move heuristic hardly change due to the decrease in the inventory value since this heuristic already puts few weldments in stock.

In the second experiment, we analyse the trade-off between the outsourcing costs due to the fixed lot sizes and the stability in the plan. We concluded that for both solution approaches, the higher the outsourcing costs, the lower the standard deviation in the relevant plan, and vice versa. However, the differences between the outsourcing costs and the stability in the relevant plan are small. This is because we only include a part (550) of the total (1,952) weldments in this research.

In the third experiment, we vary the time window per weldment to analyse how much influence a varying time window has on the stability and maximum workload of the relevant plan. From the results of this experiment, we concluded that the workload of the relevant plan can be stabilized the best if the workload per production step and the length of the ATW window are balanced.

From the experiments, we conclude that the SA-Move heuristic performs the best. The results of the MIP model and the SA-Move heuristic are comparable. The results of the MIP model are often even slightly better. Nevertheless, we advise VSM to still use the SA-Move heuristic to make the plan because this heuristic performs well regardless of the maximum inventory value. In Section 6.2, we discuss other advantages of the SA-Move heuristic over the MIP model.

6 Conclusions and Recommendations

In this chapter, we conclude our research and provide recommendations to VSM. For this, we use the results obtained in this research. Section 6.1 describes the main conclusions for this research. Section 6.2 first discusses the implementation process for introducing our planning approach in VSM. Afterwards, we discuss the recommendations to VSM in this section. In Section 6.3 we discuss the limitations of this research. The chapter ends with suggestions for further research in Section 6.4.

6.1 Conclusions

In this research, we aimed to answer the research question:

How can the planning process within VSM be organised such that the workload of the VPM 2 department is stabilized?

To achieve the objective of this research and to answer the main research question, we divide our problem approach into 5 different phases. We discuss the conclusions per phase in this section.

Currently, the plan of the VPM departments is unstable due to the high variability in the workload per production order and because VSM wants to guarantee short delivery times to their customers. To organise the planning process within VSM differently such that the workload of the VPM departments is stabilized, we started with an analysis regarding the current planning and production process. In this analysis, we quickly found out that stabilizing the workload of all departments within VSM was too complicated. That is why we focus on the plan of the VPM 2 department in this research. At the VPM 2 department, 4 of the 6 production steps that could be in a weldment are executed. When all materials are cut, drilled, and/or sawn, these materials are welded into weldments in the VPM 2 department. This is done in the production steps Sawing construction, Preparation for welding, Construction welding, and Finalize welding. When these production steps from all weldments that are in the modules that are in the machines are planned, the workload per week of the VPM 2 department is known.

To gain more knowledge to support the improvement of the plan of VSM, we conducted a literature review. In this literature review, we positioned our planning problem to be a capacity planning problem (CPP) at the tactical level. We learned that we can address the problem setting of VSM in two different ways. We can approach the planning problem as a time-driven Rough-Cut Capacity Planning (RCCP) problem or as a resource loading problem. To solve our CPP, we use an exact approach and several approximation approaches. In the exact approach, we created a MIP model based on the mathematical formulations of the time-driven RCCP and the resource loading problem. The objective of this MIP model is to minimize the maximum workload per week. In the approximation approaches, we created a constructive heuristic that imitates the current situation (CS-heuristic) and tried to improve the plan created by this heuristic using the simulated annealing algorithm with two operators, i.e., using the SA-Move heuristic and the SA-Insert heuristic. In the simulated annealing heuristics, we tried to minimize the standard deviation of the workload.

When comparing the relevant plan created by the MIP model and the heuristics, we concluded that the SA-Move heuristic creates the best plan based on the standard deviation and the maximum workload of the relevant plan compared to the CS-heuristic and the SA-Insert heuristic. The average standard deviation of the relevant plan created using 4 predefined datasets decreased from 29.267 (CS-heuristic) to 1.857 (SA-Move heuristic). In addition, the average maximum workload of the relevant plan decreased from 311.2 hours using the CS-heuristic to 259.4 hours using the SA-Move heuristic. The MIP model, however, outperforms all heuristics. The average standard deviation and maximum workload of the relevant plan created using the MIP model are 0.017 and 223.33 respectively. The disadvantage of the MIP model is that it puts many parts of weldments in stock for a long time, which is not desirable at VSM. Since both the MIP model and the SA-Move heuristic perform well, we decide to perform experiments with these two solution approaches.

In the first experiment, we decreased the maximum allowed inventory value considerably. From this experiment, we concluded that the MIP model outperforms the SA-Move heuristic until the inventory value drops below €70,000. In addition, we concluded that the MIP model is sensitive to the maximum allowed inventory value and the SA-Move heuristic not. We analysed the influence of the fixed lot sizes some weldments have (due to financial advantages) on the stability in the plan of VSM in the second experiment. For this, we presented a trade-off between the outsourcing costs and the stability in the plan. We concluded that the higher the outsourcing costs, the lower the standard deviation and the maximum workload in the relevant plan. However, the differences were minimal due to the few weldments that had to be produced in the dataset. In the third experiment, we vary the time window per weldment to analyse the influence of a varying time window on the stability and maximum workload of the relevant plan. From the results of this experiment, we concluded that the workload of the relevant plan can be stabilized the best if the workload per production step and the length of the ATW window are balanced. Table 6-1 shows an overview of the most important results per experiment.

