MASTER

The impact of different planning methods on Marel's parts production planning

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The impact of different planning methods on Marel's parts production planning

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Abstract

This research project is part of the master thesis project of Vera E.J. de Graaf and is a final aptitude test of the Master Manufacturing Systems in Industrial Engineering at the Eindhoven University of Technology. The research project is conducted at Marel and will focus on the parts production planning of Marel's site in Boxmeer. The current production planning process of Marel is reviewed. Different production planning methods are retrieved from literature. A simulation model of the parts production planning of the sheet metal department is constructed. Dispatching rules and the simulated annealing algorithm are implemented in the simulation model. From this simulation model, conclusions are drawn and recommendations are given on Marel's parts production planning method.

Note: some figures and numbers in this report are altered due to confidentiality. If this is the case, it is stated in the corresponding text.

Summary

Marel is a leading global provider of advanced processing systems, software and services to the poultry, meat and fish industries. With the vision of a world where quality food is produced sustainably and affordably. Marel strives to transform the way that food is processed by continuously expanding their service reach, product portfolio and innovative powers. The focus of this research project is on the parts production of Marel's site in Boxmeer and is conducted at the Manufacturing engineering department, which is part of Marel's Global Supply Chain. The production of Marel is characterized by a High Mix - Low Volume (HMLV) production. Making unique and complex products with customer specific requirements. This makes that the production process of Marel produces a high variety of products in small quantities. This HMLV production, together with short lead-times while having high demanding customers, is making the production planning challenging. Therefore, a research question is formulated:

What is the impact of different planning methods on the parts production planning of Marel?

The current production planning process consists of multiple steps. First, an equipment order arrives at the sales department. There, the order is accepted or declined. When accepted, the order is scheduled by the Master Production Scheduler and fed to the SAP/ERP system. At this point, service and innovation order can also be fed to the SAP system. These type of orders do not need to be scheduled by the master scheduler first. From these orders, the SAP system makes a planning according to lead-time feasibility. Since the SAP/ERP system does not consider capacity constraints, infinite capacity is assumed by the system. Therefore, a human planner is involved to level the resources and solve capacity problems. The planned orders are released to the shop-floor where the production of orders can start.

The parts production of Marel consists of two departments, the sheet-metal department and the machining department. This research project focuses on the parts production of the sheet-metal department. The part of the planning process which is considered in this research project, is the order creation in the SAP environment until part delivery to the warehouse.

The current parts production planning method of Marel is replicated in simulation with means of a discrete-event simulation. The simulation model starts with creating the initial events. The initial events all represent the creation of an order in the SAP system. When an initial event occurs, all corresponding production steps of the order are scheduled. Each of these production steps is represented by an event in the simulation model. This part represents the SAP planning. Then, the scheduling of the human planner is added to the simulation model. Every Monday, for the consecutive three weeks, the capacity resources are levelled. Since orders still can occur in this timeframe. Every production day, the current capacity is updated, and a check is done whether the required capacity is still available. When orders need to be rescheduled, orders that can be rescheduled to an earlier date are considered first, so due date can still be met. Otherwise orders are scheduled forward, the priority of rescheduling is on the latest due date of orders.

The performance of the simulation model is described by four main KPI's, delivery performance [DP], waiting factor [W], WIP-level [WIP] and mean tardiness [μT]. Comparing the simulation model with the actual realized results from the current planning method, it is concluded that the simulation model is valid. However, some differences in WIP-level and mean tardiness are observed. This is accounted to the available flexibility of a human planner that can not be simulated. In the current production planning method, approximately 70% of all orders is rescheduled.

The literature study performed, presented several production planning methods for job-shop environments. The planning methods retrieved from literature are the POLCA system, workload control, dispatching rules, meta-heuristics, mixed integer linear programming and constraint programming. The meta-heuristics are further divided in genetic algorithms and simulated annealing. In this research project, two planning methods are implemented. Namely, the dispatching rules and the simulated annealing algorithm.

Dispatching rules are used to prioritize orders waiting in the queue of a work-center. The use of dispatching rules avoids rescheduling in the planning process and the implementation of dispatching rules is relatively simple. The proposed dispatching rules are based on FIFO, Arrival time, processing time, due date, critical ratio, slack and work-in-next-queue. Each type of dispatching rule has their own characteristics and is focused on improving the performance of one KPI. The (shortest) processing time rules perform well on improving the delivery performance. While the due date based rules perform well on improving the tardy rate. However, the shortest processing time dispatching rules are not a feasible planning method in practise. Therefore, the due date based rules are the best dispatching rules. Additional dispatching rules are suggested where different rules are combined with the due date based rules (E)(M)DD. Combining the EDD rule with the CR+SPT rule or the LTWK rule shows the best performance. Both these rules show an increase in performance on the three KPI's DP, W and WIP, compared to the EDD rule alone.

In addition, a capacity analysis is done with the aid of the EDD dispatching rule. Adjusting the capacity constraints according to the capacity analysis, an increase in overall performance is obtained. Now, the EDD rule does not only show an increase in the mean tardiness performance, the performance on the other three KPI's also shows a big improvement with respect to the benchmark. In total, an overall performance increase of 57% is obtained when using the EDD dispatching rule + capacity constraints. From these results is concluded that Marel should take a look at re-allocating the capacity of the welding work-centers. The work-centers of sub-department 85 appear to have over-capacity, where the work-centers of sub-department 42 have under-capacity. Since the welding operators require the same skill-set for both departments, resources can be levelled accordingly.

The simulated annealing algorithm optimizes the sequence of orders waiting in the queue of a work-center at a daily basis. The algorithm avoids rescheduling in the planning process. The optimization of the algorithm is based on a fitness value. This value is based on the performance of the KPI's of the planning process. Therefore, the simulated annealing algorithm shows an improvement on performance on all the KPI's. The overall performance of the SA algorithm shows an improvement of 40% with respect to the benchmark. Especially the improvement in waiting factor and WIP-level increases in contrast to the EDD dispatching rule. The capacity constraints are also added to the simulated annealing algorithm. The performance of this simulation model shows a performance which is almost equal to the best possible performance that can be obtained. The overall performance increase is 60% with respect to the benchmark.

Preface

This research project is the final result of my master thesis, which is part of the master Manufacturing Systems Engineering in Industrial Engineering at the Eindhoven University of Technology. In this special section, I would like to express gratitude to all that made it possible to come to this result and for making this project successful. But, I would like to thank several people in particular.

From the Eindhoven Univeristy of Technology, I would like to thank Ivo Adan, my mentor and supervisor. You helped me from the beginning till the end with my project. First, by getting me in contact with Marel and therefore providing me with this research project. Secondly, by the insights and feedback you gave me, when shaping my research proposal and later on in the project phase itself. In addition, I would like to thank Tugce Martagan and Christina Imdahl for their time to read and give feedback to my report.

I would like to thank Marel, as a company and some people in particular who deserve a special notice. Marel is a company where I immediately felt at home. I appreciate the time and support that I have received from everyone who was, even if only a little, involved in this research project. The special thanks go to Wouter Schuwer. For his time, expertise, enthusiasm, encouragement and bad jokes. This was the first time you guided a master student in their thesis project and I can say now, you did a great job! Since you have also followed the same master program at the TU/e, your guidance was of added value for this master project, substantive and procedural. Finally, I would like to thank Saskia Orelio. The person who gave me a warm welcome at Marel and who I could go to for moral support.

After seven years of studying, I can gladly say, I did it! Now, on to the next chapter in life.

I hope you enjoy reading the report on my master thesis project.

Vera de Graaf,

Eindhoven, May 2022

Abbreviations

AT	Arrival time
CONWIP	Constant Work In Progress
CR	Critical ratio
DNA	Deoxyribonucleic acid
EDD	Earliest due date
ERP	Enterprise Resource Planning
ETO	Engineer-To-Order
FIFO	First in - First out
GA	Genetic Algorithm
GSC	Global Supply Chain
HMLV	High Mix - Low Volume
HTG	Production sub-department (Hele Taak Groep)
JIT	Just-In-Time
KPI	Key Performance Indicator
LPT	Longest processing time
LRPT	Longest remaining processing time
LTWK	Least total work-load
MDD	Modified due date
MILP	Mixed Integer Linear Programming
MPS	Master Production Scheduler
MRP-I	Material Requirement Planning
MRP-II	Manufacturing Resource Planning
MTO	Make-To-Order
MTS	Make-To-Stock
POLCA	Paired-cell Overlapping Loops of Cards with Authorization
QRM	Quick Response Manufacturing
RCCP	Rough Cut Capacity Planning
RNA	Ribonucleic acid
SA	Simulated Annealing
SAP	System Analyses and Program development
SL	Slack
SPT	Shortest processing time
SRPT	Shortest remainingprocessing time
TU/e	Eindhoven University of Technology
WINQ	Work-in-next-queue
WIP	Work-In-Progress

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Chapter 1
Introduction

This research project is part of the master thesis project of Vera E.J. de Graaf and is an final aptitude test of the Master Manufacturing Systems in Industrial Engineering at the Eindhoven University of Technology. The research project is conducted at Marel and will focus on the parts production planning of Marel's site in Boxmeer. This report consists of a project description, literature study, simulation model, a comparison of different planning methods and insights obtained throughout the research project.

In Section 1.1, a description of Marel, the company where the research is conducted, is given. Followed by a problem description and elaboration on the current parts production planning method in Chapter 2. Then, a literature study on different planning methods is conducted in Chapter 3. In Chapter 4 a simulation model of the current parts production planning is made, the KPI's are defined and the simulation model is validated. Subsequently, in Chapter 5 and Chapter 6 two different planning methods are simulated and their results are compared to the validation model. Finally, in the last chapter of this research project, Chapter 7, the explored planning methods are evaluated and compared to the current planning method. In this chapter, the insights obtained from simulation are stated and an advise is given to Marel on their parts production planning method.

1.1 Company description

The company of interest for this research project is Marel. Marel was founded in Iceland in 1977 [Marel, 2021], bringing data collection to the fishing grounds. Over the years Marel has grown to a worldwide company with sites in over 30 countries and more than 7000 employees. Marel has customers operating in over 180 countries worldwide. In the Netherlands, Marel has four sites. This research is conducted at the site in Boxmeer, one of Marel's biggest sites with over 1500 employees.

Nowadays, Marel is a leading global provider of advanced processing systems, software and services to the poultry, meat and fish industries. With the vision of a world where quality food is produced sustainably and affordably. In Figure 1.1 the matrix organisation structure of Marel can be seen, the industry centers with the different departments are depicted in this figure. The research is conducted within the manufacturing engineering department, which is a sub-department of the Global Supply Chain (GSC) of Marel. The manufacturing engineering department spreads out over all three industry centers. Marel strives to transform the way that food is processed by continuously expanding their service reach, product portfolio and innovative powers. The focus of this research project will be on the parts production of Marel's site in Boxmeer. The production of Marel is characterized by a High Mix - Low Volume (HMLV) production. Making unique and complex products with customer specific requirements. This makes that the production process of Marel produces a high variety of products in small quantities. This HMLV production, together with short lead-times while having high demanding customers, is making the production planning challenging.

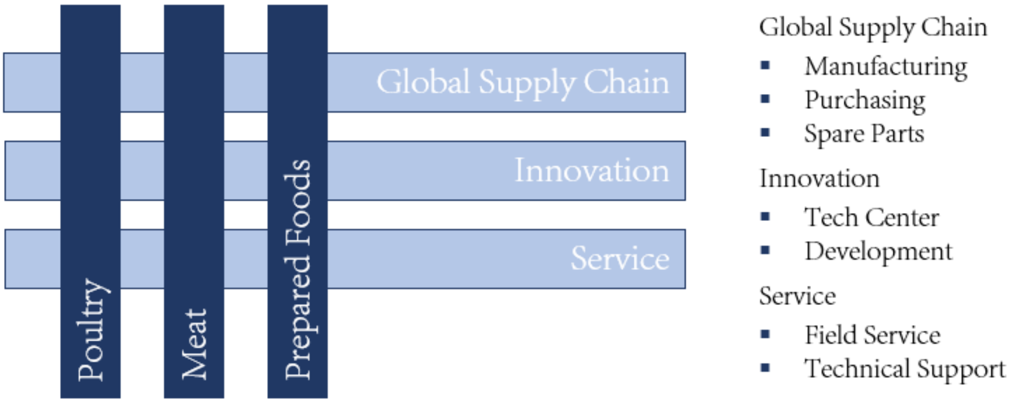


Figure 1.1: Matrix organization structure Marel

The production floor of Marel Boxmeer is divided in production areas, in general there are two departments for the parts production, namely the machining department and the sheet metal department. Within these departments there are task groups where work-centers of the same type are grouped, these groups are in dutch the so called "Hele Taak Groep" which is shortened to HTG. There is, for example, an HTG for milling and turning (HTG 88), plastics (HTG 89), sheet-metal (HTG 42) and combination parts (HTG 85). These HTG's are formed such that each part that is manufactured is routed only through one HTG. Each HTG has it's own operations manager who keeps track of the issues which occur on the production floor. The parts production planning is split over the two departments, there is a planner for machining (HTG 88/89) and a planner for sheet metal (HTG 42/85). In the remaining of this report, the HTG's are referred to as sub-departments.

Chapter 2
Problem Statement

The manufacturing engineering department of Marel focuses on the optimization of the production processes, in a supporting role to the operations management. Within the manufacturing engineering department a research project has been formulated;

Investigate, by means of simulation, which planning parameters impact the delivery performance of the produced parts within the production planning process

In this chapter of the research proposal, the problem is stated. In section Section 2.1 the total planning process, from order to delivery is described and the Key Performance Indicators (KPI's) of the production process are set. Then, in Section 2.2, the scope is defined and, in Section 2.3 the research plan is made. The research plan includes the research objective with the main research question and its corresponding sub- research questions, together with the used methodology.

2.1 Situation

As a starting point of this research project, Marel's production planning process is outlined to get an understanding of the current situation. The whole planning process from order to delivery is examined and the key performance indicators of the process are analysed.

2.1.1 The Planning Process: from Order to Delivery

The focus of this research project is on the parts production planning of Marel. The total planning process is depicted in Figure 2.1 and thoroughly explained in this section.

The production planning process consists of multiple steps. To get a clear understanding of the full process, interviews were held with various employees within the Global Supply Chain of Marel. There is, for example, spoken with the head of production, the master scheduler, different production planners and the person responsible for the SAP planning within Marel. Information retrieved from these employees is the foundation of the obtained knowledge about the planning process of Marel as shown in Figure 2.1.

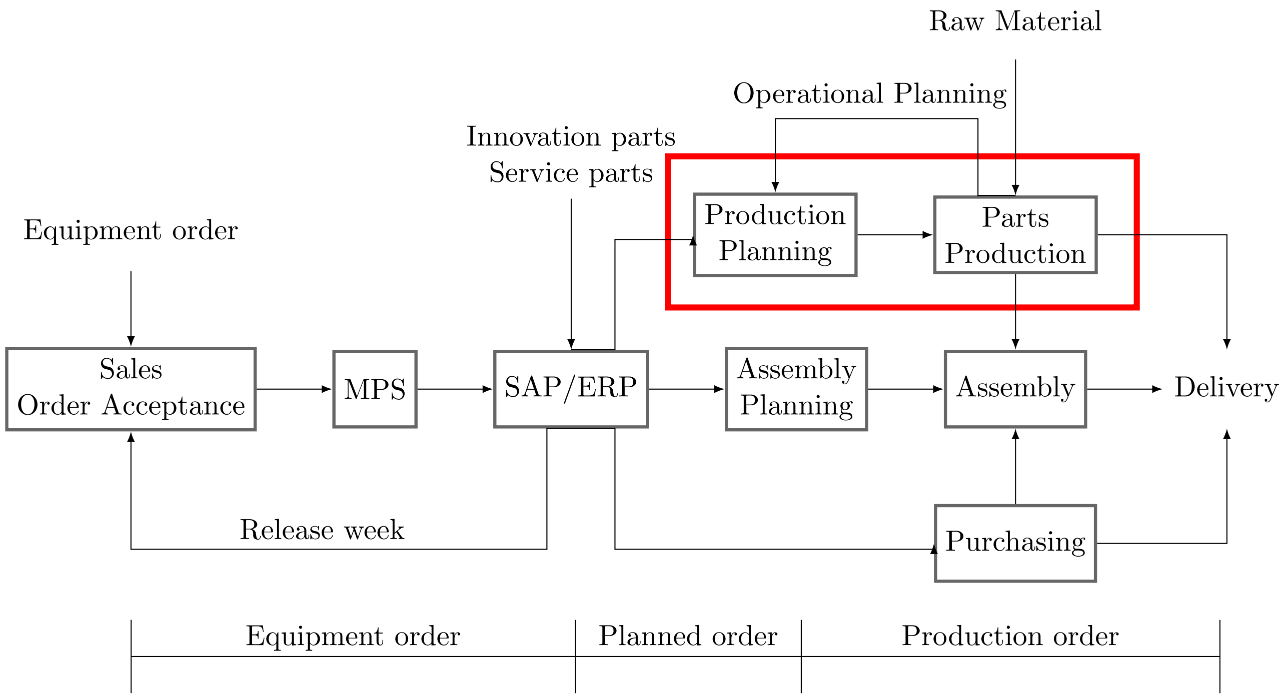


Figure 2.1: Planning Setup

The process starts when an equipment order comes in. The sales department accepts or declines this order and puts the equipment order in the system according to the set release week. The order acceptance happens according to prospected sales, type of client and lead-time feasibility. It rarely happens that an order is declined. For each incoming equipment order a lead-time of eight weeks is considered, five weeks for the parts production and three weeks for assembly. Sometimes, an order is engineer-to-order (ETO). In this case an extra five weeks is considered for engineering before the order is released to the parts production.

In general, there are three types of parts; parts that are produced in-house (E-parts), parts that are produced at a supplier (F-parts) or parts that can be produced in-house or at a supplier where the choice is made depending on in-house capacity (X-parts). Since most suppliers consider a lead-time of four weeks and the planner needs a week to determine which parts need to be manufactured at an external supplier, the lead-time for parts production is set at five weeks.

When an equipment order is accepted by the sales department, the master production scheduler (MPS) schedules the order in the time-horizon and enters it in the SAP environment, which will be elaborated on later in this section. Weekly on Friday, all orders are released to the SAP system where the planned orders are made for all required production steps. These planned orders are roughly divided in three types, parts production, assembly and purchasing orders. Each type of orders are considered as different processes, and need to be finished before continuing to the next process. This means that, for example, all parts from a corresponding order need to be manufactured before assembly of this order can start.

The SAP environment is an Enterprise Resource Planning (ERP) system with a Manufacturing Resource Planning (MRP-II). This includes an Material Requirements Planning (MRP-I), a Capacity Resource Planning (CRP) and a Rough Cut Capacity Planning (RCCP). The RCCP visualizes the capacity on forehand, at the master production schedule, where the CRP visualizes the capacity of planned orders after they are scheduled by the SAP system. The ERP system can only realize lead-time feasibility or meet the capacity requirements. It can not take both into consideration. At Marel the planning is according to lead-time feasibility and therefore infinite capacity is assumed which causes capacity problems. Because of this, a human planner is involved to level the resources and solve capacity problems [Wiers and de Kok, 2017].

The focus of this research is on the parts production. As shown in Figure 2.1, there are three streams going into the planning process. So far, only the equipment orders are discussed. However, next to equipment orders, innovation and service parts can also be fed to the SAP system. These type of orders do not follow an acceptance process, but are directly put into the system. Innovation parts are manufactured for the R&D department and can be part of an assembly product or a single part. These parts are prototypes and therefore the required production time is not known beforehand. An estimation of the production time is made by the engineers, however the actual production time can vary a lot from this estimation. Service parts are manufactured for the service department. This includes spare parts that are produced on-stock and parts that are requested by service engineers when performing an inspection on site at one of Marel's clients. It can happen that a service part is of high priority when a component at a client is defect and therefore the production is at a stop. In this case, the service parts have a shorter lead-time for parts production than the five weeks set for equipment orders, which interrupts the production planning.

