MASTER

Manpower prediction for kitting in high complex, low volume assembly lines

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Master Thesis

Manpower prediction for kitting in high complex, low volume assembly lines

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Abstract

Kitting can be defined as gathering all parts into a package or cart and feeding them to assembly lines on the right time with the right quantities. Kitting supports high mix and low volume production by providing the necessary parts to the work station depending on the assembly planning. In the literature, there is a lot of research about the benefits of kitting based on costs, quality and performance. However, there is lack of knowledge about the alignment between assembly and the kitting planning considering human and production related factors. The goal of this thesis is to predict the hourly workload to fulfill the kitting requirements affected by the assembly process.

This thesis begins with reviewing literature about time concepts, manufacturing uncertainties and prediction models used in manufacturing context. Based on the literature review, three different machine models are selected. During this thesis, the Cross Industry Standard Process for Data Mining is used to develop the prediction models. A separate prediction model has been developed for each production line of Canon Production Printing due to the different characteristics. The model tries to predict the rhythm of each kit cart. The results of the prediction model per production line are combined into one dataset. Finally, a translation has been made to the required kitting requirements. Based on information about the kitting process, a translation has been made to the hourly workforce to fulfill these kitting requirements. The hourly workload in the kit warehouse can be predicted with average accuracy of 70%. However, variation in workload in the kit warehouse is still visible due to multiple production lines. At the end, advice is given to Canon Production Printing on how to balance the workforce.

The main limitation in this research in the limited use of human factors because of privacy reasons. Moreover, the inclusion of more input factors including human factors are proposed as topic for future research.

Preface

Last August, I started with my Master Thesis at Canon Production Printing. This thesis finalizes my master Operations, Management and Logistics at the Eindhoven University of Technology. It was a great experience to apply the knowledge and skills I learned during my study to this project at Canon Production Printing. The aim of my research was developing a prediction model to predict the kitting requirements of the production lines, translated into workload in the kit warehouse. I would like to use this preface to thank some people who helped or motivated me during the master and during my master thesis.

Firstly, I would like to thank my mentor and first supervisor Banu Aysolmaz for her support, feedback and her expertise. The efficient weekly meeting kept me on track and your feedback helped me a lot with the structure of this research. Thank you for your time, meetings and critical feedback. I would also like to thank my second supervisor Remco Dijkman, who provided valuable feedback to improve the quality of my report.

Secondly, I would like to thank my company supervisors Pascal Geraeds and Lissette Contreras Llamoca for their support, enthusiasm and time during my internship. The weekly meetings with my company supervisors were essential in my understanding of the company, of the data and of the expectations of the company. I think we have done a great job convincing management of the benefits of data science in a manufacturing context. Additionally, I would like to thank the employees of the kit warehouse and assembly operators for providing valuable information and insights for my thesis. Furthermore, the R&D employees were very valuable in setting up the environment to work with Python within the Manufacturing and Logistics department.

Lastly, I would like to thank my family and friends for their support during my master and during this project. A special thanks to my boyfriend, Bjorn, who was always there for me and helped me through difficult times.

Thank you all and enjoy reading my thesis.

Esther van Maurik

Eindhoven, April 14, 2023

Executive Summary

Problem context

Kitting can be defined as gathering all parts into a package or cart and feeding them to assembly lines on the right time with the right quantities. Kitting supports high mix and low volume production by providing the necessary parts to the work station depending on the assembly planning. In the literature, there is a lot of research about the benefits of kitting based on costs, quality and performance. However, there is lack of knowledge about the alignment between assembly and the kitting planning considering human and production related factors. A difficulty with mixed-model assembly lines is that the demand of parts are not steady and there arise a high variability of required part quantities at various stations. Kitting is related to assembly to get the right materials at the right place on the right time. However, the assembly planning is hard to predict due to multiple models, human factors and production related factors such as part shortages and machine breakdowns. As a consequence, the workforce planning of the kit warehouse is hard to predict. The aim of this research is to develop a prediction model to predict the required hourly manpower to fulfill the kitting requirements affected by the assembly process.