Table 6-1: Overview results per experiment

Experiments	Scenarios	MIP model		SA-Move	
		STDEV	MAX	STDEV	MAX
Experiment 1	Max. inventory value = €350,000	0.015	260.7	1.993	293.3
	Max. inventory value = €66,000	11.971	308.2	2.003	293.3
Experiment 2	Low outsourcing costs	0.015	260.7	1.993	293.3
	High outsourcing costs	0.003	254.2	0.346	291.3
Experiment 3	ATW-heuristic	0.015	260.7	1.993	293.3
	ATW window – production step	0.015	234.4	0.820	255.4

From the analysis of the solution approaches and the experiments, we concluded that the SA-Move heuristic performs the best. The results of the MIP model and the SA-Move heuristic are comparable. Nevertheless, we concluded to use the SA-Move heuristic to make the plan because this heuristic performs well regardless of the maximum inventory value. This heuristic is also more user-friendly and easier to apply in practice.

6.2 Recommendations

Based on the conclusions and results of our research, we have various recommendations for VSM. Before we discuss these recommendations, we present instructions on how to implement our planning approach in VSM. Besides, we explain how the results of our planning approach can be read and how the planners of VSM can make a plan from these results.

As soon as it is decided to start the production of a machine, this machine can be added to the order list. This can be done easily by filling the customer name, machine, deadline week and year, and the current week in the order list. Table 6-2 provides an example of an order list. The grey coloured columns are the input values that should be given by the user. The other columns in the order list are filled using formulas.

Table 6-2: Example order list

Customer number	Machine	Deadline (week)	Deadline Year	RFC week	Time of delivery Cold start	Release date (week)	Release Year	Weeks available for production
RFC1065	V325-3000	7	2021	40	20	40	2020	20
RFC1066	V325-3000	12	2021	40	20	45	2020	20
RFC1067	V310	2	2021	40	15	40	2020	15
RFC1068	V310	4	2021	40	15	42	2020	15
RFC1069	V320-3000	6	2021	40	16	43	2020	16
RFC1070	V320-2000	10	2021	40	16	47	2020	16
RFC1071	V631-1050T	6	2021	40	18	41	2020	18

Using this order list, the ATW windows can be determined and the SA-Move heuristic can be run, after which the solution is written to an Excel file. The solution is given in terms of a production list. This production list states which production step needs to be executed in which week. In addition, we see how often this production step has to be performed, how much time it takes, how many parts from the production step of the weldment are in stock at the end of the week, and how often the production step is demanded that week. Table 6-3 presents a part of an example production list.

Table 6-3: Example production list

Customer number	Machine	Weldment	Production step	Year	Week	Production time	To Be Produced	Inventory	Demand
RFC1148	V600	000-7177	Preparation for welding	2021	15	5.000	5	4	1
RFC1148	V600	000-7678	Sawing construction	2021	15	1.280	8	7	1
RFC1148	V600	000-7678	Preparation for welding	2021	15	0.640	8	7	1
RFC1156	VSB1500-4/15	001-4355	Preparation for welding	2021	15	0.000	0	0	1
RFC1153	V613-1000M	001-5213	Sawing construction	2021	15	0.000	0	8	4
RFC1153	V613-1000M	001-5213	Preparation for welding	2021	15	0.000	0	8	4
RFC1153	V613-1000M	001-5328	Sawing construction	2021	15	0.160	1	0	1
RFC1153	V613-1000M	001-5328	Preparation for welding	2021	15	10.000	1	0	1
RFC1156	VSB1500-4/15	001-5767	Sawing construction	2021	15	1.000	1	0	1
RFC1156	VSB1500-4/15	001-5767	Preparation for welding	2021	15	5.000	1	0	1
RFC1156	VSB1500-4/15	001-5815	Preparation for welding	2021	15	0.250	1	0	1
RFC1156	VSB1500-4/15	001-5831	Sawing construction	2021	15	0.080	1	0	1
RFC1156	VSB1500-4/15	001-5831	Preparation for welding	2021	15	0.250	1	0	1
RFC1156	VSB1500-4/15	001-5837	Preparation for welding	2021	15	0.320	2	0	2
RFC1156	VSB1500-4/15	001-5838	Preparation for welding	2021	15	0.160	1	0	1
RFC1156	VSB1500-4/15	001-5844	Preparation for welding	2021	15	0.250	1	0	1
RFC1156	VSB1500-4/15	001-5849	Sawing construction	2021	15	1.000	1	0	1
RFC1156	VSB1500-4/15	001-5849	Preparation for welding	2021	15	5.000	1	0	1

This production list gives the planner of VSM an overview of all production steps that he must plan in a week. He can then plan these production steps operationally in ROB-EX, i.e., he can determine on which day of the week which production step of a weldment needs to be executed. Also, he can determine who must execute this production step. The heuristics can be run as soon as a new machine is added to the order list, to ensure that the plan remains up to date.