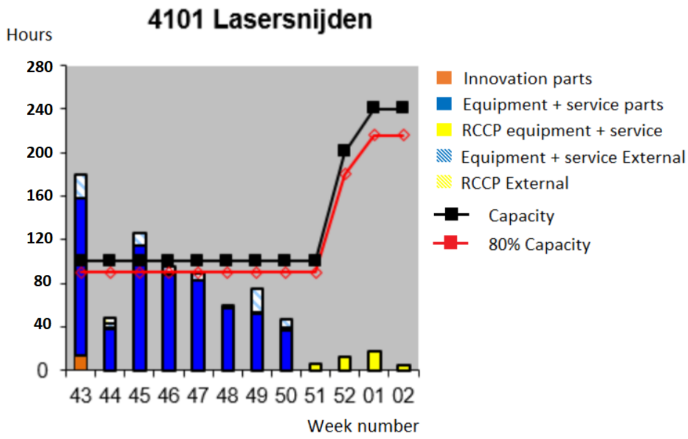


Figure 2.2: Work-center 4101 - Capacity graph week 43 2021 *(adjusted due to confidentiality)*

In the SAP environment, a graph of the total capacity for the next twelve weeks is generated, which visualizes the available and required capacity. Based on these graphs, a new release week is determined and fed back to the sales department. An example of such capacity graph is shown in Figure 2.2, this graph is for work-center 4101, laser-cutting. Graphs like this can also be made per sub-department or per department. In Figure 2.3 the capacity-overview for the total parts production of Boxmeer is shown. In this figure there are two lines which represent the available capacity, the black line is the total available capacity and the red line is the 80%-line. The production of parts is preferably planned up to the 80%-line (red line) to keep a 20% buffer for rush orders, breakdowns, re-do's, etc. For each week the required capacity is shown for the general parts production for equipment or service (blue), X-parts (hatched white-blue) for the CRP. The same is done for the RCCP in yellow. Next to that innovation parts are shown in this graph (orange). As can be seen, innovation parts are only visible in the next two weeks. These parts are often planned on a short lead-time. Looking at Figure 2.3 there are very little RCCP parts. Currently, within Marel, a project is done on improving the RCCP. This project shall hopefully, together with this research project on the parts production planning, improve the total planning for Marel in the future. Since the SAP system is set on lead-time feasibility rather than capacity feasibility, it can be denoted in Figure 2.2 that the required capacity sometimes is higher than the available capacity. Therefore the production planners need to do leveling of the capacity to make a feasible planning. This leads to the next step in the planning process, the production planning.

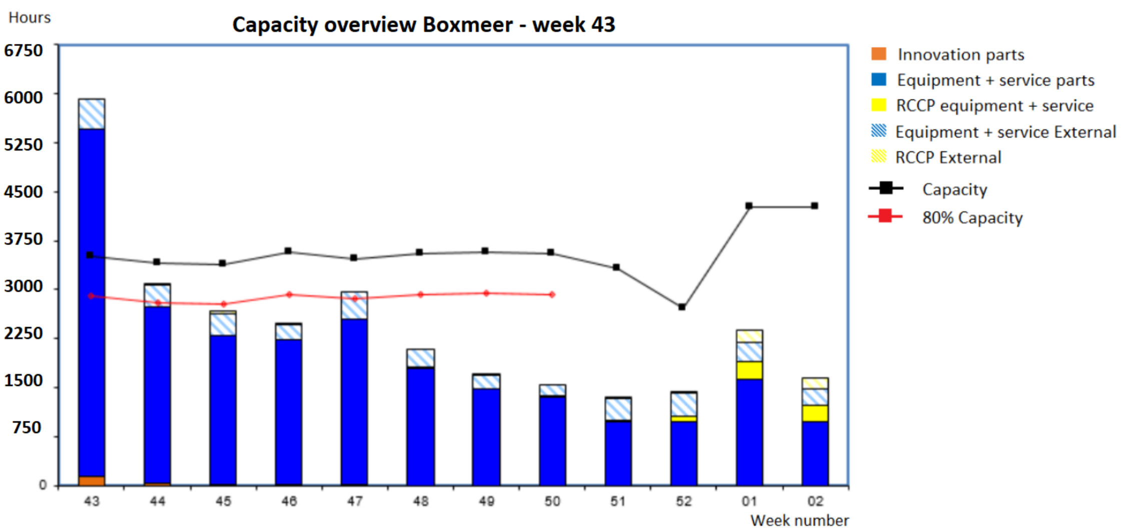


Figure 2.3: Boxmeer - Capacity graph week 43 2021 *(adjusted due to confidentiality)*

The planned orders end up at production planning where the schedule for the production floor is made, this is done for each work-center separately. For each work-center the required capacity and available capacity is analysed. The E-parts will be released as production order directly if there is sufficient capacity. Then the X-parts are analysed and depending on the capacity there is determined if an X-part order needs to be outsourced. Based on the available and required capacity the planner makes a list of X-parts which are preferred to manufacture at one of the suppliers. This list is checked by the external-parts planner, who tries to outsource these parts at suppliers. The external-parts planner provides feedback to the production planners within a week, whether it is possible to produce the parts at a supplier and which parts need to be manufactured in-house anyway. When a part can be produced at a supplier, the planned order is removed from the system. When it turns out that a part needs to be produced in-house, it is released as an internal production order.

Finally, the planned orders are released which generates the production orders. These orders are send to the production floor and the production of the parts can start. A production order consists of a list of production steps that need to be performed in order to produce the order. Each production step contains an estimated production time and work-center. It can always occur that a machine breaks down or an operator becomes unavailable. This impacts the planning of the production. Then, the operations manager of the corresponding department tries to resolve the issue, for example by assigning another operator to a work-center. If it is not possible for the operations manager to resolve the issue, the issue is discussed with the production planning to see how it can be resolved. This part of the planning is called the operational planning.

2.1.2 Bottlenecks

The knowledge and experience of employees has been used for mapping the current planning process of Marel. When talking to employees from the GSC, manufacturing and planning department, several bottlenecks on the planning process emerged. These planning problems are summarized below.

- Low delivery performance
- Planning with infinite capacity
- Planning based on experience
- Order acceptance according to sales prospects rather than capacity
- High product mix

- Product mix and customer needs are constantly changing
- No clear priority of orders
- High amount of orders on the production floor which are not in production at that time

The problems that are encountered in the planning process are the main reason for this research project. Marel would like to get insight in which planning parameters cause these problems to happen. Therefore, it is necessary to look into the key performance indicators (KPI's) of the production planning of Marel.

2.1.3 The current KPI's

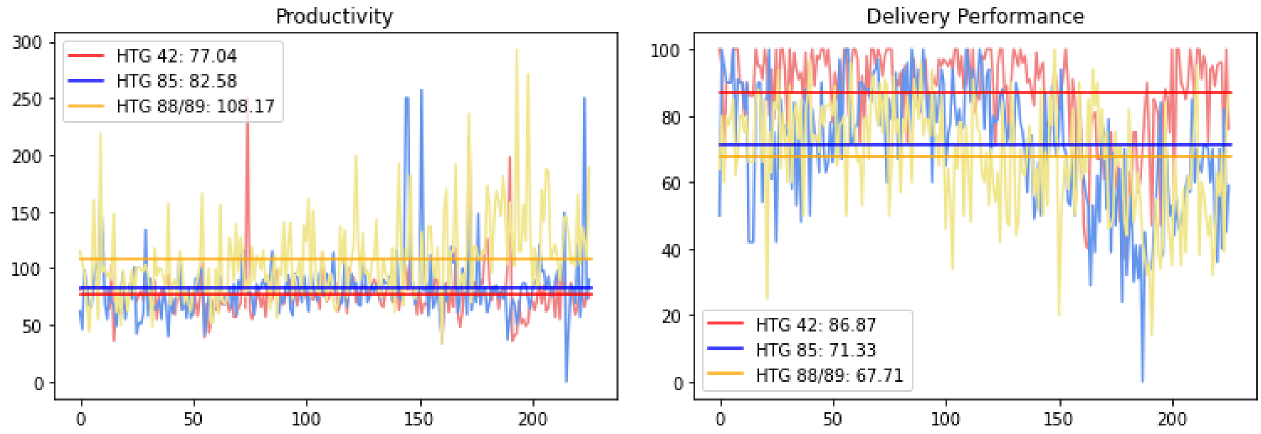
The production planning process currently has two Key Performance Indicators (KPI's). The first and most important KPI is the delivery performance. The delivery performance is measured at each work-center and is defined by the fraction of production orders that are completed within its due date. The calculation is then the on-time orders $[N^{OT}]$ divided by the total number of orders $[N]$, where $N^{OT} \leq N$, and can be found in Equation 2.1. The delivery performance is denoted in percentages [%] and must be between $0 \leq DP \leq 100$.

$$Delivery\ Performance\ (DP) = \frac{N^{OT}}{N} \tag{2.1}$$

The second KPI is the productivity. This KPI is also measured at each work-center and is defined by the sum of confirmed production hours per order, $[p_o]$, at the work-center divided by the available number of working hours of the operators at the corresponding work-center, $[WH]$, see Equation 2.2. Both KPI's are measured on a daily basis and per work-center.

$$Productivity\ (P) = \frac{\sum_o p_o}{WH} \tag{2.2}$$

Each production step has an unique set-up time and production time, depending on the to be produced product. When a production step is completed, the operator confirms the completion by scanning a bar-code on the order sheet. The operator then can choose to just confirm the set-up and production time or adjust it. In practice, the set-up and production time are only adjusted when the operator takes longer than the predefined time. When an operator is faster, the set-up and production time are not adjusted and the predefined time is confirmed as the actual production time. Therefore, it can happen that the productivity is higher than 100%.



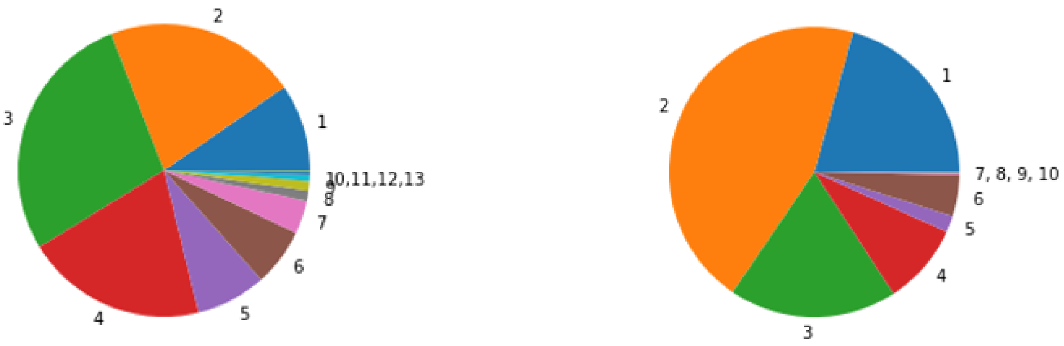
(a) Productivity (b) Delivery Performance

Figure 2.4: Performance KPI's (2018-2019)

In Figure 2.4 the performance of the KPI's over the past years is shown. In these graphs the productivity and delivery performance of sub-department 42, 85 and 88/89 is visualised. The horizontal line represents the mean performance of the KPI at the corresponding department, this number is also shown in the label of the graph. It can be denoted that the productivity of the machining department is much higher than of the sheet metal department. This is likely caused by the fact that the time an operator is working on a part at the machining department is not equal to the time the machine is producing. At the machining work-centers, the operator can prepare the product which is next in the queue, in the time another product is produced at the corresponding machine. This also applies to night production, these orders are prepared at the end of an operator shift, production of these items are during night time. Therefore, the productivity of sub-department 88/89 is often above 100%. In contrast, the delivery performance of machining is the lowest. This is likely caused by the amount of external steps in the production process of an order. The machining parts often have external production steps such as hardening in their routing. This makes the planning of and (re)scheduling of orders more complex, since external steps take a fixed amount of time. The lack of flexibility causes a lower delivery performance in the machining sub-department.

2.2 Scope

The scope of this research project is on the parts production planning. The input information is the planned orders which are generated by the SAP system, the manufactured parts are considered the output. So, the focus of the project is on the process from the planned order in the SAP system, until the finished production of an order for the parts production as described in Section 2.1. This part of the production planning process is outlined in red in Figure 2.1. There are two departments of parts production which contain multiple sub-departments, these are the sheet metal department and the machining department as described in Section 1.1. The scope of this research project is the sheet metal department. This department consists out several sub-departments 42 and 85. When defining the scope, a few choices were made.

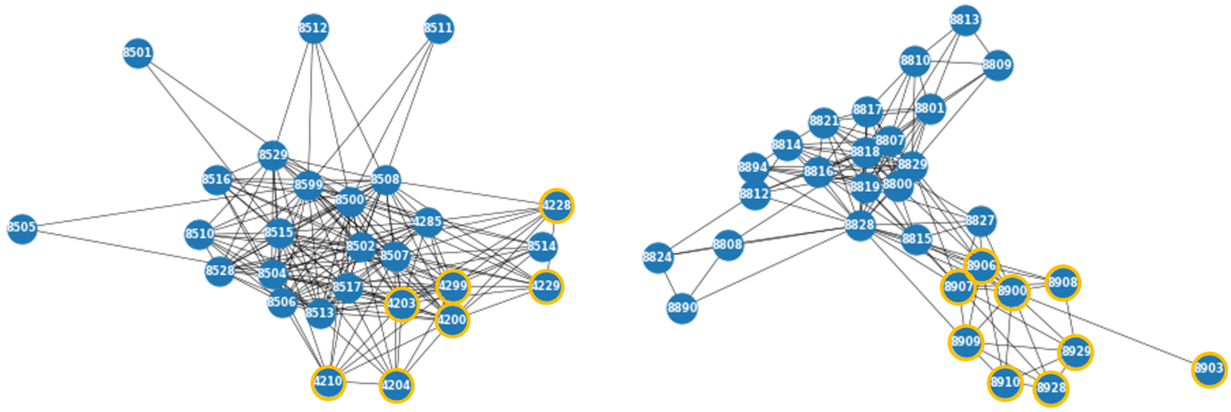


(a) Sheet Metal department (b) Machining department

Figure 2.5: Production steps per part within department

The first choice that is made is on the routing of an order. When an order is manufactured, it has to follow several production steps, these steps are bundled together in a production order list. The production floor of Marel is designed in such way that all manufacturing steps of an order are performed at one sub-department. The routing of each order starts with the release of the order to the production floor. Then all supplies are gathered from the warehouse, this includes raw material and purchased items. Then, the manufacturing of an order can start. Most orders also have finishing steps at the end of the production. Finally, the order is delivered to the warehouse. In this research project there is chosen to not include warehousing steps. Warehousing steps are considered as an external step, so they take a fixed amount of time with no variation. Therefore, the warehousing steps are also not considered in Figure 2.1, but it can be assumed that raw materials are retrieved from the warehouse and delivery is done to the warehouse as well. For both departments the number of production steps per part is visualized in Figure 2.5. The number of production steps are defined as the separate production steps, at different work-centers, that need to be performed to produce an order/part from start to finish. In this figure can be seen that the number of production steps per part in the sheet metal department has more variation than the machining department. Therefore, it can be concluded that the routing within the sheet metal department is more complex.

After the first choice, to not focus on the full routing of a part, but on the routing within an sub-department only. The next choice that is made is the scale of the research project. The scale can vary from a single work-center, a sub-department, a production department, or the whole parts production of Boxmeer. Expected is that, when focusing on a single work-center, the results retrieved from simulation are insufficient to get insights in the overall performance of the KPI's. Therefore, the minimal scale is set to sub-department-level. Within the parts production there are two departments which each consist of two sub-departments as described in Section 1.1. The routing of parts within these departments are visualized in Figure 2.6. For each work-center a line is drawn to another work-center when it is a preceding or succeeding production step in the routing of a part. In Figure 2.6b the routing of the machining department is visualized. The work-centers of sub-department 89 are circled yellow. This way, it can be seen that the relation between sub-department 88 and 89 is not that strong. They are not much dependent on each other. However, when looking at Figure 2.6a, where sub-department 42 is circled yellow, there is a much stronger relation between the two sub-departments in this department. Next to the relation between the sub-departments, it can also be denoted that this department has much more edges than the machining department in general and therefore much more existing relations between work-centers. This means a higher variation is routing which is also concluded from Figure 2.5. The conclusion that can be drawn from Figure 2.6 is that there is a clear separation between sub-departments in the machining department. So, when focusing on this department, the focus is on sub-department-level. However, this can not be done for the sheet metal department. Since the work-centers within this department have a strong relation, also between sub-departments, splitting this department in sub-department-level is not convenient.



(a) Sheet Metal department

(b) Machining department

Figure 2.6: Work-centers with preceding or succeeding parts routing

Both departments, sheet metal and machining, face their own complexities. At the machining department there are significantly more external production steps. These steps can not be influenced by the planner. External manufacturers consider fixed lead-times which makes it impossible to prioritize orders to reduce lead-time. It can also happen that an order is delayed at the external manufacturer which can cause problems with the further processing of this part. Furthermore, the operator-machine relation at the machining department is very strong. Meaning, that for each work-center an operator is assigned which cannot be assigned to another work-center. So, when a machine breaks down, or an operator is not available, this immediately effects the capacity of a work-center. In this department, for most work-centers only one operator is deployed. This operator-machine relation is less strong at the sheet metal department. Most operators are multi-skilled and can operate at multiple work-centers. Also, there are work-centers in this department where operators can work in parallel, such as the welding work-center. This causes more flexibility on the production floor, however, it also has some set backs. When multiple operators work in parallel at a work-center, a situation can occur where an operator does not follow the production list. Most of the time this happens because the operator does not like the part which should be produced next and picks another part he/she prefers. Leaving the part which should be produced according to the production list to his colleagues. This makes the production of parts at these work-centers less predictable.

Since both departments face their own complexity, and Marel does not have any preference in which department should be simulated, the choice is to focus on the sheet metal department. This choice is made because there is a higher complexity in the sheet metal department, and therefore it is expected that the simulation for this department can be easier adjusted to fit the machining department than vise-versa.

As stated before, the scope of this research project is depicted by the red square in Figure 2.1 as part of the total planning process. From this figure can be noticed that the operational planning is not a part of the scope. The operational planning occurs when a machine breaks down or an operator is not available, the planned order already is released to the production floor but because of operational issues it needs to be rescheduled. However, the occurrence of issues on the production floor is considered when releasing the planned orders in terms of capacity constraints. The availability of a work-center will be determined by historical data. This way, machine breakdown and operator availability is considered.

2.3 Research Design

Earlier in this chapter, the problem and scope are defined. The next step is to draft the research plan. The research plan consists of an objective, research questions and correspondingly the used methodology.

2.3.1 Methodology

The methodology used in this research project is the problem solving cycle from van Aken and Berends [2018]. The cycle, which can be found in Figure 2.7, is divided in five steps. For each research question the corresponding phase of the problem solving cycle is given. The research questions can be found in Section 2.3.3. This research proposal is the first phase of the problem solving cycle, the problem definition. In Section 2.1.2 the problems/bottlenecks that are encountered in the planning process are listed, this is the problem mess at the beginning of the research project. The problem mess can be found in the center of the problem solving cycle, because when the problems are analysed and a solution is designed, another problem will probably occur. Therefore, the problem solving cycle is a continuous process.

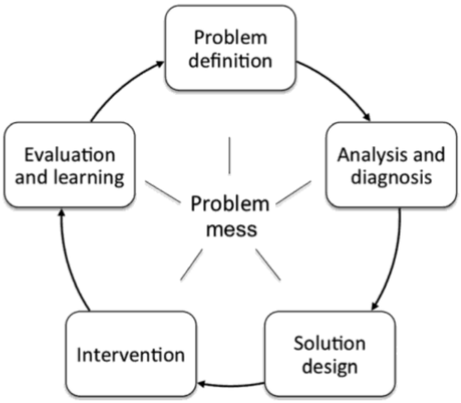


Figure 2.7: Problem Solving Cycle [van Aken and Berends, 2018]

2.3.2 Research Objective

The main objective of this research project is to give advise on the parts production planning of Marel. This is done through making a simulation of the current production planning method and exploring and implementing different methods that follow from literature. The KPI's are measured for all different planning methods, obtaining insights on the production planning of Marel. This objective leads to the following main research question:

What is the impact of different planning methods on the parts production planning of Marel?