Business Understanding

During this research, a case study is conducted at Canon Production Printing (CPP) who develops and manufactures digital printing equipment. Stakeholder meetings are organised to get more understanding of the business processes of Canon Production Printing. The stakeholders in this research are the employees of the kit warehouse, assembly operators, planners and industrial engineers. The current situation of the alignment between the kitting and assembly process is identified. Furthermore, factors which could create variation on the kitting process, assembly process and the alignment between kitting and assembly are analysed. To improve the alignment between the kitting and assembly process, the production lines used in this research are described including the different characteristics. Based on the stakeholder meetings, solution requirements are defined to determine the expectations of the company in order to deliver a specific solution to the company.

Data Preparation and Modeling

Data about the kitting process and assembly process is collected. The data was cleaned and prepared for modeling. Unfortunately, a connection between the production order and kit cart is missing. Because the assembly operators are working parallel and sometimes they are working in advance, it was impossible to obtain an actual production sequence. Furthermore, new features are created which are used to predict the kitting requirements without an actual production sequence. In this research, the prediction model estimates the rhythm of a specific kit cart by predicting the Time between two calls (TBC) of the same kit cart. A call is performed by an assembly operator when the kit cart is needed at the production line. For each production line, a separate final dataset is created.

Based on the literature review, three different machine learning techniques are tested. For each production line, the best prediction model including the optimal hyperparameters is selected. After that, the prediction results of the production lines are merged in one dataset. The records are grouped based on the predicted time point when the same kit cart is called again. Finally, the predicted number kitlines per time bucket is compared to the actual number of kitlines per time bucket. This process is done by trying different time buckets to see their effect on accuracy. the mean accuracy of the number of kitlines is remarkably higher when a time bucket of 60 minutes is used. A larger time bucket results in a higher accuracy. With a larger time bucket, there is a greater chance that the kit cart has been predicted in the correct time bucket. However, with a large time bucket, the variation within a time interval is not visible. The process of merging the prediction results and the translation to the kitting requirements is showed in Figure 1.

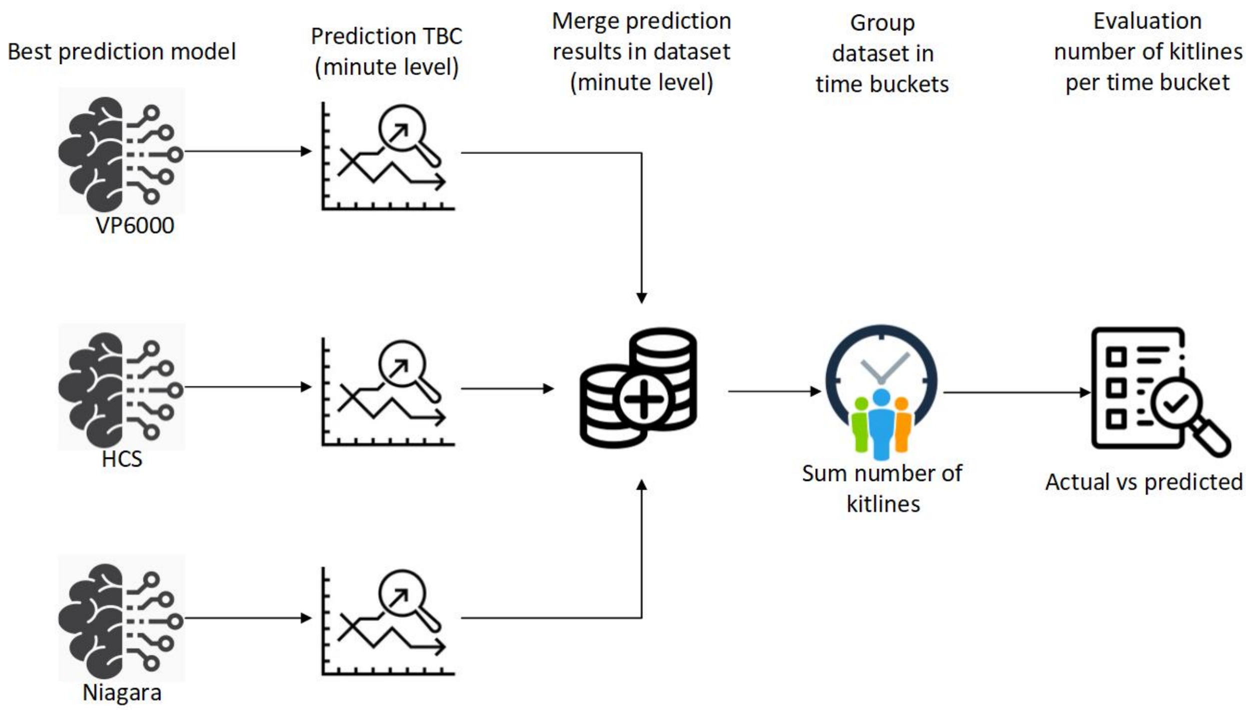

Figure 1: Process of merging the production lines

Modeling based on Time between Requests (TBR)