To manage the implementation of this planning approach properly within VSM, we recommend doing a phased implementation per department. We recommend starting with the VPM 2 department, as this research is based on the plan of this department. Before implementing the planning approach, we recommend verifying both whether the correct weldments and whether all weldments per machine are planned. We explain this in more detail in Section 6.3. If the planning approach is implemented in the VPM 2 department, we recommend first analysing for 3 months how the execution of the plan works in practice before the planning approach is implemented in the other departments. At the end of this period, we recommend discussing the results of this analysis and discussing how the planning approach can be properly implemented in the other departments.

Besides the advantages of the SA-Move heuristic compared to the MIP model mentioned in Chapter 5, the SA-Move heuristic is also more user-friendly and easier to apply in practice. For example, for the MIP model, the user would first have to run a separate heuristic that determines the ATW windows per production step. Next, the user should load these windows into the MIP model, after which the MIP model can be run, for which a solver is required. So, the user needs to perform several actions when using the MIP model, while using the SA-Move heuristic only one button has to be pressed. Also for this reason we recommend VSM using the SA-Move heuristic to generate a plan (and not the MIP model).

In addition to the instructions and recommendations given above considering the implementation of our planning approach in VSM, we also have some other recommendations. We present these recommendations below.

Organising the planning process

Our main recommendation is to organise the current planning process differently. We recommend linking the plan of VSM to the (expected) delivery date of a machine. As soon as a machine is expected to be sold, this machine will have to be added to the order list. Once the order list has been updated, we know exactly which modules have to be produced and when which department has to do what. This would allow the plan of the departments within VSM to be updated immediately. In this way, the management team gains direct insight into the influence of the production of the machine on the plan of the departments. Based on this updated plan of these departments, the management team can make an informed decision regarding the delivery date of the machine. The plan of the departments within VSM can be better stabilized by varying the delivery date of a machine in this way. In addition, we recommend using the SA-Move heuristic to create the plan. From the results of this research, we concluded that this solution approach stabilizes the plan the best and is easiest to apply in practice. The plan created by this SA-Move heuristic should be updated at least every 5 weeks. If new demand comes in earlier, the plan has to be updated more often.

Outsourcing costs versus fixed lot sizes

We recommend VSM experimenting with the outsourcing costs and the fixed lot sizes as we did in the second experiment. As indicated in this experiment, there are only minor differences between the scenarios as we defined them due to the few weldments that had to be produced in the dataset. By experimenting with the outsourcing costs and the fixed lot sizes across all weldments and the complete plan, the results will yield more significant differences. Based on these results, VSM can decide for which weldments it is beneficial to have a fixed lot size and for which weldments it is not.

Dealing with uncertainties in the execution of the plan

We advise VSM to use the proactive method in combination with the reactive method to deal with the uncertainties in the execution of the plan. This means that we recommend adding some slack in the plan to anticipate on causes that can lead to overtime. Next to this, we advise revising the plan when an unexpected event occurs last-minute. This revision can be done by a replanning approach which repairs the complete plan.

Data quality

We also recommend VSM focussing on the logging of data and the quality of this data. To be able to improve processes in a data-driven way and to verify these improvements, the presence of a high-quality database is necessary. Also, in the long term, the data must be correctly logged and monitored. At the moment, we have experienced that the data is often available, but it is difficult to find. Also, it is not always of high quality.

6.3 Discussion

There are several limitations within this research. We elaborate on these limitations in this research in this section.

First of all, we only include a part of all weldments in this research, namely 550 of the 1,952 different weldments. We made this choice because it simply took too much time to evaluate all weldments and include them in this research. Since we only include a part of the weldments, the results from the analyses cannot be copied and compared one-on-one with the current situation at VSM. In addition, we do not consider the optional modules on the machine a customer can select. These optional modules can also contain weldments that have to be produced. Excluding the optional modules also significantly reduced the number of weldments we include in our research. Besides, the planners of VSM must verify whether or not all weldments of a module are planned in the planning method and so whether there are no weldments forgotten. This also makes it difficult to draw firm conclusions about how many and which weldments should have a fixed lot size, for example.

Also, we make several assumptions in the MIP model and the heuristics that affect the quality of the simulation of the real-life situation. We assume, for example, that a production step should always be completed in the last possible week (i.e., the last week of its ATW window) while in reality, the production of a weldment can sometimes be urgent. This means that the ATW window of this weldment would be smaller in that case. We have not experimented with these smaller ATW windows in this research. We also assumed that several input parameters such as the initial inventory, the value of a weldment, and the production time of the production steps per weldment are the same for all datasets and so have not changed over time. In reality, these parameters could change but we have not yet included the option to change these parameters in our model. We have also not yet linked the MIP model/ the heuristics with SAP (ERP system of VSM). It is possible (with for example Excel Queries) but we did not invest our time in this.

Furthermore, we program our heuristics in Python but we have not created a graphical user interface yet. This makes it a bit more difficult for the users to apply the planning method at this point, as not all users master Python. Also, for the same reason, it is currently not easy to add the production steps that are not completed in a week to the workload of the following week. This is possible to do but the user should master Python for this.