2.3.3 Research Questions

The research project is divided into five research questions. These research questions represent milestones in the project. For each research question, the corresponding phase of the problem solving cycle is given.

1. What does the current production planning look like?
The first step of this research project is to get a clear understanding of the planning process, from order

to delivery. What are the different planning steps an order needs to follow, what planning decisions are made on the way and what are the bottlenecks of the process. The KPI's are determined to, in a next phase, measure if the production planning is improved when implementing a new planning method.

Deliverables:

- Description of the current production planning method
- The current KPI's of the production planning

The deliverables of this research question are a description of the current production planning process from order to delivery. The planning process can be found in Section 2.1. Together with the bottlenecks from Section 2.1.2, the description of the planning process is phase 1 of the problem solving cycle; the problem definition. The description of the current production planning process also serves as a foundation for the next phase of the problem solving cycle; analysis and diagnoses. In Section 2.1.3, the KPI's of the current production planning method are described. An analysis on these KPI's and other production planning parameters is done in Section 2.2. In this section, the scope is defined. This eventually leads to the definition of the research plan of Section 2.3.

2. What are possible planning methods for the production planning?
When the scope is defined and the current planning method is analysed, the second step of this research project is to study the literature on which planning methods can improve the KPI's. Are there planning methods that can be applied in a HMLV-environment and what value can it add in comparison to the current planning method?

Deliverables:

- An overview of possible planning methods

In the third phase of the problem solving cycle; solution design, different production planning methods are retrieved from literature. The literature study that is conducted for this research project can be found in Chapter 3. In this chapter, several production planning methods are proposed. In a later stage, some of these methods are implemented.

3. What does a representation of the current planning method look like in simulation?
The third step of this research project is to simulate the current production planning and the current performance of the KPI's. In this phase, data for simulation is gathered and the formulas for calculating the KPI's are defined. The performance of the simulation is validated with past data.

Deliverables:

- Data gathering and cleaning for simulation
- Determine formulas to calculate the KPI's based on available data
- A simulation of the current production planning process
- Performance of KPI's of the actual realized planning method (historical data)
- Performance of KPI's of the simulation current planning method
- Analysis of results, validation of the simulation model

The deliverables on this research question are part of phase 2 and 3 of the problem solving cycle. In Section 4.1 is analysed which data is needed for the simulation model. The data is gathered in phase 2 of the problem solving cycle. The data is cleaned and pre-processed to serve as input for the simulation model. Based on this data, in Section 4.2.2, the formulas for the KPI's are determined. In phase 3 of the problem solving cycle, the solution design is made. As a foundation for the solution design, the current production planning method is simulated in Section 4.2. In Section 4.3, the simulation model is validated by comparing the performance of the KPI's actually realised with the KPI performance of the simulation model. The analysis of results and validation of the simulation model are part of phase 3 of the problem solving cycle.

4. What is the performance of the KPI's when implementing the new planning methods in simulation?
In the fourth part of this research project, different planning methods, which are found in the literature, are implemented in the simulation. The performance of the KPI's on the different planning methods is determined.

Deliverables:

- A simulation of the different production planning methods
- Performance of KPI's on different planning methods
- Analysis of results

Another part of the solution design from phase 3 of the problem solving cycle, is the simulation of different production planning methods. In this research project, two different production planning methods are described, in Chapter 5 and Chapter 6. For each of these planning methods, the performance of KPI's is compared to the simulation of the current planning method. This comparison serves as an intervention, which is phase 4 of the problem solving cycle. From this comparison, results are analysed and conclusion on these different planning methods can be drawn.

5. What conclusions can be drawn, and what advise can be given to Marel on their parts production planning?
Finally, the implemented planning methods and their KPI performance give Marel insights in their parts production planning. An advise is given to Marel on the improvement and bottlenecks of the production planning and recommendations on future work are given.

Deliverables:

- Evaluation of explored planning methods
- Insights obtained from simulation
- Advise to Marel on their production planning method

The conclusions drawn from the different planning methods in phase 4 are used for the evaluation of the explored methods in phase 5 of the problem solving cycle. The overall insights obtained in this research project are summarized in Chapter 7. Also, as part of the learning phase, advise is given to the production planning method of Marel and potential future work.

Chapter 3
Literature Study

Possible production planning methods

The main objective of the research project is to analyse the impact of different planning methods on the KPI's of Marel's production planning. Therefore, in this section, different planning methods are retrieved from literature. The proposed production scheduling and control systems each impact different KPI's in a High-Mix Low-Volume production environment.

3.1 The POLCA System

POLCA is a material control system designed for MTO or ETO companies [Riezebos, 2010], focusing on HMLV manufacturing and the pressure of short lead-times. POLCA, which stands for Paired-cell Overlapping Loops of Cards with Authorization, was introduced by Suri and Burke [1998] in their book about Quick Response Manufacturing (QRM) and is based on the principles of the KANBAN system [Sugimori et al., 1977] and the CONWIP system [Spearman et al., 1990]. To apply POLCA, the shop floor is divided in flexible and multidisciplinary staffed work cells. These cells only make semi-finished products for receiving cells, when these have free capacity to process the products further. To assure that, adapted Kanban-cards are used, which circulate between the workcells. These POLCA-cards signal which workcells downstream have free capacity. The goal of the POLCA system is to improve on-time delivery performance and to reduce the WIP inventory.

3.2 Workload Control

Workload control is a production control technique which balances the load of workstations within a manufacturing system [Lodding, 2011]. A workload control system is based on three elements, a release list, the WIP accounts of the workstations and the WIP limits of the workstations. The release list contains all planned, but not yet released, orders. Generally this list is sorted according to the planned start date. For each workstation a WIP account is kept with orders that are directly or indirectly released to this workstation. The WIP account contains both the WIP on the workstation itself (direct WIP) and WIP that is still on preceding workstations that will be loaded to the workstation in the future (indirect WIP). In addition, each workstation is allocated a WIP limit. If the WIP in the WIP account exceeds the WIP limit, the release of all orders routed through the corresponding workstation is blocked. According to Hendry et al. [2013] the workload control system is proved suitable for a HMLV production of MTO companies.

3.3 Dispatching Rules

In the paper of Chiang and Fu [2007] the job-shop scheduling problem with due date-based objectives are addressed with a main focus on dispatching rules. Eighteen different dispatching rules are analysed and their performance is measured based on the tardy rate, mean and maximum tardiness.

1. Shortest processing time (SPT)
2. Shortest remaining processing time (SRPT)
3. Least total workload (LTWK)
4. Shortest processing time over total workload (SPT/TWK)
5. Earliest due date (EDD)
6. Modified due date (MDD) (combination EDD and SRPT)
7. Operation due date (ODD)
8. Longest remaining processing time (LRPT)
9. Modified operation due date (MOD) (combination ODD and SPT)
10. Cost over time (COVERT)
11. Apparent tardiness cost (ATC)
12. Critical ratio (CR)
13. Critical ratio and shortest processing time (CR + SPT)
14. Shortest remaining processing time plus shortest processing time (SRPT + SPT)
15. Least processing time plus waiting time (PT + PW)
16. Least processing time plus waiting time plus operation due date (PT + PW + ODD)
17. Work-in-next-queue (WINQ)
18. Processing time plus work-in-next-queue plus slack (PT + WINQ + SLACK)

3.4 Meta-heuristics

Meta-heuristics are nature-inspired algorithms as they have been developed based on some abstraction of nature. The two major components of any meta-heuristic algorithms are the selection of the best solutions and randomization. The selection of the best ensures that the solution will converge to the optimality, while the randomization avoids the solutions being trapped at local optima [Yang, 2010]. In this part of the literature study, two meta-heuristics are discussed, genetic algorithms and simulated annealing.

3.4.1 Genetic Algorithm

Genetic algorithms are firstly developed by Holland [1992] and are an abstraction of biological evolution. Which is based on Charles Darwin's theory of natural selection. The essential components of genetic algorithms are the use of crossover, recombination, mutation and selection of adaptive and artificial systems. Genetic algorithms are used as problem-solving strategies, and have been developed and applied to a wide range of optimization problems since Holland introduced it in the 1960s.

A genetic algorithm is proposed in the paper of Svancara et al. [2012]. They present a production schedule optimization for the High-Mix Low-Volume (HMLV) manufacturing systems by means of a genetic algorithm - simulation approach. The concept is made up of three independent parts, the simulation module, the genetic algorithm module and the main optimization module. The simulation module represents the HMLV flow-shop manufacturing system by considering the dynamic, complex and random character of the real production line. The genetic algorithm module represents the genetic searching approach. A genetic search algorithm is a modern heuristic optimization technique which relatively quick converges to an optimal (local/global) solution. The main optimization module communicates between both modules to finally find the overall optimal production schedule.

3.4.2 Simulated Annealing

Simulated annealing is a search along a Markov chain, which converges under appropriate conditions [Yang, 2010]. The search moves trace a piece-wise path. With each move, an acceptance probability is evaluated. This not only accepts changes that improve the objective, but also keeps some changes that do not improve the objective. An acceptance probability is used for controlling the annealing process.

In the paper of Bouleimen and Lecocq [2003] a simulated annealing algorithm is described for the resource-constraint project scheduling problem. The search is based on an alternated activity and time incrementing process. Parameters are set after preliminary statistical experiments done on test instances. The scheduling procedure used is the serial schedule generation scheme which is adapted to the activity list representation. The serial schedule generation scheme is alternating two operations, "start time assignment to activities" and "time incrementing", until all activities of the project are scheduled. The procedure is stopped whenever it meets the critical path value corresponding to the unconstrained problem which is calculated in the first initialisation step.

3.5 Mixed Integer Linear Programming

Mixed integer linear programming (MILP) represents an effective mathematical modelling approach to solve complex optimisation tasks and identify the potential trade-offs between conflicting objectives, which can provide a better understanding of bio-energy systems and support decision-makers elaborating the sustainable pathways towards bio-energy targets [Guo and Shah, 2015].

In the paper of Firat et al. [2021] a production planning approach for a job shop manufacturing company is proposed. The manufacturing company operates with MTO convention and has a high-mix production range. The paper proposes a MILP model that finds workload-dependent planning horizon by making order acceptance decisions. The model converts customer orders into production targets, while accounting for the production system capacity as well as the desired workload amount. The model integrates order selection with production planning and capacity management by dynamically determining a planning time horizon that flexibly adapts to the workload of the given order set. The MILP model ensures that the desired resource capacity levels are achieved regardless of the product mix in the order set.

3.6 Constraint Programming

Constraint programming is a paradigm aimed at solving combinatorial optimization problems [Baptiste et al., 2001]. These problems are often solved by defining them as one or several instances of the constraint satisfaction problem. Such instance is described by a set of variables, a set of possible values for each variable and a set of constraints between the variables. For each instance of the constraint satisfaction problem, a solution is found if there exists an assignment of values to variables such that all constraints are satisfied. A solution is found by using logic and deduction when solving these complex problems. In the book of Baptiste et al. [2001] constraint-based scheduling is introduced. Constraint-based scheduling can be defined as the discipline that studies how to solve scheduling problems by using constraint programming. Each variable of the constraint satisfaction problem has a set of possible values. This is called the domain of the variable. In the constraint-based scheduling model of Baptiste et al. [2001], deduction of the scheduling problem is done by constraint propagation. Constraints are not only used to achieve a feasible solution, they are also used to remove values from the variable domain. The removal of values from the variable domain is called domain reduction. Constraint programming is then used to check whether there is a feasible solution to the scheduling problem.

Chapter 4
Simulation model

In order to compare different planning methods to the current parts production planning method, the current planning method is simulated. This is done using discrete-event simulation (DES) in Python. First, in Section 4.1, the data gathering and preparation is discussed. Next, in Section 4.2, the DES simulation method is explained. Finally, in Section 4.3, the simulation model of the current planning method is validated by comparing the performance of the KPI's of the simulation model with the actual achieved KPI performance.

4.1 Data gathering and preparation

To simulate the current parts production planning, historical data is needed. Namely, data from all the produced orders in the sheet-metal department and data on the available capacity for the corresponding timeframe. There are three data-sets used as input for the simulation. Firstly, a dataset containing all production steps that are created in the sheet metal department. The dataset provided contains all orders created and finished within time interval [01-01-2018, 01-11-2021]. Only orders that are created within the sheet-metal department are included in the dataset, these work-centers are shown in Table 4.1.

At work-center 8600, raw material for machining parts is received from an external supplier. Production steps at this work-center are not added to the first dataset because it also contains production steps at other departments. Therefore, a separate second dataset is used where all order numbers are provided which needed raw material from work-center 8600. Because raw material is received from an external supplier and the agreed lead-time for these steps is three working days, the production time of all 8600-steps is set to three days. In total, in this time interval, at these work-centers, there are 209888 production steps performed (excluding 8600-steps). For each production step the following information is provided in the dataset:

- Order number
- Activity number
- Work-center
- Quantity
- Set-up time
- Machining time
- SAP creation date
- Order due date
- Actual start date
- Actual finish date

Sub-department	Work-center	Operation	Operator type
41 - Sheet metal supply	4101	Laser cutting	2D operator
42 - Sheet metal parts	4200	Sheet metal general	Welding
	4203	Bending	Bending
	4204	Welding robot	Robot operator
	4210	Preparation welding robot	Robot operator
	4285	Innovation parts	Welding
47 - Finishing 42 parts	4700	Blasting	Finishing
86 - Raw material supply	8600	Raw material machining parts	None
85 - Combination parts	8500	Combination parts general	Welding
	8502	Turning	Turning
	8503/8516	Milling Uniport unmanned	None
	8504	Bending	Bending
	8505/8515	Milling Uniport	Uniport operator
	8506	Welding robot	Robot operator
	8507/8517	3D welding	3D operator
	8508	Milling Unipro	Unipro operator
	8510	Combination parts general R&D	Welding
	8511	Preparation external supplier	Welding
	8512	Milling Unipro unmanned	None
	8513	Drilling and tapping	Drill/tap operator
	8514	Rubber pad forming	None
83 - Finishing 85 parts	8300	Blasting	Finishing
	8301	Tumbling	Finishing
	8302	Polishing	Finishing

Table 4.1: Overview work-centers sheet metal department

With these two datasets an orderlist is created in the form of a numpy array. The initial dataset is aggregated by order number. The quantity, creation date and due date of an order is the same for all underlying production steps. The other variables are gathered in a list and sorted according to the activity numbers. In Table 4.2 an example of an order is shown. This order consists of three regular production steps and one 8600-step. The 8600-step is added with a machine-time, setup-time, start date and finish date set to zero. Orders which only consist of finishing steps, work-center 8300/8301/8302, are removed from the orderlist. This is because the machining department also uses these finishing work-centers. So, when an order only consists of finishing steps, the order is most likely from the machining department and therefore not within scope. After the data preparation, the result is an orderlist of 200000 orders *(adjusted due to confidentiality)*.

Order number	101366737
Work-center	[8502, 8500, 8502]
Quantity	2
Machine-time	[0.315, 0.147, 0.304]
Setup-time	[0.817, 0.128, 0.171]
Creation date	4
Due date	35
Start date	[32, 35, 35]
Finish date	[32, 35, 35]

Table 4.2: Order example

A third dataset is used to determine the capacity of the work-centers. This dataset contains all the clock-hours of the operators of the sheet-metal department in time interval [01-01-2019, 01-01-2022]. When an operator arrives at the Marel facility, they need to “clock in” with their Marel-badge, and when the operator leaves, they “clock out”. This way the hours each operator is present that day is registered. A standard amount of break hours is deducted to get the actual production hours of the operator. The available data on the clock-hours, is only from operators which still work at Marel. In the dataset the operator type and sub-department per operator are stated. With this data, the work-center capacity is determined. The planning is made considering 6.6 production hours per day per available operator. Based on past data, it is known when an operator was present at Marel and at which days. For each operator present at a corresponding day, 6.6 hours of capacity are accounted to the work-center of the operator type. Doing this, it is assumed that every day an operator was present at Marel, it was scheduled, and he/she was available for production. In practise, it occurs that an operator is less or more hours than planned available for production. The actual capacity of that day can differ from the planned capacity. The actual capacity is the clock-hours minus the break hours, and is multiplied by 80% considering the productivity of operators. As can be seen in Table 4.1, there are work-centers which require operators of the same operator type. When determining the capacity of the work-center, first the required capacity is analysed. Then the capacity is spread over these work-centers according to the requirements as a fixed percentage. For example, sub-department 42 has two welding work-centers, 4200/4285. The welding operators of sub-department 42 are for 65% accounted to work-center 4200 and 35% to work-center 4285.

The timeframe of the orderlist and the capacity do not match, [01-01-2018, 01-11-2021] and [01-01-2019, 01-01-2022] respectively. Next to that, the available data on the employee capacity is only stored for employees which are currently still working at Marel. When analysing the capacity data, it can be concluded that from 01-09-2019 onward the data is approximately complete and therefore reliable. The timeframe that is therefore used in simulation is [01-09-2019, 01-11-2021]. So, the simulation contains 789 days, of which 565 working-days. Holidays are considered indirectly, as the capacity on these days is zero. Only orders which are created and have a due date within this timeframe are considered. The total amount of orders used in the simulation model is reduced to 100000 orders *(adjusted due to confidentiality).*

4.2 Discrete-event simulation

To simulate the parts production planning of Marel, the DES method is used. A discrete-event simulation models the operation of a system as a discrete sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system. Between consecutive events, no change in the system is assumed to occur. Thus, the simulation can directly jump in time from one event to the next [Page and Kreutzer, 2006].

The basis of the simulation is the SAP planning method. As described in Section 2.1, the SAP system is an Enterprise Resource Planning (ERP). An ERP system can only realize lead-time feasibility or meet the capacity requirements. The SAP system at Marel does plan according to lead-time feasibility and therefore assumes infinite capacity. SAP aims for JIT delivery by scheduling orders backwards. The final production step is scheduled such that it is finished on the due date. With a backward-pass all preceding production orders are scheduled. Two succeeding steps are always scheduled with a working day between, so there is time to pick and place the order at the right work-center. When the order is scheduled backwards, a check on the start date is performed. The first production step of an order can start one working day after the creation date at the earliest. If this is not possible, the order is scheduled forward. The first production step of the order starts at the working day after creation of the order. All succeeding steps are scheduled such that the start date is one working day after the finish date of the preceding step. These orders are automatically finished after the order due date.

The discrete-event simulation starts with creating the initial events. All events contain an order as shown in Table 4.2, a start date, due date and event type. The start date of an initial event is the creation date. At this date, the order is released to the SAP system and therefore visible to the planner. The initial events are of type “RELEASE”. When an event of type “RELEASE” occurs in simulation, all production steps of this order are scheduled according to the procedure as just described. When scheduling the orders, for each production step the required capacity at the corresponding work-center, at that time, is stored in a list. This list of required capacity is later used for rescheduling. The events of the production steps consists out of four types; “START”, “PRODUCTION”, “FINISH” and “ONESTEP”. A distinction between these type of events is made for storage of the results. The first production step is denoted by the “START” event, the last production step is denoted by the “FINISH” event. All events in between are denoted by the “PRODUCTION” event. The event “ONESTEP” is used when an order only consists out of one production step.