6.4 Further research

Based on the findings and remarks gained in this research, we propose to do further research on several areas. We present these suggestions for further research below.

First, it might be beneficial for VSM to investigate alternative forecast methods. Despite this has already been researched within VSM earlier, we recommend changing the current forecast method. At the moment, the planner of (among others) the VPM 2 department knows too late which machine should be produced and when. The current way of forecasting could still be used but then the plan has to be linked to the (expected) delivery dates of the machines as discussed in Section 6.2. By changing the current forecast method, less replanning will be required.

Second, it can be interesting for VSM to investigate which weldments or modules might be beneficial to put in stock. By creating stocks for the right weldments or modules, the plan can be stabilized even better. Putting complete weldments or modules in stock also causes fewer urgent orders that will have to be done by VSM.

Lastly, it can be beneficial to investigate how the planning method can be linked to different systems and tools within VSM. If this is possible, the planning process can be partially automated. This also contributes to the further standardization and automation of the (production) process of the machines. Further standardization and automation will simplify the production process more, making the process less prone to errors.

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Appendix A Production Order Process

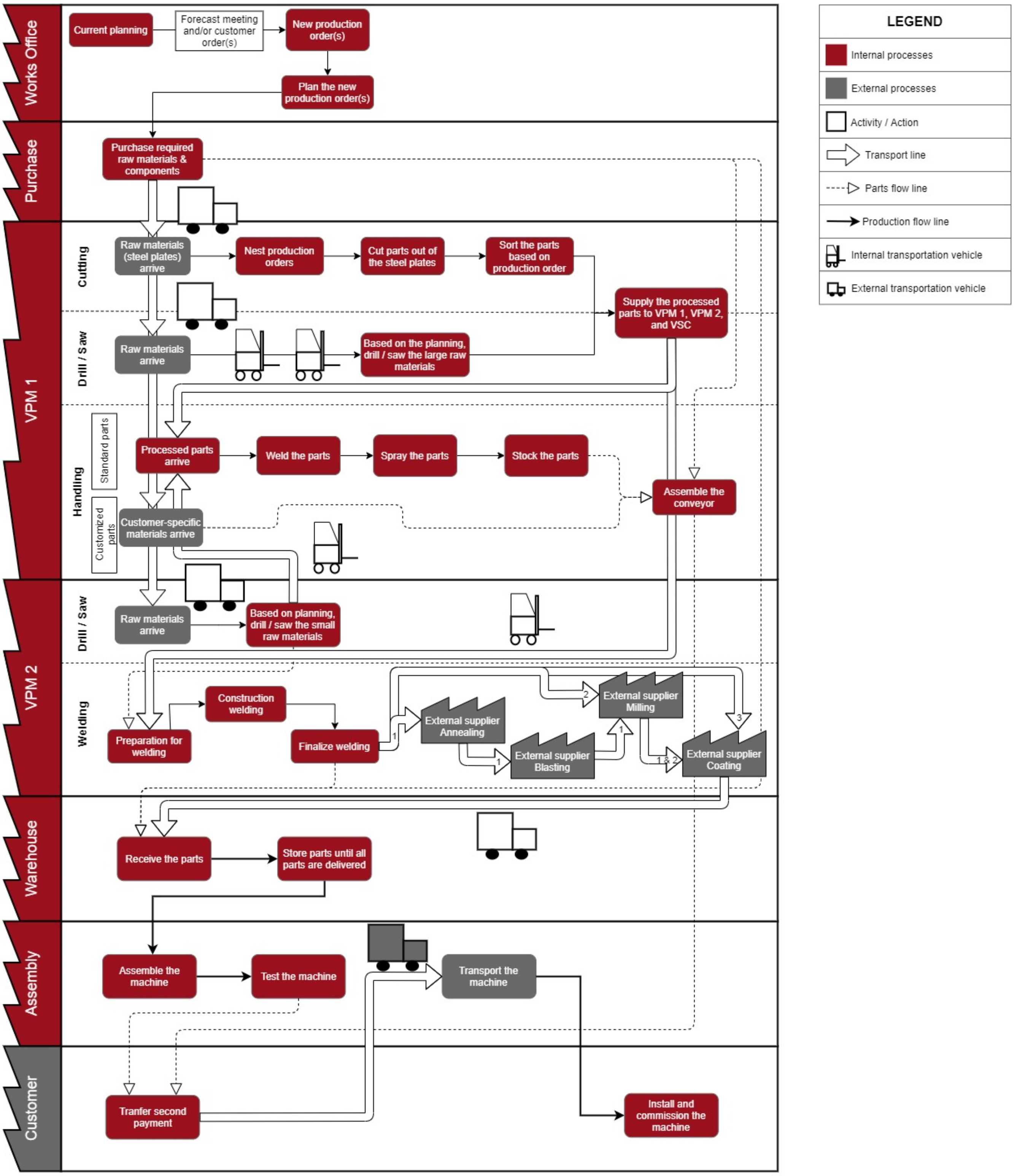

Figure A-1: Complete flow chart production process

Appendix B Tables workload calculation Assembly department

Table B-1: Standard hours machine

Machines	Throughput time in weeks									Penultimate production week	Last production week	Disassembly
V304								27	78	47	54	8
V310								89	28	26	39	8
V302										40	40	24
V320								68	169	75	60	8
V325-3000	105	105	105	105	55	55	55	40	40	40	40	30
V550-7						111	108	61	115	70	36	39
V505-160M						145	177	117	49	39	39	16
V200										78	39	15
V600										39	39	25
SAW										48	39	16
V613/V630							78	68	43	43	43	8
DRILL							80	88	123	100	40	38
V8xx									60	50	60	40
VSB								80	80	80	65	65