However, this is not the complete parts production planning method of Marel. After the order are scheduled by the SAP system, a human planner reviews the required and available capacity and performs resource leveling where needed. Rescheduling is done every Monday, and aims for a feasible planning for the upcoming five weeks. Rescheduling is also done via backward- and forward pass scheduling. The first step of a planner is to check if there are orders which are not yet in production. These orders can be scheduled backwards. The production step which needs to be rescheduled and all its preceding production steps are then rescheduled. Orders with the earliest due date are rescheduled backwards first. A backwards reschedule is only possible when there is available capacity and when the start date of the first production step of the order does not exceed the current time. When the backwards rescheduling is done and there is still an overload of required capacity, the forward pass is performed. Orders with the latest due date are scheduled forward first. So, every Monday a feasible planning at each work-center for the coming five weeks is made. There needs to be noted that when an order is rescheduled, the planner only reschedules one production step. All the production steps which need rescheduling because of this, are rescheduled by the SAP system. Therefore it often happens that more than one reschedule needs to be done for this order. Next to weekly rescheduling, rescheduling is done when not all planned orders are finished on the day the production step was planned. This occurs when there is more capacity planned than there was actually capacity available. Rescheduling of these orders is done with the same procedure. It needs to be denoted that the simulation model works according to the procedure described before, there is no further flexibility in the model. A further elaboration on this topic can be found in Section 4.3, where the simulation model is compared to actual achieved results and validated.

4.2.1 Model Parameters

For the implementation of the parts production planning in simulation, a set of model parameters are defined. The data retrieved from the gathered datasets in Section 4.1 is the starting point for the simulation model. This data is translated to the model parameters which are described in Table 4.3. Next to the model parameters, some model variables are declared in the simulation model. Together, the parameters and variables serve as the foundation of the simulation model. The model parameters and model variables are also necessary to calculate the KPI performance of the planning method which is simulated.

Parameter	Definition
O	set of n orders, $O = \{1, ..., n\}$
M	set of work-centers, $M = \{4101, 4200, ..., 8302\}$
$S_{i,o}$	set of n_o production steps for order $o \in O$, with $i = \{1, ..., n_o\}$
CD_o	Creation date of order $o \in O$
DD_o	Due date of order $o \in O$
$ODD_{i,o}$	Operation due date of production step $S_{i,o}$ of order $o \in O$
$p_{i,o}$	Processing time of production step $S_{i,o}$ of order $o \in O$
$WC_{i,o}$	Work-center where production step $S_{i,o}$ of order $o \in O$ is performed
$CAP_{wc,d}$	Available capacity in hours for day d at work-center $wc \in M$
t	Current time
c_o	Current production step of order $o \in O$

Table 4.3: Model parameters

Variable	Definition
SD_o	Start date of order $o \in O$
FD_o	Finish date of order $o \in O$
L_o	Lead time of order $o \in O$ in days
S_o	Sojourn time of order $o \in O$ in days
$d_{i,o}$	Number of days an operator was working on production step $S_{i,o}$ of order $o \in O$
N^E	Number of early orders $N^E \in N$
N^{JIT}	Number of JIT orders $N^{JIT} \in N$
N^T	Number of tardy orders $N^T \in N$
$R_{wc,d}$	Required capacity in hours for day d at work-center $wc \in M$
$WIP_{wc,d}$	Work-in-progress in number of orders N for day d at work-center $wc \in M$

Table 4.4: Model variables

The scheduling and rescheduling rules as described in Section 4.2 are implemented in the simulation model of the current planning method. The main difference between the simulation model and the actual planning method is the flexibility. In the actual planning method, rescheduling is done manually. Therefore, many decisions that are made in the planning process are biased.

Another difference between the real-life planning and the simulation model is the capacity constraint. As described in Section 4.2, the capacity is planned for 6.6 hours per employee per day, and the actual worked hours are accounted for 80% of the clocked hours of an employee. However, when analysing the capacity requirement and the capacity constraint, it is noted that the requirement often exceeds the constraint. When removing the 80% restriction, and setting the planned capacity to 8 hours per employee per day and the actual worked hours to 100%, the capacity is leveled. Only for work-center 4200 a 101% capacity is required. For the other work-centers utilization below 1 is obtained. Therefore, it is assumed that there is worked at full capacity all the time and employees have a productivity of 100%. This assumption is valid because processing times of production steps often take less time than put in the system.

In the simulation of the current planning method, the planning is made based on the order due date $[DD_o]$. However, in the dataset, the operation due date of all production steps are provided $[ODD_{i,o}]$. When an order is rescheduled, the (operation) due date of an order changes in the SAP environment. As described in Section 4.2, the SAP system schedules all orders with a backward-pass starting with the last production step finishing on the order due date and than scheduling backwards. This way, for each production step, an operation due date is determined. When rescheduling one of the production steps to an earlier date, all preceding steps are also rescheduled to an earlier date. This causes the operation due date of the rescheduled production step and all its preceding steps to change. The operation due dates of the succeeding production steps remains the same. However, when one of the production steps is rescheduled to a later date, all succeeding steps are also rescheduled to a later date. This then causes the ODD of the rescheduled production step and all its succeeding steps to change. Whereas the ODD of all preceding production steps remains the same. In the simulation model, the SAP planning method is considered as the initial planning. After that, resource leveling is done, in terms of rescheduling, to meet the capacity constraints. Since the operation due date of production steps changes when an order is rescheduled, the operation due date of the production steps from the dataset are compared to the initial planning in the simulation model. Comparing the SAP planning to the actual planning determines how many orders are rescheduled. All orders where the ODD does not seem to be the same in the SAP planning as in the dataset can be assumed rescheduled. A total of 30000 orders *(adjusted due to confidentiality)* appear to have the same ODD for all corresponding production steps in simulation as in the dataset. Which are therefore not rescheduled. Meaning that only 30% of all orders, 30000 of the 100000 orders, are not rescheduled. So, in total 70% of all orders are rescheduled.

4.2.2 The KPI's

To calculate the performance of the simulation model, KPI's are defined. As described in Section 2.1, Marel currently uses two KPI's to analyse the performance of the production process. Namely, the delivery performance and the productivity. Since the productivity can not be measured in simulation, only the delivery performance remains relevant to use in the validation model. To get the complete picture of the performance of the parts production planning method of Marel, additional KPI's are defined. These KPI's are put together based on the input of various employees within the GSC, manufacturing engineering and production planning department of Marel.

The first KPI is the delivery performance. The delivery performance is defined by the fraction of production orders that are completed within its due date. The calculation is then the on-time orders $[N^{OT}]$ divided by the total number of orders $[N]$, where $N^{OT} \leq N$, and can be found in Equation 4.4.

$$Early\ Delivery\ [DP_E] = \frac{N^E}{N} \tag{4.1}$$

$$JIT\ Delivery\ [DP_{JIT}] = \frac{N^{JIT}}{N} \tag{4.2}$$

$$Tardy\ Delivery\ [DP_T] = \frac{N^T}{N} \tag{4.3}$$

$$Delivery\ Performance\ [DP] = \frac{N^{OT}}{N} = \frac{N^E + N^{JIT}}{N} \tag{4.4}$$

To get a better understanding of the delivery of order. For each order the finish date is compared to the due-date. This way, the orders are split in early orders, where $[N^E]$ is the total number of early orders. The just-in-time orders, where $[N^{JIT}]$ is the total number of orders delivered on its due date. And the tardy orders, where $[N^T]$ is the total number of orders which are not delivered on-time and therefore are tardy. Where $N^E + N^{JIT} + N^T = N$. For each delivery type the performance is measured, early delivery Equation 4.1, JIT delivery Equation 4.2 and tardy delivery Equation 4.3. Where the on-time orders are a sum of the early and just-in-time orders, $N^{OT} = N^E + N^{JIT}$. For all tardy and early orders, the number of days an order is tardy or early is calculated. This results in the mean tardiness, Equation 4.6, and mean earliness, Equation 4.5, of orders. Where $O_T \subseteq O$ and $O_E \subseteq O$.

$$Mean\ Earliness\ [\mu E] = \frac{1}{N^E} \sum_{o \in O_E} \{DD_o - FD_o\} \tag{4.5}$$

$$Mean\ Tardiness\ [\mu T] = \frac{1}{N^T} \sum_{o \in O_T} \{FD_o - DD_o\} \tag{4.6}$$

The second KPI is the average waiting factor $[W_o]$. The waiting factor is the time an order is waiting divided by the sojourn time of that order. The sojourn time is measured in days, and starts on the day that an order enters the shop-floor and ends when the order is finished and brought to the warehouse, $(S_o = FD_o - SD_o)$, this included weekend days. The waiting factor of an order is the sojourn time minus the processing days of all production steps divided by the sojourn time of an order. The average waiting factor of all orders defines the waiting factor KPI of the simulation model, see Equation 4.7.

$$Waiting\ factor\ [W] = \frac{1}{N} \sum_{o \in O} \{\frac{S_o - \sum_i d_{i,o}}{S_o}\} \tag{4.7}$$

The final KPI is the Work-In-Progress $[WIP]$. This KPI is in correlation with the waiting factor, the longer an order is waiting on the shop-floor, the higher the WIP will be. The WIP inventory are all parts which are in the queue or in process of a work-center. Where N_{wc} is the number of parts in the system of the work-center. Therefore, the equation for the WIP inventory can be found in Equation 4.8.

$$WIP = \sum_{wc \in M} N_{wc} \tag{4.8}$$

The four main KPI's, which determine the overall performance of the planning method, are the delivery performance $[DP]$, the waiting factor $[W]$, the WIP-level $[WIP]$ and the mean tardiness $[\mu T]$.

4.3 Validation

Now that the current planning method is implemented in a simulation model, it needs to be validated. To validate the simulation model, the performance of the KPI's that is actually realized in the job-shop is compared to the KPI's from the simulation model. In Table 4.5, the results of three planning methods are compared. First, the KPI performance from the current planning method, as realized on the shop-floor, is given. These KPI's are retrieved from the historical data over the same timeframe as the simulation model, namely [01-09-2019, 01-11-2021]. Then, the KPI performance that is actually realized in the job-shop is compared to the KPI performance of the simulation model to validate the simulation model. These results are given in Table 4.5. In this table, also the results are given if infinite capacity is assumed and the only planning needed is the SAP planning. Since, this planning method assumes infinite capacity, there are no waiting times and therefor a waiting factor $[W]$ of zero can be observed. There is a WIP-level $[WIP]$ of 223.1 $orders$, which is close to the minimum of 175 $orders$ calculated in Section 4.2.2. Furthermore, a high delivery performance is obtained when no capacity constraint is assumed. The delivery performance $[DP]$ of 95.8% states that 4.2% of the orders can not be produced within the given lead-time. Therefore, the best possible delivery performance that can be achieved in simulation is 95.8%.

The simulation delivery performance $[DP]$ is 59.7%. With an actual realized delivery performance of 60.4%, this validates the simulation model. The delivery performance is split in an early, on-time and tardy delivery, which is 7.8%, 51.9% and 40.3% respectively for the simulation model. Where in the actual job-shop, the early, on-time and tardy delivery is 42.8%, 17.6% and 39.6% respectively. The simulation model has a better on-time delivery than actual, this is likely caused by the manual rescheduling which now is done by scheduling rules rather than human choices. The actual planning method includes flexible rescheduling which is not possible in the simulation model. Because the low early delivery rate of the simulation model, this planning method also achieves a relatively low mean earliness of 3.29 $days$. Compared to a mean earliness of 6.03 $days$, which is actually realized in the job-shop. However, the mean tardiness appears to be much higher in the simulation model, 29.03 $days$, than is realized in the job-shop, 5.22 $days$. Together with the higher WIP-level $[WIP]$ in the simulation model compared to the job-shop realized, 695.6 $orders$ and 360.4 $orders$ respectively. But the waiting factor $[W]$, 30.9 $days$ in simulation is slightly lower compared to 35.9 $days$ in the actual realized situation. It can be concluded that in the simulation model, almost half of the orders are produced according schedule. 51.9% of the orders is delivered exactly on-time and the average waiting factor of an order is relatively low compared to the real-life situation. However, orders that are delivered late, and are tardy, 40.3%, are delivered very late, with a mean tardiness or 29 $days$ (including weekend days), and a high average WIP-level of 695.6 $orders$. In the simulation model 75% of all orders needed to be rescheduled compared to 70% rescheduling in the actual realized production.

KPI's Dispatching rule	DP [%]	W [%]	WIP [$orders$]	Early [%]	JIT [%]	Tardy [%]	Mean earliness [$days$]	Mean tardiness [$days$]
SAP planning method without capacity constraint	95.8	0.0	223.1	0.4	95.4	4.2	1.03	3.51
Simulation model current planning method	59.7	30.9	695.6	7.8	51.9	40.3	3.29	29.03
Actual realized current planning method	60.4	35.9	360.4	42.8	17.6	39.6	6.03	5.22

Table 4.5: KPI performance validation model

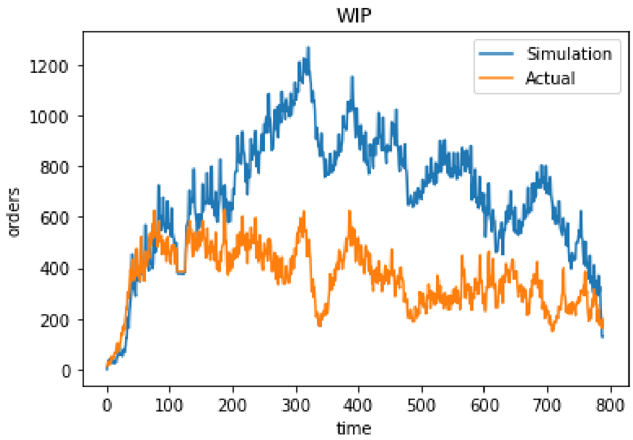


Figure 4.1: WIP-level validation model

4.4 Conclusion

In Section 4.2 the current parts production planning method is translated to a discrete-event simulation model. For this model, model parameters and variables are set. With these variables and parameters, the KPI's, that are needed to validate the simulation model on the parts production planning of Marel, are defined. These KPI's are a combination of performance indicators which Marel currently uses to analyse the production performance, and indicators that are put together by talking to various employees within the Global Supply Chain to get a complete picture of the production performance. To implement the current parts planning method in simulation, the data from Section 4.1 is used. This data contains order lists and availability of operators. To validate the simulation model, the KPI performance is compared to the performance of the KPI's actually realized in production. The validation of the simulation model can be found in Section 4.3. From this section, it can be concluded that the simulation model of the current planning method is valid. The obtained results in simulation are comparable to the results actually realized at the job-shop. Especially the delivery performance corresponds strongly. A decrease in WIP-level and tardiness performance is observed in simulation. This is because of the available flexibility of a human planner that can not be simulated. In the current production planning method, approximately 70% of all orders is rescheduled. However, the waiting factor shows improvement in the simulation model. Overall, the performance of the simulation model are as expected. Therefore, the simulation model of the current parts production planning method is valid.

Chapter 5

Comparison planning method: Dispatching Rules

To get an understanding of the impact of different planning methods on Marel's part production planning. Different planning methods are implemented in the simulation model. Various planning methods are described in Chapter 3. The POLCA system is a physical planning method. Therefore, this planning method is difficult to replicate in simulation. The workload control method constraints the WIP-level at each workstation. This method only focuses on the WIP-level. In contrary, the dispatching rules planning method focuses on the performance of different KPI's. Each different dispatching rule aims to improve another KPI and therefore this planning method is implemented. This way, the impact of the different planning rules on the KPI's can be analysed. Dispatching rules are also known to be easily implemented on the shop-floor.

In this chapter, the dispatching rules planning method is compared to the current planning method. First, the planning method is explained. Then, in Section 5.1, the implementation of the dispatching rules is described. In Section 5.2, the results on this planning method are given. In addition, a capacity analysis is done in Section 5.3. Finally, in Section 5.4, the planning method is evaluated and the conclusion is given.

The objective of the different planning methods is to observe the change in performance of the KPI's compared to the benchmark. The benchmark on the KPI performance in Table 5.1 are the results from the validation simulation model performed in Chapter 4.

KPI	Performance
Delivery Performance [DP]	59.7%
Waiting factor [W]	30.9%
Work-in-progress [WIP]	695.6 $orders$
Early	7.8%
JIT	51.9%
Tardy	40.3%
Mean earliness	3.29 $days$
Mean tardiness	29.03 $days$

Table 5.1: KPI performance - Benchmark

The dispatching rules planning method, as introduced in Section 3.3, is described in this section. Dispatching rules are used to prioritize order waiting in the queue of a work-center. The use of dispatching rules ensures that no rescheduling needs to be done. According to Raghu and Rajendran [1993] the foundation of dispatching rules can be categorized in four ways:

1. Processing time based rules
2. Due date based rules
3. A combination of processing time and due date based rules
4. Neither processing time or due date based rules

The dispatching rules that are selected to use in the simulation model is a selection of rules retrieved from the papers of Rajendran and Holthaus [1999] and Chiang and Fu [2007]. The papers both are comparative studies on the performance of dispatching rules in job-shops. A description of the prioritization of orders using the chosen dispatching rules from these papers is given below. A summary of the used dispatching rules and the mathematical formulation of the rules is given in Table 5.2.

First in - First out

The First in - First out (FIFO) dispatching rule prioritizes orders that first entered the queue. According to Lodding [2011] the FIFO dispatching rule increases the delivery reliability. The rule is easy to implement and leads to minimal variance on the throughput times. However, this dispatching rule does not consider due dates and/or the tardiness of orders.

Processing time rules

One of the categories according to Rajendran and Holthaus [1999] is the dispatching rules based on processing times. The shortest processing time (SPT) rule is one of the most common benchmark rules, according to Chiang and Fu [2007], and assigns priority to orders based on the processing time. When the shop-floor has a high utilization level or tight due dates the SPT rule provides a good performance on minimizing the tardy rate, i.e. maximizing the delivery performance. The SPT rule is extended with the shortest remaining processing time (SRPT) rule, the least total workload (LTWK) rule and the shortest processing time over total workload (SPT/TWK) dispatching rule. The shortest processing dispatching rules lead to low WIP levels and high delivery performance. In addition, the longest (remaining) processing time (L(R)PT) is considered. These rules decrease the overall performance of the job shop. The LPT rules increase the WIP level and have no effect on the delivery performance. For work-centers which have a high utilization, the (S(R)PT, L(R)PT) rules are expected to increase the maximum earliness and/or -tardiness due to orders which keep getting pushed back in the queue.

Arrival time

A rule which is not a due date based rule, nor a processing time based rule, is the arrival time (AT) dispatching rule. The arrival time is defined as the order creation date, i.e. the day that an order is created in the SAP system. This rule has a lot in common with the FIFO rule. However, this rule considers at each production step the job-shop arrival date, whereas the FIFO rule considers the work-center arrival date. Just like the FIFO rule, the AT rule leads to minimal variance on the throughput times [Rajendran and Holthaus, 1999].

Due date rules

The earliest due date (EDD) dispatching rule prioritizes the orders with the earliest order due date. The order due date is the requested delivery date of an order. In addition to the EDD rule, the modified due date (MDD) is considered. The MDD rule takes the maximum of both the order due date or the current time + remaining operation days. This makes MDD a combination of EDD and SRPT. When all orders have a positive slack, the MDD considers the order due date as priority. Whereas all orders with negative slack, the current time plus the remaining processing days is considered as priority.

According to Rajendran and Holthaus [1999], due date based rules are often used in industries for its simplicity of implementation in the shop floor. The EDD and MDD rule both improve the delivery performance and perform well with respect to minimizing the maximum tardiness [Rajendran and Holthaus, 1999].

Critical Ratio

The critical ratio (CR) is defined as the time between the due date and the current time, divided by the number of processing days. The critical ratio dispatching rule is a combination of due date priority and processing time priority. The critical ratio and processing time rule (CR+SPT) prioritizes the order based on the processing time of the current production step when the order already can not be delivered on time, $CR < 1$. Especially the CR+SPT rule is shown to provide good performance on minimizing the mean tardiness [Chiang and Fu, 2007].

Slack

The slack of an order (SL) is defined as the time between the due date and the current time, minus the number of processing days. So, the number of days left, where no production is needed, to still complete the order on time. The slack dispatching rule is a combination of due date priority and processing time priority. A modification of the SL rule is the slack per operation (SL/OP) dispatching rule. This rule takes the slack of an order and divides it by the number of production steps still needed to finish the whole order. According to Lodding [2011], “the idea behind the slack rule is delaying an order that has less slack more often leads to a late completion than with orders that have more slack”.