Legend	
	Assembly
	Testing
	Disassembly

Table B-2: Workload calculation including production for forecasted machines

Weeks	Week numbers	Assembly							
		Released production workload with new machines	Sold production workload	FTE normally (hours)	FTE reality (hours)	FTE normally	FTE reality	Too few # FTE	Too many # hours
Wk 04	4	23	1176	1210	1157	31	30	1	42
Wk 05	5	12	1308	1210	1281	31	33	1	39
Wk 06	6	-	1367	1210	1334	31	34	1	33
Wk 07	7	73	1339	1210	1311	31	34	3	101
Wk 08	8	195	1198	1210	1296	31	33	3	97
Wk 09	9	718	728	1210	1228	31	32	8	218
Wk 10	10	438	836	1210	1228	31	32	2	46
Wk 11	11	503	718	1210	1198	31	31	1	23
Wk 12	12	591	852	1210	1266	31	33	6	177
Wk 13	13	552	693	1210	1266	31	33	-1	-21
Wk 14	14	313	530	1210	997	31	26	-5	-154
Wk 15	15	466	360	1210	1247	31	32	-15	-421
Wk 16	16	345	251	1210	1255	31	32	-23	-659
Wk 17	17	450	110	1210	1010	31	26	-16	-450
Wk 18	18	521	97	1210	1183	31	31	-19	-565
Wk 19	19	598	101	1210	727	31	19	-1	-28
Wk 20	20	615	25	1210	1217	31	31	-20	-577
Wk 21	21	382	-	1210	966	31	25	-20	-584
Wk 22	22	225	-	1210	1231	31	32	-35	-1006
Wk 23	23	224	-	1210	1232	31	32	-35	-1008
Wk 24	24	75	-	-	-	-	-	-	-
Wk 25	25	60	-	-	-	-	-	-	-
Wk 26	26	8	-	-	-	-	-	-	-

RFC Week 04			
Week numbers	Workload not released production slots	Released production workload without new machines	
15	89	377	466
16	28	317	345
17	195	255	450
18	351	170	521
19	501	97	598
20	440	175	615
21	311	71	382
22	209	16	225
23	223	1	224
24	75	0	75
25	60	0	60
26	8	0	8

Appendix C KPI tree

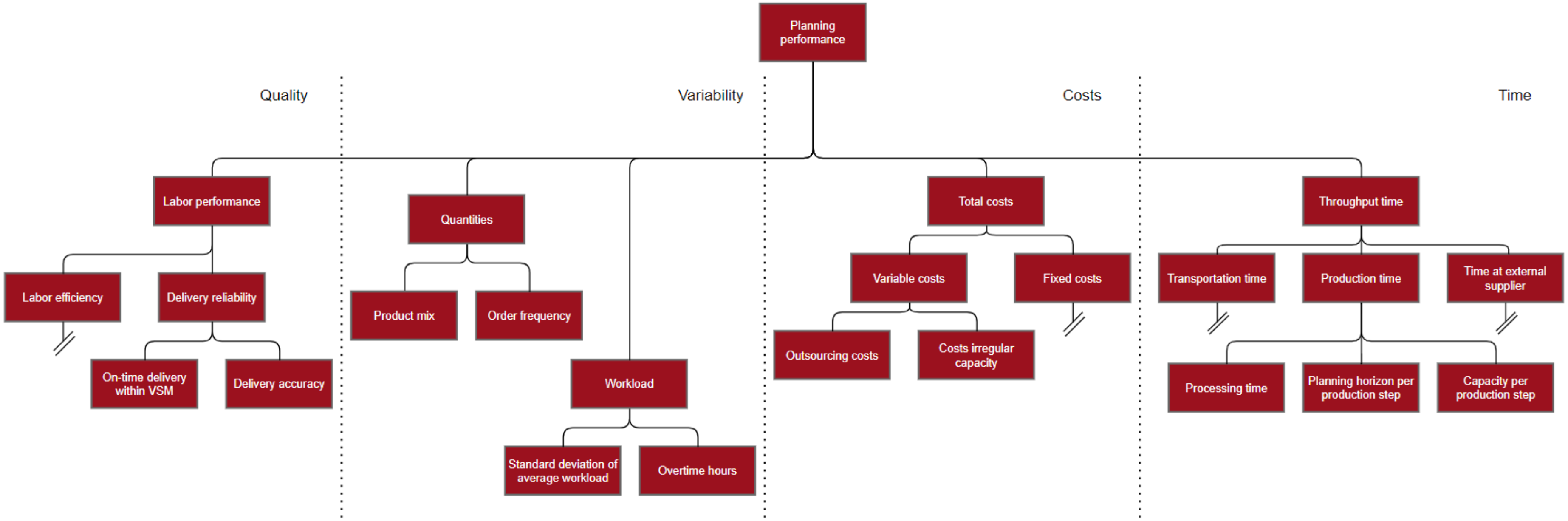

Figure C-1: KPI tree

Appendix D Resource Loading Problem MILP

Hans (2001) and Hans et al. (2002) use the following notation to model the Resource Loading Problem as a Mixed Integer Linear Programming problem:

Indices	Description	
j	orders;	$j \in \{J_1 J_2, \dots, J_n\}$
i	machine groups;	$i \in \{M_1 M_2, \dots, M_m\}$
b	jobs of order J_j;	$b \in \{B_{1j}, B_{2j}, \dots, B_{n_j j}\}$
t	time buckets (weeks);	$t \in \{0,1, \dots, T\}$

Parameters	Description
μ_{bj}	machine group on which job B_{bj} must be processed
p_{bj}	processing time of job B_{bj}
Π_j	set of all feasible order plans (for order J_j)
$a_{j\pi}$	π-th order plan for order J_j with elements $a_{bjt\pi}$
$\overline{mc}_{it}$	total regular capacity of machine group M_i in week t
mc_{it}	capacity of machine group M_i in week t in regular operator time
c_t, o_t, h_t	operator regular, overtime, hiring capacity in week t
s_{it}	outsourcing capacity in week t
$\bar{o}_t, \bar{h}_t, \bar{s}_t$	overtime, hiring, outsourcing cost per hour
w_{bj}	minimum duration in weeks of job B_{bj}
δ	minimum time lag (0 or 1 week) between adjacent jobs to impose a one-job-per-week policy
$r_j, d_j, \bar{d}_j$	release date, due date, deadline of order J_j
r_{bj}, d_{bj}	internal release, due date of job B_{bj}
$\rho_{j\pi}$	allowed tardiness of order plan $a_{j\pi}$ for order J_j
θ	penalty cost for one week of order tardiness
κ	maximum number of jobs of the same order that are allowed to be produced in the same week

Decision variables	Description
O_t	overtime hours in week t
H_t^R	hired hours in week t in regular operator time
H_t^N	hired hours in week t in nonregular operator time
S_{it}	outsourced production hours in week t for machine group M_i
U_{it}	number of hours on machine group M_i in week t in nonregular operator time
$X_{j\pi}$	$\begin{cases} 1 \text{ if order plan } a_{j\pi} \text{ is selected for order } J_j \\ 0 \text{ otherwise} \end{cases}$
Y_{bjt}	fraction of job B_{bj} processed in week t

Using these notations, the model is formulated as follows:

Mathematical model:

$$\min \ \sum_{t=0}^{T}\left(\bar{o}O_t + \bar{h}\left(H_t^R + H_t^N\right) + \bar{s}\sum_{i=1}^{m} S_{it}\right) + \sum_{j=1}^{n}\sum_{\pi\in\Pi_j}\rho_{j\pi}X_{j\pi}\theta \qquad (0)$$

subject to

$$\sum_{\pi\in\Pi_j} X_{j\pi} = 1 \qquad \forall\, j \qquad (1)$$

$$Y_{bjt} - \frac{\sum_{\pi\in\Pi_j} a_{bjt\pi}X_{j\pi}}{w_{bj}} \le 0 \qquad \forall\, b,j,t \qquad (2)$$

$$\sum_{t=r_j}^{T} Y_{bjt} = 1 \qquad \forall\, b,j \qquad (3)$$

$$\sum_{b,j} p_{bj}Y_{bjt} \le c_t + O_t + H_t^R + H_t^N + \sum_{i=1}^{m} S_{it} \qquad \forall\, t \qquad (4)$$

$$\sum_{\{(b,j)|\mu_{bj}=M_i\}} p_{bj}Y_{bjt} \le mc_{it} + U_{it} + S_{it} \qquad \forall\, i,t \qquad (5)$$

$$U_{it} \le \overline{mc}_{it} - mc_{it} \qquad \forall\, i,t \qquad (6)$$

$$\sum_{i=1}^{m} U_{it} = O_t + H_t^N \qquad \forall\, t \qquad (7)$$

$$O_t \le o_t \qquad \forall\, t \qquad (8)$$

$$H_t^R + H_t^N \le h_t \qquad \forall\, t \qquad (9)$$

$$\sum_{i=1}^{m} S_{it} \le s_t \qquad \forall\, i,t \qquad (10)$$

$$\text{all variables} \ge 0 \qquad (11)$$

$$X_{j\pi} \ \in \ \{0,1\} \qquad (\forall\, j,\pi \ \in \ \Pi_j \subset \Pi) \qquad (12)$$

The objective function (0) penalizes the sum of the total nonregular capacity usage costs and the total tardiness penalty costs. Constraints (1) and (12) guarantee that exactly one order plan is selected for each order J_j. Constraint (2) stipulates that for each order J_j, the order schedule (formed by variable Y_{bjt}) is consistent with the selected order plan. It also stipulates that when a job B_{bj} has a minimum duration of w_{bj} weeks, no more than $1/w_{bj}$-part of the job can be performed per week. Constraint (3) stipulates that all work is done. Constraint (4) forms the operator capacity constraint. Constraints (5-7) form the machine group capacity constraints. The variable U_{it} indicates the machine capacity usage in nonregular operator time. Accordingly, constraint (7) stipulates that the total machine capacity usage in nonregular operator time is equal to the operator capacity usage in nonregular operator time. Constraints (8-11) are the variables' upper and lower bounds. Note that constraint (10) sets an upper bound on the total subcontracted capacity in each week t.

Appendix E Simulated Annealing parameter experiments

To find appropriate parameters for our SA algorithm, we performed several experiments. The results of these experiments are given in this appendix. Initially, we executed 10 experiments and evaluated the results of these experiments afterwards. We used Dataset 2 and the SA-Insert strategy to determine the parameters. The parameters and results of these experiments can be found in Table E-1.

Table E-1: Results of first 10 experiments

Experiment	Start Temp	Temp LB	Markov Chain length	Decrease factor	Running time	Objective function value
1	5	1	100	0.90	225.9	100.992
2	5	1*10^-3	100	0.90	960.0	100.151
3	2	1*10^-3	100	0.90	862.8	100.507
4	2	1*10^-3	100	0.80	409.5	100.037
5	2	1*10^-7	100	0.80	890.3	98.544
6	2	1*10^-7	75	0.80	676.2	98.666
7	2	1*10^-8	75	0.80	746.8	98.537
8	0.5	1*10^-8	75	0.80	703.0	93.078
9	0.5	1*10^-8	75	0.70	441.4	98.898
10	0.5	1*10^-10	75	0.70	581.6	93.777

When we analysed the results, we noticed that it is possible in our algorithm that the objective function value does not change after we selected a neighbourhood solution. This is because some weldments have a fixed lot size (see Section 4.2.3 for a more detailed explanation). Since it is possible that the objective function value does not change, and we always accepted the neighbourhood solution in that case, the acceptance ratio became never 0. Figure E-1 shows the acceptance ratio graph of Experiment 8.

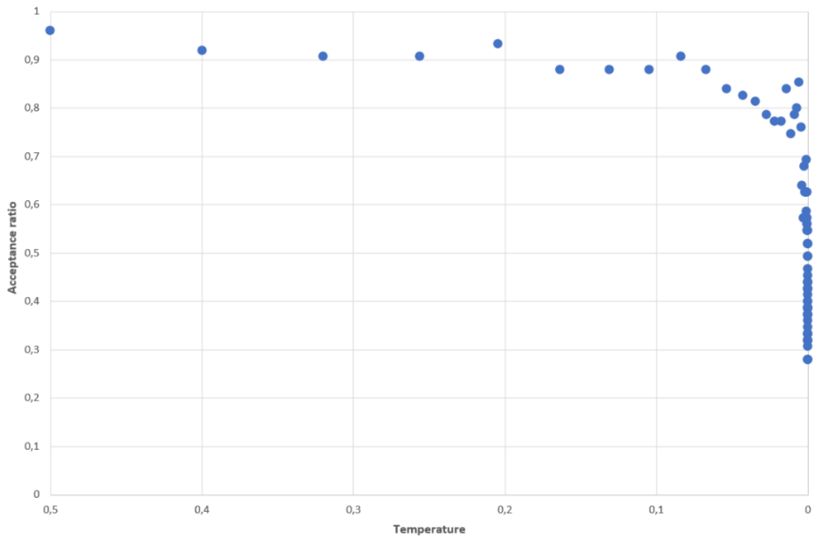

Figure E-1: Acceptance ratio graph Experiment 8

Since we do not always want to accept the neighbourhood solution when the objective function value does not change, we added an extra option to the SA algorithm. In the experiments before, we always accepted the neighbourhood solution if the difference between that solution and the currently selected solution is 0 because of the probability P(accepted) = random number < e^0 = 1, i.e., the solution is always accepted. In the extra option we added to the SA algorithm, we accept the neighbourhood solution if a random number between 0 and 1 is less than the (decrease factor)$^{\text{number of cycles been}}$. The parameters and results of the experiments using this extra option can be found in Table E-2.

Table E-2: Results of experiments using extra option

Experiment	Start Temp	Temp LB	Markov Chain length	Decrease factor	Running time	Objective function value
1	0.5	1*10^-8	75	0.80	588.3	95.390
2	0.5	1*10^-4	75	0.80	310.2	100.051
3	50	1*10^-4	75	0.80	442.0	100.252
4	20	1*10^-4	75	0.80	408.9	95.068
5*	20	1*10^-3	75	0.80	251.8	97.169
6*	20	1*10^-3	75	0.90	268.1	101.154
7*	20	1*10^-3	150	0.90	487.7	101.6
8**	20	1*10^-3	150	0.90	1320.7	100.69
9*	20	1*10^-3	150	0.80	484.4	100.363
10	20	1*10^-3	150	0.85	864.2	100.647

* algorithm stopped since the solution did not change after 2 cycles.