Work-in-next-queue

The final group of dispatching rules prioritizes orders based on the least total work in the next queue (WINQ). The processing times of all orders in each queue is stored (WIQ). Each day orders of a queue are prioritized by the least work in the next queue (WIQ_{c+1}). This will control the flow of orders through the job-shop. In addition to the WINQ rule, the work-in-next-queue plus processing time is considered (PT + WINQ). This dispatching rule adds the processing time of the current production step to the work-in-next-queue to determine the priority. In addition, the arrival time (PT + WINQ + AT) and slack (PT + WINQ + SL) are also considered as an addition to this dispatching rule. The WINQ priority rules are ordered on smallest value first. These dispatching rules focus on optimizing the flow of orders on the shop-floor [Rajendran and Holthaus, 1999].

5.1 Implementation

Dispatching rules are priority rules for dispatching jobs to the system. When an order arrives in the system, it immediately joins the queue of the work-center where the first production step of that order needs to be executed. Every day, the queue is sequenced according to the dispatching rule. The amount of orders produced every day depends on the capacity of the work-center. When an order is produced, it joins the queue of the next work-center on the next day. So, the queue is not updated throughout the day. When the last production step is finished, the order is delivered to the warehouse. From there, the order is distributed to either the assembly floor or to the customer.

For the implementation of the dispatching rules the model parameters, as stated in Table 4.3, are defined for simulation. To implement these dispatching rules in simulation, the simulation model has been adjusted. When an order is created in the SAP system, it arrives at the queue of it's first work-center. Each day, the order of processing at each queue is defined based on the dispatching rule. If the capacity of that day is used, all waiting orders remain in the queue of the work-center for the next day. When an order is finished, it arrives upon the queue of the next work-center a day after the finishing day of the previous work-center. To determine priority, a few variables are declared in simulation. The total workload of an order; TWK, the remaining processing time of an order; RPT, the remaining slack of an order; RSL and the total work in each queue; WIQ. These variables are only used to minimize computational time. The priority rules are described in Table 5.2.

Rule	Priority	Description
$FIFO$	t	First in - First out
SPT	$p_{i,o}$	Shortest processing time
$SRPT$	$\sum_{i=c}^{n_o} p_{i,o}$	Shortest remaining processing time
LPT	$p_{i,o}^-$	Longest processing time
$LRPT$	$\sum_{i=c}^{n_o} p_{i,o}^-$	Longest remaining processing time
$LTWK$	$\sum_{i=1}^{n_o} p_{i,o}$	Least total work-load
SPT/TWK	$p_{i,o}/\sum_{i=1}^{n_o} p_{i,o}$	Shortest processing time over total work-load
AT	CC_o	Arrival time (Creation date)
EDD	DD_o	Earliest due date
MDD	$\max\{DD_o, t + \sum_{i=c}^{n_o} d_{i,o}\}$	Modified due date
CR	$(DD_o - t)/(\sum_{i=c}^{n_o} d_{i,o})$	Critical ratio
$CR + SPT$	$\max\{CR \cdot p_{i,o}, p_{i,o}\}$	Critical ratio and processing time
SL	$sl_o = DD_o - t - \sum_{i=c}^{n_o} d_{i,o}$	Slack
SL/OP	$sl_o/(n_o - c + 1)$	Slack per remaining operation
$WINQ$	WIQ_{c+1}	Work-in-next-queue
$PT + WINQ$	$p_{i,0} + WIQ_{c+1}$	Processing time + WINQ
$PT + WINQ + AT$	$p_{i,o} + WIQ_{c+1} + CC_o$	Processing time + WINQ + arrival time
$PT + WINQ + SL$	$p_{i,o} + WIQ_{c+1} + \min\{sl_o, 0\}$	Processing time + WINQ + slack

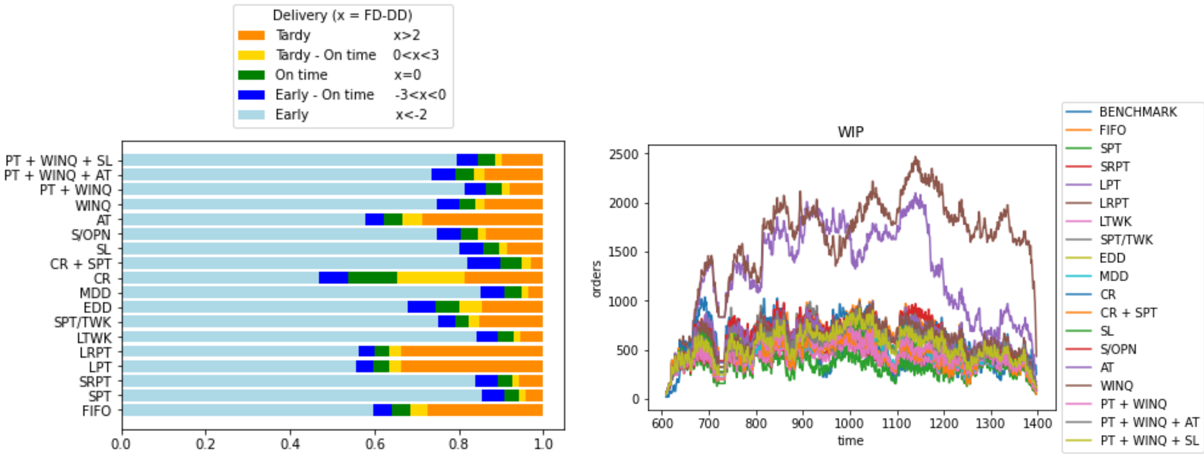
Table 5.2: Dispatching rules

5.2 Results

For each dispatching rule the performance of the KPI's is given in Table 5.3. Three main KPI's formulated are the delivery performance $[DP]$, waiting factor $[W]$ and the work-in-progress level $[WIP]$. The delivery performance is split in early orders, JIT orders and tardy orders. For the early and tardy orders, the mean number of days are also given in the table. The mean tardiness $[\mu T]$ is added as the fourth main KPI. The delivery performance is depicted in Figure 5.1a, for each dispatching rule the percentage of tardy orders, are shown in orange. Orders which are delivered tardy but within 2 days after its due date are shown in yellow. The percentage of orders delivered exactly on-time are shown in green. Orders which are delivered before its due date are blue, where dark blue are the orders delivered within just 2 days before due date. The WIP-level trough-out the simulation, for each dispatching rule, is shown in Figure 5.1b.

KPI's / Dispatching rule	DP [%]	W [%]	WIP [$orders$]	Early [%]	JIT [%]	Tardy [%]	Mean earliness [$days$]	Mean tardiness [$days$]
Benchmark	59.7	30.9	695.6	7.8	51.9	40.3	3.29	29.03
$FIFO$	68.7	45.0	657.6	63.8	4.9	31.3	19.06	13.86
SPT	94.2	14.5	331.8	90.5	3.7	5.8	21.89	19.47
$SRPT$	92.7	15.8	400.9	88.7	3.9	7.3	21.56	33.98
LPT	64.0	45.5	1269.2	59.1	4.9	36.0	19.98	69.38
$LRPT$	64.0	45.4	1583.3	59.5	4.5	36.0	20.83	107.75
$LTWK$	92.9	15.8	395.6	88.9	4.1	7.1	21.49	32.89
SPT/TWK	82.5	28.4	571.9	78.7	3.8	17.5	22.29	46.63
EDD	80.2	36.7	571.6	74.2	6.0	19.8	15.87	6.32
MDD	94.8	27.4	454.7	90.4	4.3	5.2	17.38	20.62
CR	65.4	44.5	643.2	53.6	11.9	34.6	16.62	4.59
$CR + SPT$	94.9	28.5	442.7	89.5	5.5	5.1	17.57	11.51
SL	89.7	27.8	537.9	85.1	4.5	10.3	17.32	30.51
SL/OP	84.5	30.2	662.8	79.8	4.7	15.5	17.67	42.94
AT	66.9	46.7	651.5	61.9	5.0	33.1	18.87	13.19
$WINQ$	83.9	27.0	616.0	79.6	4.4	16.1	20.22	38.48
$PT + WINQ$	90.2	20.8	443.3	86.0	4.3	9.8	20.87	28.52
$PT + WINQ + AT$	83.5	30.7	550.6	78.4	5.1	16.5	19.39	22.29
$PT + WINQ + SL$	88.5	24.8	543.7	84.2	4.3	11.5	19.34	35.67

Table 5.3: KPI performance initial dispatching rules



(a) Delivery Performance (b) WIP-level

Figure 5.1: Performance initial dispatching rules

In Table 5.3 the results from the initially used dispatching rules are shown. In this table, the three KPI's delivery performance [DP], waiting factor [W] and WIP-level [WIP] are stated. In addition to the KPI's, the delivery performance is split into early-, JIT- and tardy delivery. Also, in this table, the results on the mean earliness and mean tardiness of early and tardy orders are given. First, the results from the benchmark are stated. These results are used to compare the results of the dispatching rules. To give a better insight in what the results from the dispatching simulation model mean, in Table 5.4 the percentile difference compared to the benchmark is calculated. The total performance improvement of the dispatching rule is then calculated by taking the average of the four KPI's. The mean tardiness is accounted for twice in this calculation. This is done because the mean tardiness is most important for customer-satisfaction. The four KPI's are equally important for the company, but to keep customers satisfied, it is most important to minimize the tardy rate of an order rather than maximizing the delivery performance. The waiting factor of an order and the WIP-level of the shop-floor do not directly affect the customer-satisfaction.

For a better visualization of results the table is color coded according the following color scheme:

$(-\infty, -50]$	$(-50, -20]$	$(-20, 20)$	$[20, 50)$	$[50, \infty)$

The results given in Table 5.4 are sorted according to the dispatching rules with the best overall performance. The best scoring rules are the CR+SPT, EDD, SPT, MDD and LTWK dispatching rules.

Dispatching rule	Percentile difference with benchmark $[DP]$	$[W]$	$[WIP]$	$[\mu T]$	Total
SPT	58	53	52	33	46
$CR + SPT$	59	8	36	60	45
EDD	34	-19	18	78	38
MDD	59	11	35	29	33
CR	10	-44	8	84	28
$PT + WINQ$	51	33	36	2	25
$LTWK$	56	49	43	-13	24
$SRPT$	55	49	42	-17	22
$PT + WINQ + AT$	40	1	21	23	22
$FIFO$	15	-46	5	52	16
AT	12	-51	6	55	15
SL	50	10	23	-5	15
$PT + WINQ + SL$	48	20	22	-23	9
$WINQ$	41	13	11	-33	0
S/OPN	42	2	5	-48	-9
SPT/TWK	38	8	18	-61	-11
LPT	7	-47	-82	-139	-80
$LRPT$	7	-47	-128	-271	-142

Table 5.4: KPI performance compared to benchmark

Overall, the delivery performance improves when using the dispatching rules as a production planning method. However, the increase in DP is relatively low when using the L(R)PT, CR, FIFO or AT dispatching rules. The highest increase of delivery performance is measured at the (CR+) S(R)PT, LTWK, MDD dispatching rules, which are also the top scoring rules. Also, the PT+WINQ and SL rule give a good DP. The EDD and CR are also high performing dispatching rules, but they have a relatively low delivery performance. The waiting factor shows a big increase in performance with the use of the S(R)PT and LTWK rule. These rules all focus on the shortest processing times. Again the L(R)PT, CR, FIFO or AT dispatching rules have a bad performance. These rules show a decrease in waiting factor performance. However, while the performance on DP and W is low, these dispatching rules, CR (+SPT), FIFO, AT show, together with the EDD rule, a great improvement on the mean tardiness. The mean tardiness is the most important KPI of the job-shop since it not only affects company-satisfaction, but more importantly it effects the customer-satisfaction. The improvement of the mean tardiness often leads to an increase in the waiting factor. The WIP-level overall decreases with the use of dispatching rules. Only the L(R)PT rule has a big increase in WIP-level. This is likely the case because of the high utilization of several work-centers. When prioritizing long lead-time orders, the operators are working for a long period of time on these orders while the, probably many, short lead-time items are queuing at the work-center and therefore increase the WIP-level. In contrary, the S(R)PT rule most likely has a good performance because the long lead-time items are only produced when there is a low utilization, and therefore this rule also shows a relatively bad result when it comes to the tardy rate (μT). The S(R)PT rules cause long lead-time items to be rarely produced, which is not likely. When looking at the overall performance, together with the reasoning behind it, the EDD and MDD dispatching rule are considered the best performing dispatching rules. These rules are easy to implement in the job-shop and do not cause a high variability of lead-times.

Since the EDD dispatching rule has a good overall performance and, most importantly, a low mean tardiness, an addition to this rule is made to see if an even better performance could be obtained. The EDD rule, as-well as the MDD rule, is extended to include the processing times. The additional rules can be found in Table 5.5. With the (E)(M)DD&xx rules, orders are prioritized by the earliest/modified due date first. Orders with the same due date are than prioritized by the additional dispatching rule (SPT, CR, CR+SPT, LTWK). For both EDD and MDD an additional rule including the slack is provided, (E)(M)DD+SL. And finally, the critical ratio is also added to the PT+WINQ rule, to hopefully improve the tardy rate which is very low when only using the CR dispatching rule.

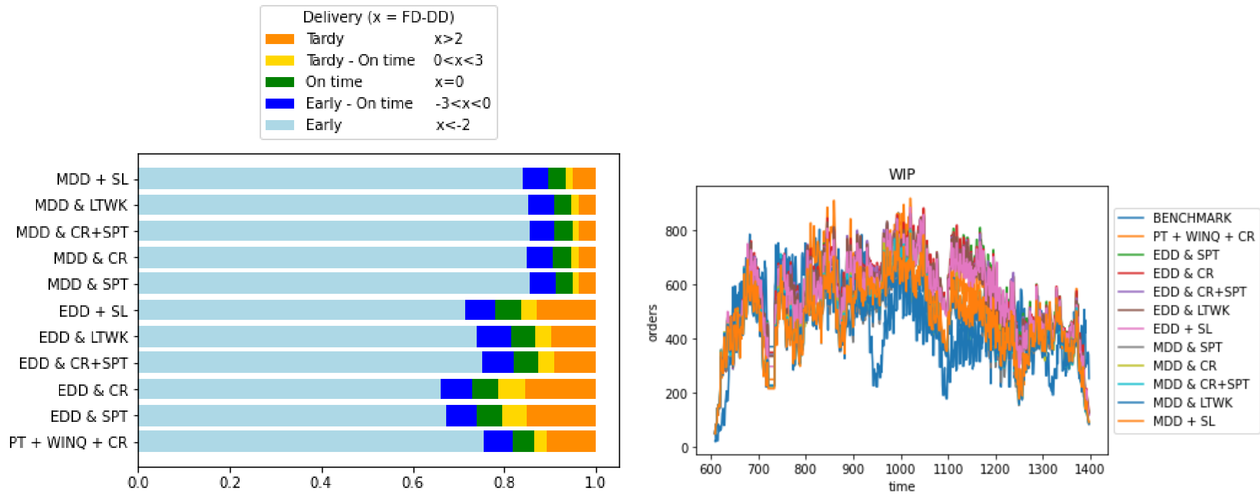
Rule	Priority
$PT + WINQ + CR$	$p_{i,0} + WIQ_{c+1} + CR$
EDD & SPT	$[DD_o, p_{i,0}]$
EDD & CR	$[DD_o, (DD_o - t)/(\sum_{i=c}^{n_o} d_{i,o})]$
EDD & $CR + SPT$	$[DD_o, \max\{CR \cdot p_{i,o}, p_{i,o}\}]$
EDD & $LTWK$	$[DD_o, \sum_{i=1}^{n_o} p_{i,o}]$
$EDD + SL$	$DD_o + sl_o$
MDD & SPT	$[\max\{DD_o, t + \sum_{i=c}^{n_o} d_{i,o}\}, p_{i,0}]$
MDD & CR	$[\max\{DD_o, t + \sum_{i=c}^{n_o} d_{i,o}\}, (DD_o - t)/(\sum_{i=c}^{n_o} d_{i,o})]$
MDD & $CR + SPT$	$[\max\{DD_o, t + \sum_{i=c}^{n_o} d_{i,o}\}, \max\{CR \cdot p_{i,o}, p_{i,o}\}]$
MDD & $LTWK$	$[\max\{DD_o, t + \sum_{i=c}^{n_o} d_{i,o}\}, \sum_{i=1}^{n_o} p_{i,o}]$
$MDD + SL$	$\max\{DD_o, t + \sum_{i=c}^{n_o} d_{i,o}\} + sl_o$

Table 5.5: Dispatching rules - extension

When implementing the dispatching rules from Table 5.5, the results as shown in Table 5.6 are retrieved. In this table, the three main KPI's delivery performance $[DP]$, waiting factor $[W]$ and WIP-level $[WIP]$ are stated. In addition to the KPI's, the delivery performance is split into early-, JIT- and tardy delivery. Also, in this table, the results on the mean tardiness and mean earliness of the orders are given. The mean tardiness $[\mu T]$ is added as the fourth main KPI. First, the results from the benchmark are stated. These results are used to compare the results of the additional dispatching rules given in Table 5.5. In Figure 5.2a the delivery performance for the dispatching rules if visualised. Besides, in Figure 5.2b the WIP-level over time is shown. Since the WIP performance is comparable for the different dispatching rules, the figure is hard to analyze.

KPI's / Dispatching rule	DP [%]	W [%]	WIP [$orders$]	Early [%]	JIT [%]	Tardy [%]	Mean earliness [$days$]	Mean tardiness [$days$]
Benchmark	59.7	30.9	695.6	7.8	51.9	40.3	3.29	29.03
$PT + WINQ + CR$	86.5	30.5	555.9	81.2	5.4	13.5	18.04	24.37
EDD & SPT	79.7	36.7	575.7	73.5	6.1	20.3	16.00	6.57
EDD & CR	78.6	37.3	577.5	72.5	6.1	21.4	15.97	6.15
EDD & $CR + SPT$	87.6	34.9	535.9	81.7	5.8	12.4	15.52	6.67
EDD & $LTWK$	86.7	34.9	539.8	80.9	5.9	13.3	15.56	6.71
$EDD + SL$	83.7	33.9	559.9	77.7	6.0	16.3	15.79	9.24
MDD & SPT	94.9	27.0	451.7	90.6	4.2	5.1	17.50	20.74
MDD & CR	94.7	28.1	460.5	90.3	4.3	5.3	17.23	20.54
MDD & $CR + SPT$	94.9	27.5	453.1	90.6	4.2	5.1	17.42	20.36
MDD & $LTWK$	94.8	27.3	454.8	90.6	4.2	5.2	17.42	20.61
$MDD + SL$	93.5	27.6	473.2	89.2	4.3	6.5	17.09	21.44

Table 5.6: KPI performance extra dispatching rules



(a) Delivery Performance (b) WIP-level

Figure 5.2: Performance extra dispatching rules

To get a better understanding of the results from Table 5.6, compared to the benchmark and to the other results from Table 5.3, the percentile difference compared to the benchmark of the top results are shown in Table 5.7. As can be seen, the results on the (CR+) SPT rules are not outperformed. However, as already stated, these results cause long lead-time items to never/rarely be processed at high utilization work-centers. This is in reality however not possible and therefore these dispatching rules will not be considered when determining the best performing dispatching rule. When adding the (CR+) SPT or LTWK rule to the (E)(M)DD rule, items are prioritized according to their due date and subsequently also on their processing time. This way, long lead-time items have less priority but they still will be processed when a work-center has high utilization.

What can be noticed from the results in Table 5.7, is that the extended rules have a great comparison to the original (E)(M)DD rules. This was expected since these rules only have a second priority order when the (E)(M)DD rule assigns priority to multiple orders. The (E)(M)DD & CR+SPT have the overall best performance compared to the base rule. The CR+SPT rule is also the second best overall performing dispatching rule. So, when combining these dispatching rules, a realizable and good performing rule is created. Since minimizing the tardy rate is chosen as main performance indicator, the EDD rules come to a better overall score. When not doing this, the MDD rules would have scored higher because of the deterioration of the waiting factor when using the EDD rules.

Dispatching rule	Percentile difference with benchmark				Total
	$[DP]$	$[W]$	$[WIP]$	$[\mu T]$	
SPT	58	53	52	33	46
$CR + SPT$	59	8	36	60	45
EDD & $CR + SPT$	47	-13	23	77	42
EDD & $LTWK$	45	-13	22	77	42
EDD	34	-19	18	78	38
EDD & SPT	33	-19	17	77	37
$EDD + SL$	40	-10	20	68	37
EDD & CR	32	-21	17	79	37
MDD & $CR + SPT$	59	11	35	30	33
MDD & SPT	59	13	35	29	33
MDD & $LTWK$	59	12	35	29	33
MDD	59	11	35	29	33
MDD & CR	59	9	34	29	32
$MDD + SL$	57	11	32	26	30
CR	10	-44	8	84	28
$PT + WINQ$	51	33	36	2	25
$LTWK$	56	49	43	-13	24
$SRPT$	55	49	42	-17	22
$PT + WINQ + AT$	40	1	21	23	22
$PT + WINQ + CR$	45	1	20	16	20

Table 5.7: KPI performance (extra rules) compared to benchmark

5.3 Capacity analysis

As an addition to the dispatching rules planning method, a capacity analysis is done on the best performing dispatching rule. When looking at actual implementation, the EDD rule is easiest implemented in the production planning of the job-shop. Therefore it is chosen that the EDD dispatching rule is used for the capacity analysis. The capacity analysis is done to provide practical insights to Marel on how to optimally implement dispatching rules in their system. When chosen for a dispatching based production planning, it is convenient to know how many operator hours are required on which work-center. To do this, for each work-center the optimal amount of work-hours is determined with use of the simulation model. In the capacity analysis, it is assumed that operators work full shifts. But the productivity factor is also considered, so the optimization of work-hours are per # shifts of 6.6 hours. The optimal number of shifts will be determined based on the performance of the KPI's.

Work-center	Required capacity [h/week]	(assuming 80% UT) Required capacity [h/week]	Current capacity [h/week]	Utilization [%]
4101	100.0	125.0	163.4	61.2
4200	388.8	486.0	383.5	101.4
4203	69.8	87.2	98.7	70.7
4204	49.7	62.1	68.1	73.0
4210	40.1	50.1	59.6	67.3
4285	138.6	173.2	156.2	88.8
4700	42.8	53.5	86.7	49.4
8300	28.3	35.4	49.4	57.3
8301	3.3	4.1	5.5	60.3
8302	31.2	38.9	54.8	56.8
8500	350.5	438.1	566.5	61.9
8502	27.1	33.8	40.1	67.5
8504	41.2	51.5	42.3	97.4
8506	33.0	41.3	42.6	77.6
8508	60.9	76.2	85.2	71.6
8510	33.6	42.0	80.9	41.5
8511	71.7	89.6	161.9	44.3
8513	37.1	46.4	40.1	92.6
8515	50.3	62.9	145.3	34.7
8517	61.7	77.2	138.8	44.5
Total Welding	983.1	1228.9	1348.9	72.9
Total	1659.7	2074.7	2469.4	67.2

Table 5.8: Capacity Analysis *(adjusted due to confidentiality)*

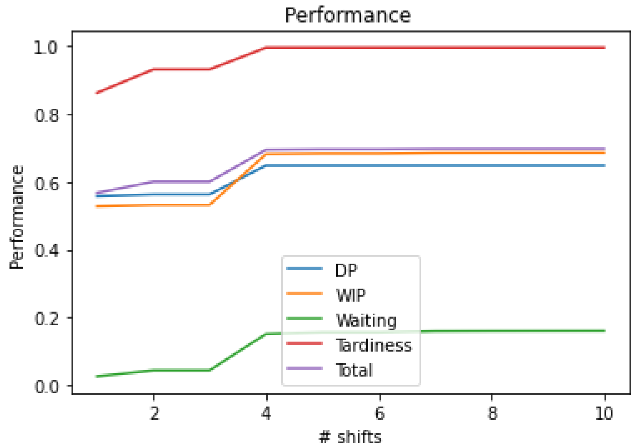
The first part of the capacity analysis is visualized in Table 5.8. In the first column, for each work-center, the on average required production hours per week is retrieved from simulation. According to (Van) Enns [1995], the optimal utilization level when using the EDD dispatching rule is 78.1%. Therefore, in this capacity analysis, an utilization of 80% is assumed. The total required capacity when using 80% utilization is then calculated in the second column. In addition, the current number of production hours are retrieved from the data set. The current capacity is also a weekly average. In simulation, for each work-center, a simulation run is done to determine the optimal number of shifts weekly. The KPI performance of the simulation is compared to the benchmark, and the percentile difference is calculated. Since work-center 8512, 8514 and 8516 are unmanned work-centers, these are not considered in the capacity analysis. For work-center 4200, 4285, 8500, 8510 and 8511 the welding work-centers, a total shared capacity of 1650 [$h/week$] (= 250 $shifts$) is available. For work-center

4101, two operators can work per shift. With two shifts per five working days, assuming 6.6 production hours per shift, a total possible capacity of 128 $[h/week]$ $(= 20\ shifts)$ is available for work-center 4101. For all remaining work-centers one operator can work per shift, giving a total possible capacity of 66 $[h/week]$ $(= 10\ shifts)$ per work-center.

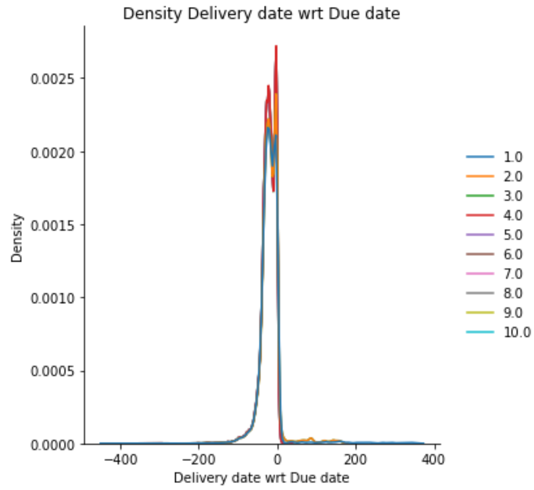
The work-centers are split in three groups, the first group is the unmanned work-centers, which are not part of the capacity analysis. The other two groups are the welding work-centers and the non-welding work-centers. The non-welding work-centers have an one machine, one operator policy. So, for these work-centers, the weekly capacity can be between one and ten shifts. Except for work-center 4101, this work-center can work at the speed of two operators per machine. For these non-welding work-centers, the required capacity is shown in Table 5.9. For each work-center, the required capacity is also calculated in required number of shifts per week. Then, in the next column, the simulation range on the optimization of number of shifts is shown. For all of the work-centers this is [1, 2, 3, ..., 10]. Only work-center 4101 can have a range of [1, 2, 3, ..., 20] shifts per week, since two operators can work simultaneously on this work-center. Shifts are spread over the week starting on Monday. When having, for example, 8 shifts a week, the production hours are $[16, 16, 16, 8, 8]$, for [Mon, Tue, Wen, Thu, Fri]. It is assumed that shifts are equally spread over the week starting from Monday, since the SAP system releases new orders in weekends. When performing the capacity analysis for a work-center, all other work-centers are assumed infinite capacity. This way, only the work-center where the number of shifts is to be optimized, is the bottleneck of the job-shop.

In the following paragraph, an example on the capacity analysis is given. Due to confidentiality, the number of the work-center in the example is not stated and is referred to as work-center X. This paragraph is mainly for explanatory purposes on how the capacity analysis is done.

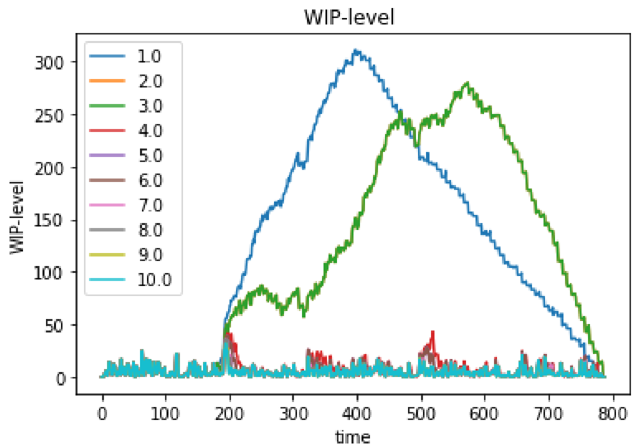
To get a better understanding of the optimization of capacity at a work-center, the capacity analysis of work-center X is shown in Figure 5.3. Work-center X is a non-welding work-center with a one machine, one operator policy. Therefore, the capacity at this work-center can range from one to ten shifts per week. In Figure 5.3a, the percentile difference in KPI performance is shown with respect to the benchmark. The percentile difference is visualized for each KPI separately and the purple line represents the total percentile difference. The calculation of the percentile difference shown in this figure is comparable to the KPI performances calculated in Table 5.7. As can be seen, the performance is overall better than the benchmark. This is because only the capacity of work-center X is constraint. Other work-centers are assumed infinite. Therefore, the overall performance improves in all possible cases. However, in Figure 5.3a, it can be noticed that the improvement of performance stalls at four shifts. Increasing the # of shifts further than four shifts per week has no notable improve on the overall performance. In Figure 5.3b the density of delivery date with respect to due date is shown, $FD_o - DD_o$. Orders delivered early are negative, on-time orders are zero and tardy orders are positive. In this graph can be seen that, at four shifts per week, the density is highest around zero, which is preferable. The delivery performance can be found in Figure 5.3d. In this figure, the early, on-time and tardy delivery is shown. From this figure can also be concluded that the delivery performance is highest when using four shifts for work-center X. Increasing the number of shifts does not effect the delivery performance. When looking at the WIP-level of work-center X in Figure 5.3c, it can be noted that the WIP-level increases exponentially when using one, two or three shifts. When using four or more shifts at work-center X, the WIP-level becomes steady. Analysing all figures, it can be concluded that, for work-center X, the optimal number of shifts is four. Such analysis is done for every work-center.



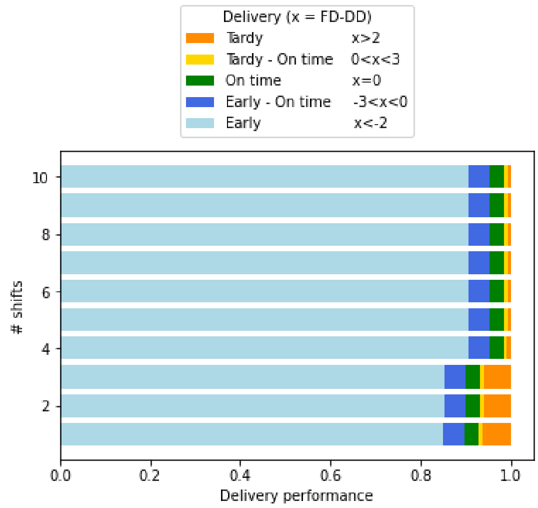
(a) Percentile difference in performance



(b) Density delivery date wrt due date



(c) WIP-level



(d) Delivery performance

Figure 5.3: Capacity Analysis: work-center X

In Table 5.9, the results on the calculations for the non-welding work-centers are shown *(numbers are adjusted due to confidentiality)*. For each work-center, the average amount of production hours per week are calculated over the total time period [01-09-2019, 01-11-2021]. For work-center 4101 an average of 100 production hours ($100/6.6 \approx 15.2$ shifts) per week is required. Currently, an average of 24.8 shifts per week are scheduled. The optimal amount of shifts for this work-center is 18 shifts per week. This is difference of -26% with the number of shifts that is currently planned. When looking at Table 5.9, there can be seen that for most work-centers less capacity is optimally required than currently planned. At all non-welding work-centers combined, a total of 19% of all shifts is currently planned can be reduced. From Table 5.9 can be concluded that the non-welding work-centers are not the bottleneck of the job-shop. However, over capacity is planned multiple work-centers. Reducing the capacity on these work-centers, and allocating these operators to different work-centers elsewhere in the job-shop, can solve capacity issues at other work-centers. *(due to confidentiality, the optimal number of shifts can exceed the max. of 10 shifts per week)*

Work-center	Required capacity [h/week]	[shifts/week]	Simulation [shifts/week]	Currently [shifts/week]	Optimal	Difference [%]
4101	100.0	15.2	[1,...,20]	24.8	18	-26%
4203	69.8	10.6	[1,...,10]	15.0	13	-15%
4204	49.7	7.5	[1,...,10]	10.3	11	+10%
4210	40.1	6.1	[1,...,10]	9.1	10	+9%
4700	42.8	6.5	[1,...,10]	13.2	10	-25%
8300	28.3	4.3	[1,...,10]	7.5	6	-25%
8301	3.3	0.5	[1,...,10]	0.8	1	+20%
8302	31.2	4.7	[1,...,10]	8.4	7	-15%
8502	27.1	4.1	[1,...,10]	6.1	6	-7%
8504	41.2	6.2	[1,...,10]	6.4	7	+11%
8506	33.0	5.0	[1,...,10]	6.5	7	+9%
8508	60.9	9.2	[1,...,10]	12.9	11	-12%
8513	37.1	5.6	[1,...,10]	6.1	7	+16%
8515	50.3	7.6	[1,...,10]	22.1	10	-55%
8517	61.7	9.4	[1,...,10]	21.1	13	-40%
Total	676.6	102.5	-	170.1	137	-19%

Table 5.9: Capacity Analysis - Non-welding work-centers *(adjusted due to confidentiality)*

For the welding work-centers, not all possible options on how to distribute the operators can be explored due to computation time. Therefore, the required capacity, at 100% and 80% utilization, from Table 5.8 is considered. Work-center 8500, for example, approximately requires between $350.5/6.6 \approx 53.1$ and $438.1/6.6 \approx 66.4$ operator shifts per week *(numbers are adjusted due to confidentiality)*. Taking $+/-3$ shifts, a simulation for work-center 8500 is performed using $[35, 36, 50, ..., 70]$ shifts. When performing the capacity analysis for work-center 8500, all other work-centers are assumed to have infinite capacity. This way, only work-center 8500 is the bottleneck of the job-shop. For the welding work-centers, a similar capacity analysis is done as the analysis of work-center X shown in Figure 5.3, only with these different ranges in the number of shifts.

In Table 5.10, the results of the capacity analysis for the welding work-centers are shown. For each work-center, the required number of shifts per week at a 100% and at a 80% utilization are calculated. From these results, a simulation range is defined. A simulation run is performed for each work-center, with it's corresponding range, to determine the optimal number of shifts per week. In addition, the currently used shifts per week are shown in the table. From these two columns, the accumulative result is calculated. As can be seen, there is a capacity shortage at work-center 4200 and 4285, making these work-centers the bottleneck of the job-shop. On the other hand, there is an overage of capacity at the other welding work-centers, work-center 8500, 8510 and 8511. Since these work-centers require the same operator skill, welding, the operators can be distributed differently between these work-centers to level the resources. Overall, the currently planned capacity for the welding work-centers is 204.2 shifts per week. Where the optimal amount of shifts per week is only 178 shifts. The maximum amount of shared capacity possible among these work-centers is 250 shifts per week. Overall 13% of the shifts can be reduced.

Work-center	100% UT Required capacity [shifts/week]	80% UT Required capacity [shifts/week]	Simulation	Currently [shifts/week]	Optimal [shifts/week]	Difference [%]
4200	58.9	73.6	[55,...,76]	58.0	67	+15%
4285	20.9	26.2	[18,...,29]	23.6	28	+20%
8500	53.1	66.4	[50,...,70]	85.8	62	-27%
8510	5.1	6.4	[2,...,9]	12.3	10	-20%
8511	10.9	13.6	[8,...,16]	24.5	11	-54%
Total	148.9	186.1	-	204.2	178	-13%

Table 5.10: Capacity Analysis - Welding work-centers *(adjusted due to confidentiality)*

The overall reduction in production hours is 16%. In the capacity analysis a constant capacity level for each work-center is assumed. However, in practise, this is not always possible. Operator availability can be uncertain. Operators can get ill, take a vacation, or not enough operators can be employed. Also, productivity and skills are not considered. Some operators perform better at doing their jobs than others. This can also cause differences in practice compared to simulation.

KPI's / Dispatching rule	DP [%]	W [%]	WIP [$orders$]	Early [%]	JIT [%]	Tardy [%]	Mean earliness [$days$]	Mean tardiness [$days$]
Benchmark	59.7	30.9	695.6	7.8	51.9	40.3	3.29	29.03
EDD	80.2	36.7	571.6	74.2	6.0	19.8	15.87	6.32
$EDD + capacity$	94.9	25.7	375.4	91.2	3.7	5.1	17.22	5.42

Table 5.11: KPI dispatching + capacity

To check if these optimal number of shifts improve the overall performance, a final simulation run is done where the capacity limit for each work-center is set to the optimal number of shifts. In Table 5.11 the performance of the benchmark and EDD rule are shown, as a comparison for results on the EDD dispatching + capacity analysis. The results from the capacity optimization give overall very good results. This analysis improves performance on all KPI's and outperforms all results retrieved so far.

Dispatching rule	Percentile difference with benchmark [DP]	[W]	[WIP]	[μT]	Total
EDD	34	-19	18	78	38
$EDD + capacity$	59	17	46	81	57

Table 5.12: KPI performance dispatching + capacity analysis compared to benchmark

The results on the EDD dispatching rules combined with the capacity optimization are also compared to the benchmark. These results are shown in Table 5.12. Compared to the benchmark, the EDD + capacity rule has a positive percentile difference for all KPI's. Compared to the EDD rule without capacity constraints, the EDD + capacity also improves on all KPI's. Especially the DP, W and WIP are improved. Gaining an overall 57% increase of performance with respect to the benchmark, and an increase of 19% with respect to the general EDD results. The use of these new capacity constraints will not only improve the production planning performance, but will also have financial advantages. The production performance will increase with 57% compared to the benchmark. Together with a decrease in needed production hours of 16%. The capacity analysis will provide practical guidelines in how to improve the production planning even further with the use of the EDD dispatching rule.

5.4 Conclusion

The first planning method, which is compared to the current planning method of Marel, is the dispatching rule planning method. This planning method makes a sequence of orders based on priority rules for each work-center, every day. Jobs are dispatched to the operators based on these dispatching rules, no scheduling is done beforehand. Therefore, dispatching rules avoid rescheduling in the planning process. Eighteen dispatching rules are implemented in simulation. Using dispatching rules as production planning method improves the performance of Marel's parts production.

The (shortest) processing time based rules perform well on improving the delivery performance. While the due date based rules perform well on improving the tardy rate. The best performing rules compared to the benchmark are the (CR+)SPT rules. However, the (shortest) processing time based rules cause that long lead-time orders keep getting pushed back in the queue, and with a high utilization at some work-centers, this causes that some of these orders are never/rarely produced. Therefore, in practise, the processing time based rules can not be used. The longest processing time rules L(R)PT show a decrease in performance with respect to the benchmark, where the shortest processing time rules S(R)PT show an increase in performance. Therefore, it can be concluded that long lead-time items are a bottleneck in the job-shop.

The due date based rules, (E)(M)DD, are the second best performing dispatching rules. The EDD dispatching rule shows a big increase in the tardy rate performance, and the MDD rule shows a big increase in delivery performance. The four KPI's are equally important for the company, but to keep customer-satisfaction it is most important to minimize the tardy rate of an order rather than minimizing the delivery performance. Therefore, the EDD rule has a better overall performance score. The due date based rules cause all orders to be processed, orders do not keep getting pushed back in the queue as with the processing time based rules. Therefore, the due date based rules are feasible planning rules.