** algorithm was not allowed to stop if the solution did not change after 2 cycles.

After an analysis of the results of these experiments, it appeared that the acceptance ratio gradually decreased from 1 to 0. However, the value of the objective function was higher than in the previous experiments. To get a lower (and so in this case a better) value for the objective function, we changed the probability of accepting a neighbourhood solution when the objective function value is not changed to P(accepted) = (decrease factor)$^{(\text{number of cycles been} / d)}$. Using this probability, we performed again several experiments. The parameters and results of the experiments using this probability can be found in Table E-3.

Table E-3: Results of experiments using other probability

Experiment	Division	Start Temp	Temp LB	Markov Chain length	Decrease factor	Running time	Objective function value
1	d = 5	20	1*10^-3	150	0.85	828.6	100.496
2	d = 4	20	1*10^-4	150	0.80	763.0	95.742
3	d = 4	20	1*10^-4	130	0.85	916.0	94.550
4	d = 3	20	1*10^-4	130	0.85	899.7	100.290
5	d = 3	20	1*10^-4	200	0.80	963.6	95.579
6	d = 5	20	1*10^-5	150	0.80	962.3	94.900
7	d = 4	20	1*10^-5	150	0.80	937.0	96.922
8	d = 3	20	1*10^-5	150	0.80	818.1	100.778
9	d = 4	10	1*10^-5	150	0.80	921.8	94.985
10	d = 10	10	1*10^-5	150	0.80	846.9	95.244
11	**d = 4**	**1**	**1*10^-5**	**150**	**0.80**	**727.0**	**96.261**
12	d = 4	1	1*10^-5	200	0.80	887.6	101.0

Based on the trade-off between computational time, objective function value, and acceptance ratio, we decided to use the parameters as given in Experiment 11. The acceptance ratio graph of this experiment is given in Figure E-2.

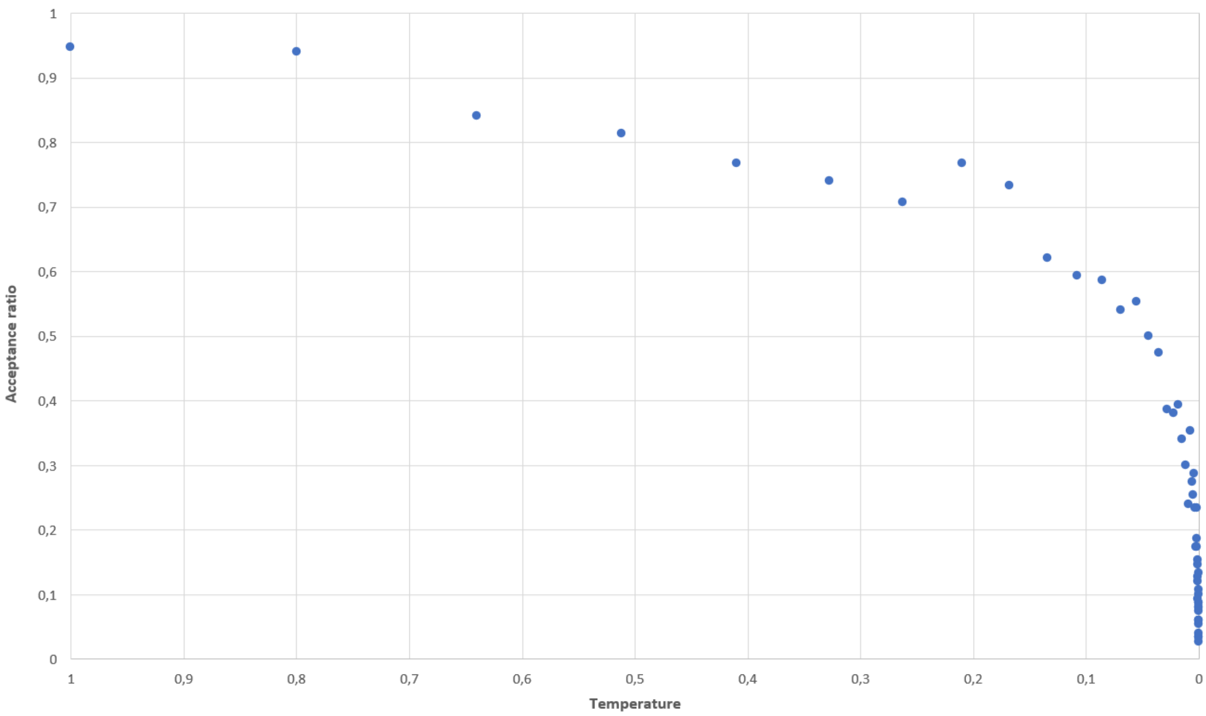

Figure E-2: Acceptance ratio Experiment 11

Appendix F CONFIDENTIAL

This appendix is excluded for confidentiality reasons.