Since the shortest processing time based rules do not give a feasible planning, and the due date based rules are the second best performing rules, the (E)(M)DD dispatching rules are extended with a second priority on processing time based rules. Combining these rules creates a feasible planning and generate a slight increase in overall performance. Again the EDD rules mainly improve on tardy rate, where the MDD rules mainly improve on delivery performance. The EDD & CR+SPT or EDD&LTWK rule, give the overall biggest increase in performance with respect to the benchmark.

As an addition to the implementation of the dispatching rules, a capacity analysis is done in Section 5.3. This capacity analysis is done with the EDD dispatching rule as a base since this rule is feasible and has the best performance. In the capacity analysis, for each work-center, the optimal number of operator shifts per week is determined. With these optimal number of shifts per work-center, a final simulation run is done to compare the results to the benchmark and the EDD dispatching rule without capacity analysis. Using the capacity optimization has a positive impact on the performance of all four KPI's. The overall performance increases with a 19% difference of the EDD rule where no capacity changes were made and with a 57% difference compared to the benchmark. To achieve these results, Marel should re-allocating the capacity among the welding work-centers. The implementation of these new capacity constraints also comes with great financial advantage, cutting 16% of all shifts weekly. However, illness, productivity and days off are not considered in this capacity analysis. Nevertheless, the results show such great improvement that it is worth considering to use the capacity analysis, along with the dispatching rules, in Marel's part production planning.

Chapter 6

Comparison planning method: Simulated Annealing

To get an understanding of the impact of different planning methods on Marel's part production planning. Different planning methods are implemented in the simulation model. Various planning methods are described in Chapter 3. In previous chapter, Chapter 5, is described why the POLCA system and workload control planning method are not implemented in simulated. The dispatching rules planning methods was described in the previous chapter and the results where compared to the current planning method. In this chapter, an optimization algorithm is implemented in the simulation model. Namely, the simulated annealing algorithm. Simulated annealing is a meta-heuristic, as is the genetic algorithm. Since the optimization problem is not complex, the genetic algorithm is expected to give comparable results as the simulated annealing. Where the simulated annealing algorithm is easier implemented in simulation. The other proposed optimization algorithms, mixed integer linear programming and constraint programming, are discrete algorithms. Since the flexibility of a human planner can not be captured in a simulation model, these discrete optimization algorithms will not represent a planning method that can be implemented in the current production planning of Marel.

In this chapter, the simulated annealing algorithm (SA) planning method is implemented. First, the planning method is described. Then, in Section 6.1, the implementation of the SA algorithm is described. In Section 6.2, the results on this planning method are given. Finally, in Section 6.3, the planning method is evaluated and the conclusion is given.

The objective of the different planning methods is to observe the change in performance of the KPI's compared to the benchmark. The benchmark on the KPI performance in Table 6.1 are the results from the validation simulation model performed in Chapter 4.

KPI	Performance
Delivery Performance $[DP]$	59.7%
Waiting factor $[W]$	30.9%
Work-in-progress $[WIP]$	695.6 $orders$
Early	7.8%
JIT	51.9%
Tardy	40.3%
Mean earliness	3.29 $days$
Mean tardiness	29.03 $days$

Table 6.1: KPI performance - Benchmark

In this part of the chapter, the second planning method, the simulated annealing algorithm, is described. A SA algorithm is a meta-heuristic, which means it is a nature-inspired algorithm. A brief literary review is done on meta-heuristics in Section 3.4. Meta-heuristics select global/local optimal solutions based on randomization. The nature-inspired algorithm is based on the genetic annealing process and the metallurgy (material science) annealing process. Genetic annealing is the process of heating and cooling two single-stranded oligonucleotides with complementary sequences. Oligonucleotides are short DNA or RNA molecules [Lindon, 2010]. Heat breaks all hydrogen bonds, and cooling allows new bonds to form between the sequences. Metallurgy annealing is a heat treatment that alters the physical and sometimes chemical properties of a material to increase its ductility and reduce its hardness, making it more workable. It involves heating a material above its recrystallization temperature, maintaining a suitable temperature for an appropriate amount of time and then cooling [Wu and Fan, 2020]. According to Erdinc [2017], the SA algorithm is one of the most preferred heuristic methods for solving the optimization problems. The algorithm is based on an iterative movement along a Markov chain according to the variable temperature parameter. This imitates the annealing transaction of the metals.

Simulated annealing is a relatively simple optimization algorithm which compares iteratively the output of the base solution with a neighbour solution in the domain. If the neighbour generates a better fitness value, it is saved as the base solution for the next iteration. When the fitness value of the neighbour solution has a worse performance than the current solution, the solution is accepted according to the Metropolis formula [Fischetti and Stringher, 2019] in Equation 6.1.

$$P = \exp(-\frac{\Delta f}{T}) \tag{6.1}$$

The Metropolis formula for the acceptance probability consists out of the annealing temperature and the absolute difference in fitness value between the base solution and the neighbour solution, Fischetti and Stringher [2019]. The algorithm is initialized with a starting temperature [T_o]. Each N iterations the temperature is decreased according to the temperature reduction function. According to Liang [2020], there are three main types of temperature reduction rules:

1. Linear reduction $T = T - \alpha$
2. Geometric reduction $T = T \cdot \alpha$
3. Slow-Decrease $T = \frac{T}{1+\alpha T}$

Each reduction rule decreases the temperature at a different rate. Each method is better at optimizing a different type of model. According to Erdinc [2017], the Geometric reduction function is preferred in the optimization of a job-shop. In the reduction function, *alpha* is the temperature reduction factor.

The SA algorithm consists out of three parameters that need to be set by the constructor. T_o, the initial temperature, α the temperature reduction factor and N the number of iterations after which the temperature is updated. Lower values of α restrict the search space at a faster rate. The value of N does not affect the result of the algorithm, but can be set to N between 5 and 10. The initial temperature should be set to accept approximately 98% of the solutions. The termination temperature should be set low enough that the solution does not improve (much).

A flowchart of the Simulated Annealing algorithm is shown in Figure 6.1. At first the three parameters T_o, α and N should be set. Then, the algorithm starts by generating a random base solution and calculating its fitness value. The base solution consists out of a sequence in which orders need to be processed. This sequence based algorithm is based on the theory of Markov Chains. Next, a neighbour of the base solution is selected. This can be done with a predefined rule or at random. There are no guidelines on predefined rules for the neighbour selection. The selection of a neighbour solution fully depends on the situation in which the algorithm is used. When performing a search for a neighbourhood solution, one item of the sequence is changed. Performing a search along the Markov Chain. This way, the neighbour solution is generated and its fitness value is calculated. The fitness value of the base solution is compared to the fitness value of the neighbour solution. In this case, the objective is to minimize the fitness value. This will be further elaborated on in Section 6.1. When the neighbour solution has a better fitness value, it is immediately accepted. When it performs less than the base solution, the neighbour solution is accepted according the acceptance probability of the Metropolis formula in Equation 6.1. If the solution is accepted, it will be the new base solution. Then, the termination criteria is checked. The termination consists out of two possibilities. The termination temperature is met. The temperature reached a very low point where a new solution will not improve (much) anymore. Or, the current solution has a perfect fitness value. Other solutions will not perform better, only equal, to this solution. Therefore, this solution is accepted as the optimal solution. When the termination criteria is not yet met, a new neighbour solution is generated. Each iteration, before a new solution is generated, there is checked if the temperature needs to be decreased. For each temperature N iterations are done. Regardless of whether the solution is accepted.

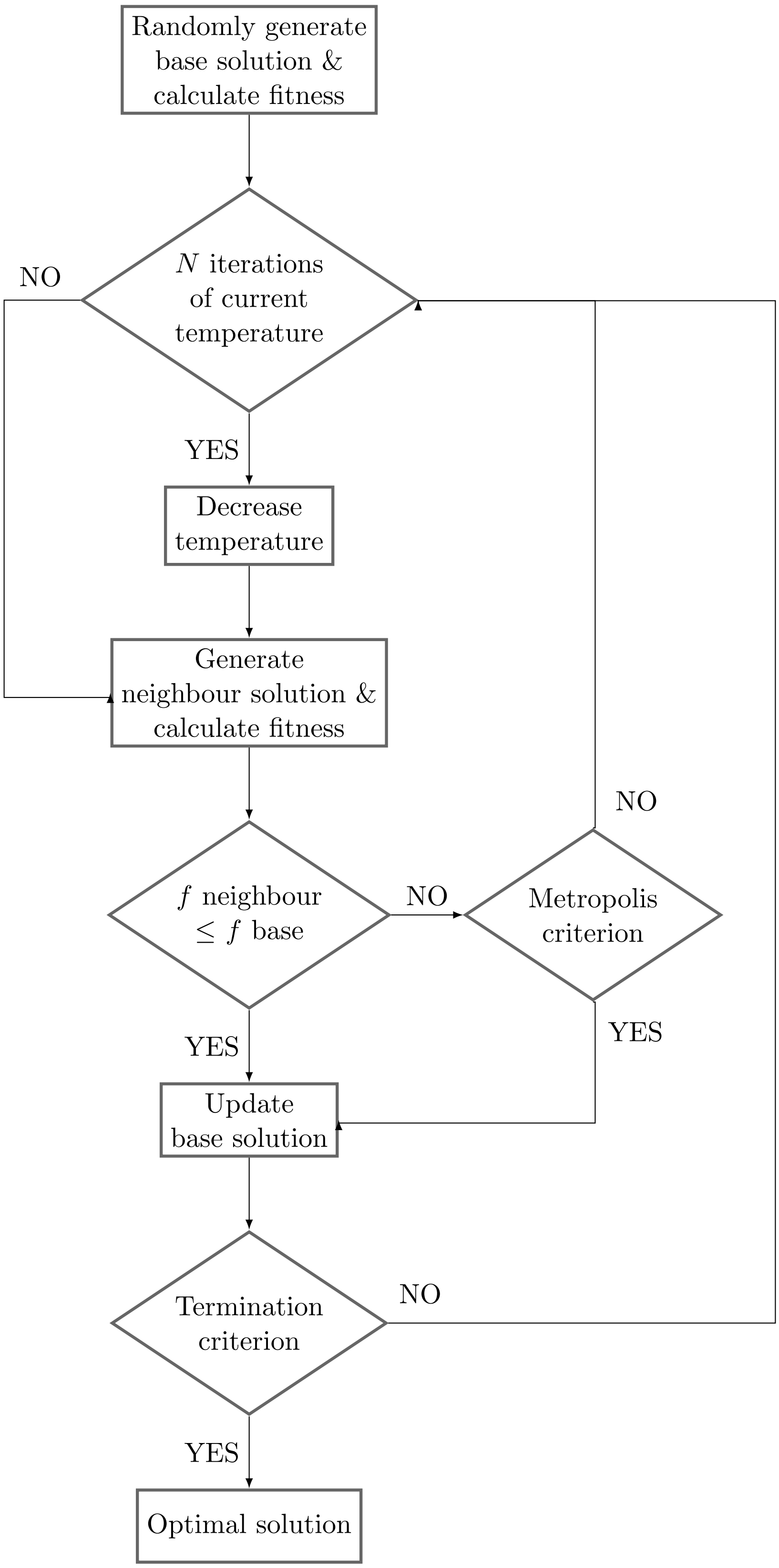


Figure 6.1: Simulated Annealing Flowchart

6.1 Implementation

The SA algorithm aims to optimize the sequence in which orders need to be produced at a certain work-center. The objective is to only optimize the order sequence of each work-center at each day. It does not consider the effect of the sequence on later production steps of orders. So, each day, for each work-center, the SA algorithm is performed. The algorithm has three input parameters, the initial temperature [T_o], the temperature reduction factor [α] and the number of iterations [N] that are performed for each temperature. The temperature reduction function that is best used for the job-shop scheduling problem, is the geometric reduction. Fischetti and Stringher [2019] states that $\alpha = 0.85$ should be chosen by default and T_o should be chosen such that 0.98% of the initial solutions is accepted. Since lower values of α restrict the search space to fast, Fischetti and Stringher [2019] claims that a value between 0.80 and 0.99 should be chosen for α.

The fitness value of a solution sequence is defined by a combination of the KPI formulas. To define the fitness value for a production sequence at a work-center, no longer only the order due date is considered. Now, the operation due date (ODD), due date for a production step, also needs to be considered. The ODD is calculated for each step according to the SAP scheduling method. Meaning that the order due date is equal to the operation due date for the last production step. When calculating backwards, the latest due date for each preceding production step is determined. As described in Section 4.2, between two succeeding production steps, always a day in between is considered. So, to each order in the orderlist, a list of operation due dates for each corresponding production step is added. An example of an order is shown in Table 6.2, where the ODD is depicted in blue.

Order number	101366737
Work-center	[8502, 8500, 8502]
Quantity	2
Machine-time	[0.315, 0.147, 0.304]
Setup-time	[0.817, 0.128, 0.171]
Creation date	4
Due date	35
Operation due date	[31, 32, 35]
Start date	[32, 35, 35]
Finish date	[32, 35, 35]

Table 6.2: Order example with ODD

$$f = (1 - \frac{DP + P}{2}) \cdot \mu T \tag{6.2}$$

In Equation 6.2, the fitness formula is given. This formula consists of the KPI's delivery performance [DP] and mean tardiness [μT]. In this case, for each order in the queue, there is determined if it can be processed today, with the available capacity. All orders that can be processed divided by the total number of orders in the queue, determine the delivery performance. If an order can not be processed today, it is assumed to be processed on the next possible production day. So the finish day of that production step is, $FD_{i,o} = t + 3$ when today is a Friday and $FD_{i,o} = t + 1$ on any other day. Next to the delivery performance, the tardiness for each order in the queue that is going to be late is determined. Since the expected finish date of the production step is already defined, the tardiness of the production step of that order is $T_{i,o} = FD_{i,o} - ODD_{i,o}$. The mean tardiness is the sum of the tardiness of all tardy orders, divided by the total number of tardy orders.

To complete the fitness value, the production factor $[P]$ is added. The production factor is defined as the fraction of order in the queue that can be processed. This factor is added to represent the KPI's waiting factor $[W]$ and WIP-level $[WIP]$. To minimize the waiting factor and WIP-level, as many orders as possible should be processed each day. The objective of the fitness value is to minimize the mean tardiness and to maximize the delivery performance and the production factor. Since the delivery performance and production factor are both a value below 1 and the mean tardiness is above 1, the mean tardiness has the heaviest weight. The optimal fitness value is zero. Therefore, the mean of the delivery performance and production factor is taken and subtracted. Doing this, $(1 - \frac{DP+P}{2})$ obtains a low value, which optimally is also zero. As is the optimal value of the mean tardiness. In case of a mean tardiness of zero, the delivery performance is 1, which is subtracted to zero.

The initial temperature T_o is computed every time the simulated annealing algorithm is used within simulation. This will be done each day, for each work-center separately. There is assumed that no orders are processed that day, the mean tardiness of all orders in the queue is calculated as if they were processed at the next possible processing day. This is namely the maximum fitness value of any possible sequence. Assuming that, according to Liang [2020], the initial temperature should accept approximately 98% of all solutions, Equation 6.3 should hold. Therefore, the initial temperature T_o, is calculated with Equation 6.4.

$$P = \exp(-\frac{f_{initial}}{T_o}) = 0.98 \tag{6.3}$$

$$T_o \approx 49.4983 \cdot f_{initial} \tag{6.4}$$

The last parameter left to set is the temperature reduction factor, α. According to Fischetti and Stringher [2019], the value of α should be chosen between 0.80 and 0.99. Therefore, an analysis on the selection of α is done. Since T_o and N are already defined, the selection of α can be done iteratively. For each type of reduction rule, linear, geometric or slow-decrease a simulation is performed with $\alpha = [0.80, 0.85, 0.90, 0.95, 0.99]$. The simulated annealing algorithm has variation on the results. Therefore, a simulation of 10 runs is done for every reduction rule and every value of α. The results on the four main KPI's and a 95% confidence interval (min/max) on the performance is given in Table 6.3.

	KPI's	DP [%]			W [%]			WIP [$orders$]			μT [$days$]		
	α	min	mean	max	min	mean	max	min	mean	max	min	mean	max
linear	0.80	86.5	86.8	87.1	29.1	29.4	29.6	412.9	418.7	424.4	12.80	13.25	13.69
	0.85	86.7	86.9	87.1	29.2	29.3	29.5	412.8	416.1	419.3	12.72	12.99	13.27
	0.90	86.5	86.8	87.1	29.1	29.3	29.6	412.6	416.8	421.0	12.91	13.13	13.34
	0.95	86.6	86.7	86.9	29.3	29.4	29.5	415.9	418.5	421.2	12.86	13.16	13.46
	0.99	86.5	86.7	86.9	29.3	29.5	29.6	416.7	419.6	422.6	12.99	13.21	13.42
geometric	0.80	86.5	86.6	86.8	29.3	29.5	29.7	417.1	419.4	421.8	12.60	12.83	13.06
	0.85	86.6	86.8	87.0	29.2	29.4	29.5	415.8	418.6	421.3	12.77	12.99	13.22
	0.90	86.6	86.9	87.1	29.1	29.3	29.4	413.3	416.7	420.1	12.75	12.95	13.15
	0.95	86.6	86.8	86.9	29.2	29.4	29.6	416.9	419.6	422.2	12.95	13.13	13.31
	0.99	86.7	86.8	87.0	29.1	29.4	29.6	414.8	418.0	421.2	12.74	12.92	13.11
slow-decrease	0.80	86.6	86.8	87.0	29.3	29.4	29.6	416.0	419.2	422.3	13.06	13.28	13.51
	0.85	86.6	86.7	86.9	29.1	29.4	29.6	416.3	419.0	421.8	13.01	13.22	13.43
	0.90	86.4	86.7	86.9	29.3	29.5	29.7	417.1	420.3	423.5	13.01	13.21	13.40
	0.95	86.6	86.7	86.9	29.3	29.5	29.7	417.2	420.1	423.0	13.02	13.25	13.47
	0.99	86.5	86.8	87.1	29.2	29.4	29.6	414.8	418.2	421.7	12.85	13.11	13.38

Table 6.3: KPI performance - SA reduction function

The results on the reduction function simulation, for various rules and values of α, can be found in Table 6.3. As can be seen, the results for all possibilities are approximately equal. Since Erdinc [2017] states that the geometric reduction rule is often used in job-shop optimization problems, the geometric reduction rule is chosen for the implementation. In addition, Fischetti and Stringher [2019] states that $\alpha = 0.85$ should be chosen by default. Therefore the temperature reduction function for the simulated annealing algorithm is formulated in Equation 6.5.

$$T_{new} = 0.85 \cdot T_{old} \tag{6.5}$$

As can be seen in Figure 6.1, at each iteration of the algorithm, a neighbour solution to the base solution is generated. Neighbour solutions can be generated at random, or with a rule determined by the constructor. In this case, a rule is constructed. A simulated annealing algorithm is based on an iterative movement along a Markov chain. Therefore, a neighbour solution of a sequence is the change of one item in the chain. In this algorithm, the constructed rule for generating the neighbour solution is as follows; one of the orders, which is produced in the current sequence, takes a random new position in the neighbour sequence. So, a random order is chosen among the produced orders. This order is re-positioned to a random place in the queue.

For example, a queue is considered with six orders. The order sequence of this queue is [01, 02, 03, 04, 05, 06], where 01 represents an order number. For this sequence a fitness value is calculated. Then, a neighbour solution needs to be generated. In this example, orders [01, 02, 03] can be produced considering the capacity for the corresponding day. As a result, orders [04, 05, 06] are not produced. Subsequently, one of the produced orders is chosen at random. Let's say, the random selected order is order 02. Then, order 02 is relocated in the sequence at random. The neighbour solution obtained could then be; [01, 03, 04, 02, 05, 06].

6.2 Results

The simulated annealing algorithm aims to find the optimal order sequence for the queue of a work-center. However, the results of the simulated annealing algorithm can show some variation. This makes the algorithm stochastic. Therefore, the results for the simulated annealing algorithm are based on a simulation of 100 runs. For all KPI's, the mean value and a 95% confidence interval (min/max) on the results is shown in Table 6.4.

Algorithm	KPI's	DP [%]	W [%]	WIP [$orders$]	Early [%]	JIT [%]	Tardy [%]	Mean earliness [$days$]	Mean tardiness [$days$]
Benchmark		59.7	30.9	695.6	7.8	51.9	40.3	3.29	29.03
	min	86.73	29.31	417.5	81.95	4.08	13.15	20.76	12.91
Simulated	mean	86.79	29.38	418.4	82.01	4.10	13.21	20.77	12.97
Annealing	max	86.85	29.44	419.3	82.06	4.12	13.27	20.78	13.03

Table 6.4: KPI performance - simulated annealing

In Table 6.4, the results from the simulated annealing algorithm are compared to the benchmark. In this table, the three KPI's delivery performance [DP], waiting factor [W] and WIP-level [WIP] are stated. In addition, the delivery performance is split into early-, JIT- and tardy delivery. Also, in this table, the results on the mean earliness and mean tardiness of early and tardy orders are given. First, the results from the benchmark are stated. These results are used to compare the results of the simulated annealing. As can be seen in Table 6.4, the variance on the results is neglectable. Therefore, the mean results can be compared to the benchmark.

In addition, the simulation of simulated annealing algorithm is also done with the capacity constraints from Section 5.3. In this section, a capacity analysis is done to optimize the number of operator shifts per week for each work-center. This optimization is done with the aid of the EDD dispatching rule. For the dispatching rule planning method, the use of capacity constraints gave a 19% increase of performance. Therefore, the capacity constraints are also implemented in the SA algorithm. To improve the performance of the simulated annealing planning method even further. For this simulation, again 100 runs are performed. In Table 6.5, the KPI performance of the simulation are shown, together with a 95% confidence interval (min/max) on the results.

Algorithm	KPI's	DP [%]	W [%]	WIP [$orders$]	Early [%]	JIT [%]	Tardy [%]	Mean earliness [$days$]	Mean tardiness [$days$]
Benchmark		59.7	30.9	695.6	7.8	51.9	40.3	3.29	29.03
Simulated	min	91.42	21.66	297.9	86.7	4.3	8.5	21.26	6.10
Annealing	mean	91.46	21.70	298.3	86.8	4.3	8.5	21.27	6.13
+ capacity	max	91.50	21.74	298.7	86.8	4.3	8.6	21.28	6.16

Table 6.5: KPI performance - simulated annealing + capacity

The results from the simulated annealing + capacity simulation, as shown in Table 6.5, are almost as good as possible. As described in Section 4.3, the best possible KPI values that could be achieved in simulation are a delivery performance of 95.8%, a waiting factor of 0%, a WIP-level of 223.1 orders and a mean tardiness of 3.51 days. The simulated annealing + capacity simulation has a delivery performance of 91.5%, a waiting factor of 21.7%, a WIP-level of 298.3 orders and a mean tardiness of 6.13 days, the results are very close to the best KPI performance possible.

To give a better insight in what the results from the dispatching simulation model mean, in Table 5.4 the percentile difference compared to the benchmark is calculated. The total performance improvement of the dispatching rule is then calculated by taking the average of the four KPI's. The mean tardiness is accounted for twice in this calculation. This is done because the mean tardiness is most important for customer-satisfaction. The four KPI's are equally important for the company, but to keep customer-satisfaction it is most important to minimize the tardy rate of an order rather than minimizing the delivery performance. The waiting factor of an order and the WIP-level of the shop-floor do not directly affect customer-satisfaction.

For a better visualization of results the table is color coded according the following color scheme:

$(-\infty, -50]$	$(-50, -20]$	$(-20, 20)$	$[20, 50)$	$[50, \infty)$

The results of the simulated annealing algorithm, with and without the capacity constraints, are compared to the benchmark. The results are shown as a percentile difference with respect to the benchmark, according to the color scheme visualised above, and are shown in Table 6.6. The percentile difference is positive for every KPI. This implies that both planning methods outperform the current production planning method. The simulated annealing algorithm obtains an increase of 40% in overall performance compared to the benchmark. Adding the capacity constraint, a total increase of 60% of the overall performance compared to the benchmark is measured. The percentile difference on the mean tardiness shows the biggest increase in performance for both algorithms. The mean tardiness weighs heavily in the fitness value of the simulated annealing algorithm, since the mean tardiness is the most important KPI of the planning process. Therefore, it was expected that the results on the performance of the mean tardiness KPI improved the most. Because the percentile difference with respect to the benchmark is positive for all KPI's, it can be concluded that the simulated annealing algorithm optimizes on all KPI's.

Algorithm	Percentile difference with benchmark				Total
	$[DP]$	$[W]$	$[WIP]$	$[\mu T]$	
SA	45	5	40	55	40
$SA + capacity$	53	30	57	79	60

Table 6.6: KPI performance simulated annealing compared to benchmark

6.3 Conclusion

The second planning method, which is compared to the current planning method of Marel, is the simulated annealing algorithm. This planning method optimizes the sequence of orders in the queue of a work-center on a daily basis. When an order is created in the SAP system, it arrives at the queue of the first work-center on the production-list. Every day, for each work-center, the optimal order sequence of the queue is determined with the simulated annealing algorithm. The SA algorithm planning method, such as the dispatching rules, avoids rescheduling. Which again proves to improve the production planning process. The proposed algorithm seeks to optimize the order sequence in the queue of a work-center, but does not consider other work-centers and/or succeeding production steps of orders.

The fitness value of the simulated annealing algorithm is based on the four KPI's, delivery performance [DP], waiting factor [W], WIP-level [WIP] and mean tardiness [μT]. As a result, the algorithm improves the performance of the production planning process on all four KPI's. Since the mean tardiness weighs heavily in the fitness value, the biggest improvement in performance is on this KPI. The overall improvement in performance of the simulated annealing algorithm is 40% with respect to the benchmark. When optimization of the job-shop is preferred on different KPI's the fitness value of the SA algorithm can be adjusted accordingly.

In addition, the capacity analysis from Section 5.3 is considered. In this analysis, the capacity in terms of number of operator shifts per week is optimized. From this analysis, capacity constraints are determined. These constraints are implemented in the SA algorithm in order to see if performance can be improved even further. From the results on the SA algorithm + capacity can be concluded that the capacity constraints give an increase in performance. Compared to the best possible results from Section 4.3, the results of the simulated annealing algorithm with capacity constraints give almost perfect results. The SA + capacity simulation has an overall performance improvement of 60% compared to the benchmark. As a result, the performance on the SA + capacity simulation shows an improvement of 20% in comparison with the SA simulation without capacity constraints.

Chapter 7
Conclusion and Recommendation

This chapter concludes the research of this thesis. The main question of this research project, which is formulated in Section 2.3, is answered in Section 7.1. Then, limitations on the research project are given in Section 7.2. Finally, recommendations on implementation and further research are given in Section 7.3. The main research question which is answered in this research project is:

What is the impact of different planning methods on the parts production planning of Marel?

7.1 Conclusion

In order to answer the main question, the research project is divided into five research questions. These research questions were formulated in Section 2.3.3 and represent milestones in the research project. In this section, each research question is answered individually.

1. What does the current production planning look like?

The current production planning process consists of multiple steps. First, an equipment order arrives at the sales department. There, the order is accepted or declined. When accepted, the order is scheduled by the Master Production Scheduler and fed to the SAP/ERP system. At this point, service and innovation orders can also be fed to the SAP system. These type of orders do not need to be scheduled by the master scheduler first. From these orders, the SAP system makes a planning according to lead-time feasibility. Since the SAP/ERP system does not consider capacity constraints, infinite capacity is assumed by the system. Therefore, a human planner is involved to level the resources and solve capacity problems. The planned orders are released to the shop-floor where the production of orders can start.

The parts production of Marel consists of two departments, the sheet-metal department and the machining department. This research project focuses on the parts production of the sheet-metal department. The part of the planning process which is considered in this research project, is the order creation in the SAP environment until part delivery to the warehouse.

2. What are possible planning methods for the production planning?

The literature study, performed in Chapter 3, presented several production planning methods for job-shop environments. The planning methods retrieved from literature are the POLCA system, workload control, dispatching rules, meta-heuristics, mixed integer linear programming and constraint programming. The meta-heuristics are further divided in genetic algorithms and simulated annealing. In this research project, two planning methods are implemented. Namely, the dispatching rules and the simulated annealing algorithm.

Dispatching rules are used to prioritize orders waiting in the queue of a work-center. The use of dispatching rules avoids rescheduling in the planning process and the implementation of dispatching rules is relatively simple. The proposed dispatching rules are based on FIFO, Arrival time, processing time, due date, critical ratio, slack and work-in-next-queue. Each type of dispatching rule has their own characteristics and is focused on improving the performance of one KPI.

The simulated annealing algorithm optimizes the sequence of orders waiting in the queue of a work-center. The optimization of the algorithm is based on a fitness value. This value is based on the performance of the KPI's of the planning process. Therefore, optimizing the planning process on all four key performance indicators.

3. What does a representation of the current planning method look like in simulation?

The current parts production planning method of Marel is replicated in simulation with means of a discrete-event simulation. The simulation model starts with creating the initial events. The initial events all represent the creation of an order in the SAP system. When an initial events occurs, all corresponding production steps of the order are scheduled. Each of these production steps is represented by an event in the simulation model. This part represents the SAP planning. Then, the scheduling of the human planner is added to the simulation model. Every Monday, for the consecutive three weeks, the capacity resources are levelled. Since new orders can still occur, every production day, the current capacity is updated. Then, a check is performed on whether the required capacity is still available. When orders need to be rescheduled, orders that can be rescheduled to an earlier date are considered first, so due date can still be met. Otherwise orders are scheduled forward, the priority of rescheduling is on the latest due date of orders.

The performance of the simulation model is described by the four main KPI's, delivery performance [DP], waiting factor [W], WIP-level [WIP] and mean tardiness [μT]. By comparing the simulation model with the actual realized results from the current planning method, it is concluded that the simulation model is valid. However, some differences in WIP-level and mean tardiness are observed. This is accounted to the available flexibility of a human planner that can not be simulated. In the current production planning method, approximately 70% of all orders is rescheduled.

4. What is the performance of the KPI's when implementing the new planning methods in simulation?

Two different planning methods are implemented in the simulation model, dispatching rules and simulated annealing. The KPI performance of these models are compared to the benchmark.

Different types of dispatching rules are implemented in the simulation model. The (shortest) processing time rules perform well on improving the delivery performance. While the due date based rules perform well on improving the tardy rate. However, the shortest processing time dispatching rules are not a feasible planning method in practise. Each dispatching rule improves on a different KPI. However, the KPI performance of at least one KPI decreases with each dispatching rule. Therefore, additional dispatching rules are suggested where different rules are combined with the due date based rules (E)(M)DD. Combining the EDD rule with the CR+SPT rule or the LTWK rule shows the best performance. Both these rules show an increase in performance on the three KPI's DP, W and WIP, compared to the EDD rule alone.

In addition, a capacity analysis is done with the aid of the EDD dispatching rule. Adjusting the capacity constraints according to the capacity analysis, an increase in overall performance is obtained. Now, the EDD rule does not only show an increase in the mean tardiness performance, the performance on the other three KPI's also shows a big improvement with respect to the benchmark. In total, an overall performance increase of 57% is obtained when using the EDD dispatching rule + capacity constraints.

The simulated annealing algorithm is implemented in simulation. Since the fitness value of the algorithm is designed according to the four KPI's, the simulated annealing algorithm shows an improvement on performance on all the KPI's. The overall performance of the SA algorithm shows an improvement of 40% with respect to the benchmark. Especially the improvement in waiting factor and WIP-level increases in contrast to the EDD dispatching rule. The capacity constraints are also added to the simulated annealing algorithm. The performance of this simulation model shows a performance which is almost equal to the best possible performance that can be obtained. The overall performance increase is 60% with respect to the benchmark.

5. What conclusions can be drawn, and what advise can be given to Marel on their parts production planning?

The results obtained from the simulation model, as well as the implemented planning methods, dispatching rules and simulated annealing, give insight in the parts production planning of Marel.

First, conclusions are drawn from the simulation model in Section 4.4. The foundation of the production planning is the SAP/ERP system. This system plans on lead-time feasibility and therefore does not consider capacity constraints. This causes that 70% of the orders need to be rescheduled by a human planner. Comparing the simulation results to the actual realized results from the shop-floor, the results on the WIP-level and mean tardiness are higher in simulation than in reality. This is caused by the flexibility in planning a human planner has. The flexibility obtained by the human planners can not be simulated, and can therefore not be taken over by a system.

Secondly, the dispatching rules planning method is concluded in Section 5.4. From the implementation of this planning method is concluded that the use of dispatching rules avoids rescheduling in the planning process. Prioritizing orders on the shortest processing time gives the best performance. However, this dispatching rule appears to be infeasible for actual implementation. The best feasible dispatching rule is the earliest due date rule. This rule can be extended with the least total workload rule or the critical ratio plus shortest processing time rule to improve performance even further. However, it can be advised to Marel, to firstly implement the EDD dispatching rule since this will be the easiest to implement. When taking a next step, Marel could consider to extend the dispatching rule with the CR+SPT or LTWK rule as second priority. In addition, Marel should take a look at re-allocating the capacity of the welding work-centers. The work-centers of sub-department 85 appear to have over-capacity, where the work-centers of sub-department 42 have under-capacity. Since the welding operators require the same "basic" skill-set for both departments, resources can be levelled accordingly.

Finally, from the implemented simulated annealing algorithm a conclusion is drawn in Section 6.3. The simulated annealing algorithm avoids rescheduling in the planning process. The algorithm optimizes the order sequence of the queue at each work-center on a daily basis. The fitness value of the SA algorithm is based on all four KPI's. Therefore, the algorithm optimizes the planning process on all the KPI's. Adding capacity constraints improves the KPI performance even further. This gives results that are almost as good as the best possible results that could have been obtained.

7.2 Limitations

In this section, the limitations of the research project are discussed.

The first limitation is the data that was available for the research project. The available data contains the estimated set-up and production time for each production step. The estimated production time is used in the production planning. When a production step is finished, the set-up and production time are confirmed by the operator. The confirmed times are also stored in data. When finishing a production step, the operator can choose to just confirm the set-up and production time or adjust the time before it is stored in data. In practice, the set-up and production time are only adjusted when the operator takes longer than the predefined time. When an operator is faster, the set-up and production time are not adjusted and the predefined time is confirmed as the actual production time. Therefore, the data used in simulation was not completely accurate and results retrieved can vary from reality. A similar situation occurs with the due date that is stored in the system. The due date found in the data files is not necessarily the actual, original due date. When a human planner decides to push the order in a later time frame, the due date is pushed as well. The due date found in the data files is the last stored due date in the system and therefore often not the due date that is originally assigned to the order.

In addition to data availability, the type of data used in the simulation model is a limitation. The data used in simulation is historical and deterministic data. Orders have a fixed creation date, production time and due date based on the production of orders in a historical timeframe. This causes the simulation model to be deterministic. Since the production environment is characterized by a High-Mix Low-Volume production, demand is uncertain and hard to predict. Therefore, it is not possible to simulate with a stochastic distribution of orders.

Another limitation of the research project is that the flexibility of a human planner could not be included in the simulation model. Therefore, the simulation model not fully represents the reality. When implementing the proposed planning methods in the actual job-shop, there can be a big variation between the results obtained in the simulation model than in reality. The same holds for the theoretical approach of the research project, the results in practice are never equal to theoretical results.

7.3 Recommendations

Now that the research project is concluded, recommendations can be given to the parts production planning of Marel.

7.3.1 Data availability

The available data contains the estimated and confirmed set-up and production time for each production step. As mentioned in the limitations, the confirmed set-up and production times are not accurate. Therefore, it is recommended to store the confirmed time data in a different way. The orders are scanned at the start and finish of a production step, if the time between scanning is stored. These scanned hours can represent the total production time (set-up + production) of the production step of an order. Another data point that is not always accurate is the order due date. When an order is pushed forward by the planner, the new due date overwrites the actual due date. It is therefore advised, to store the actual due date as well as the new due date. Finally, when it comes to data availability, it is recommended to Marel to give orders a priority ranking.

7.3.2 Forecasting

The current simulation model only reflects the past production since it is build on historical data. When a prediction or forecast model is available, the simulation model can also reflect the future production planning of Marel. This way, a stochastic simulation model can be created where more flexibility is incorporated. A forecast model of orders that will be created in the SAP environment, for the equipment orders, as well as the innovation and service parts. This forecast model will also help with allocating resources, operators, to the work-centers. In addition, when a forecast is made of the load, this can be incorporated in the schedule and rescheduling can be avoided.

7.3.3 Rescheduling

From the research project it is concluded that, when rescheduling is avoided, the production planning performance improves. The current parts production planning of Marel is based on an ERP/SAP planning with infinite capacity. Subsequently, rescheduling is done to meet capacity constraints. In the current planning method, 70% of all orders is rescheduled. As a result that the lead-time constraints is also no longer feasible. When planning based on capacity constraints rather than lead-time feasibility. A more feasible and reliable planning can be obtained where less rescheduling needs to be done. From the implemented planning methods can be concluded that avoiding rescheduling improves performance on all KPI's from Marel's parts production planning.

7.3.4 Due date based planning

The due date based dispatching rules have proven to improve the most important KPI's from Marel's parts production planning. When dispatching orders to a work-center based on their earliest due date, indirectly there is planned on lead-time feasibility. It is recommended to Marel to implement the EDD dispatching rule. The dispatching rule planning method is easily implemented in a job-shop environment. With this planning method, earliest due date dispatching, rescheduling is avoided and an increase in delivery performance and reduction of mean tardiness is obtained. In addition, The EDD dispatching rule can be extended with a second priority on the least total work-load (LTWK) or the critical ratio plus shortest processing time (CR+SPT). The second priority of orders on both these rules improves the performance of the production planning even further. It is advised to Marel, when implementing dispatching rules on the shop-floor, the EDD dispatching rule is implemented first, before a next step is taken to implement the EDD & LTWK or the EDD & CR+SPT rule.

7.3.5 Capacity

A capacity analysis is performed with the aid of the EDD dispatching rule. From this analysis is concluded that Marel should take a look at re-allocating the capacity of the welding work-centers, 4200, 4285, 8500, 8510 and 8511. The welding work-centers have a shared capacity, since the welding operators require the same skill-set. Therefore, resources can be levelled accordingly. The work-centers of sub-department 85 appear to have over-capacity, where the work-centers of sub-department 42 have under-capacity. Hence, it is recommended to Marel to re-allocate operators or to join all welding capacity and assign operators every day to the work-center where capacity is required.

7.3.6 Optimization algorithms

The best performing planning method is the simulated annealing algorithm. This algorithm optimizes the sequence of order is a queue of a work-center on a daily basis. The results on the implementation of this algorithm show a great improvement of overall performance. However, the algorithm only considers the optimization of the queue of a work-center. For this optimization, the algorithm does not consider the queues of work-center of pre- or succeeding production steps. Therefore, the algorithm only optimizes the work-center queues at that moment and not the entire system. For future work, it is recommended to extend this algorithm, such that the simulated annealing will consider the entire system. So, optimization will not only be done on the parts production, but also on the assembly and warehousing of orders.

7.3.7 Future work

In this research project, only the parts production of Marel's sheet metal department is considered. For future research, it is recommended to apply similar research techniques to the machining department. To a large extend, only data gathering and preparation needs to be performed to implement this research on the machining department. Considering that the planning methods, which are simulated, remain the same. As already mentioned, Marel could consider several optimization techniques, such as the simulated annealing, over its entire production process. This research focuses on parts production on the sheet metal department. For future research, the optimization of the entire parts production, assembly and warehousing could be considered. This can be in the form of a simulated algorithm. Other planning optimization techniques, that have been proposed in the literature study, could be considered as well. Therefore, this project could be the starting point of Marel's future in improving their production planning process.

Chapter 8
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