In case of CPP, prediction based on Time between Calls (TBC) does not work well because the assembly operators give a signal to refill the empty kit cart. The workload in the kit warehouse is dependent on signals of the assembly operator. A kit cart is requested to be refilled directly when the previous production is finished, but the assembly worker can sometimes be early or late with requests. Requesting to refill a kit cart could contain some extra human behavior. This human behavior is identified by comparing the results based on Time between Calls (TBC) and Time between Requested (TBR). The prediction of the kitlines based on TBR is slightly worse than TBC which can be explained as human behavior of the assembly operators.

Based on the prediction when the kit cart is requested again by the assembly operator, a new kit cart queue is calculated. Based on the predicted requested timestamp, predefined duration and predefined available time to kit, a translation is made to the workload. The start and end kitting timestamps of a kit cart are calculated. The calculation of the new kit cart queue is shown in Figure 2.

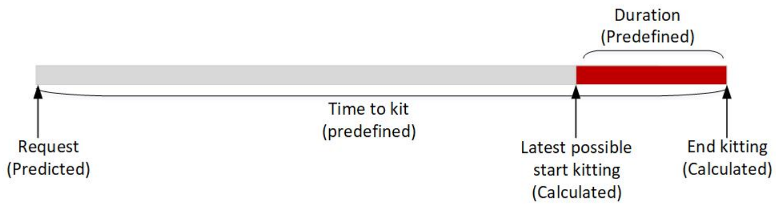

Figure 2: Calculation of the kit cart queue

During this thesis the kitting requirements for the production lines are predicted based on Time Between Calls (TBC) and Time Between Requests (TBR). The average accuracy per 60 minutes is for both around the 63%. The median accuracy of TBC is slightly better. The differences can be explained by human behavior of the assembly operators. Based on information about the kitting process, a translation is made to the hourly workforce to fulfill the kitting requirements. The workload per 60 min has an average accuracy of 70%. Based on the possible causes of variation, advice is given to Canon Production Printing on how to balance the workforce.

Conclusions

This research provides contributions to the literature. First, the prediction model contributes to the literature by supporting decision making in kitting planning considering multiple production lines and varying processing times. Secondly, the prediction model contributes to the alignment between kitting and assembly by including information about production amounts and varying processing times.

The main limitation of this research is the lack of human factors such as experience and age of the kiting employees and assembly operators due to privacy reasons. Varying processing times are added to include human behaviour of the assembly operators. Secondly, a limitation in this thesis is that the same prediction model including the optimized hyperparameters is used for both time between calls (TBC) and time between request (TBR) prediction. Lastly, this research is limited to the three biggest production lines of CPP.

Finally, directions of further research are suggested. Research to more input features including human factors are proposed. Moreover, the connection between the kit cart and the production order can result in a production sequence. Based on this production sequence, simulation can be applied. As future research, comparison between machine learning, time series forecasting and simulation is suggested. Lastly, validation for the generalization of the results is proposed.

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Acronyms

AGV Automatic Guided Vehicle

AI Artificial Intelligence

ANN Artificial Neural Network

CPP Canon Production Printing

CRISP-DM CRoss-Industry Standard Process for Data Mining

DES Discrete Event Simulation

JIT Just In Time

MAE Mean Absolute Error

MAPE Mean Absolute Percentage Error

MPS Master Production Scheduling

MSE Mean Squared Error

MTO Make To Order

MTS Make To Stock

PPC Production Planning and Control

RMSE Rooted Mean Squared Error

RNN Recurrent Neural Network

SVR Support vector regression

TBC Time Between Calls

TBR Time Between Requests

TO Transfer Order

TR Transfer Request

Chapter 1

Introduction

1.1 Research Context

In manufacturing assembly lines, for customized and complex products, it is typical that multiple variants of the same product are produced on the same line. These variants differ slightly from each other which requires an efficient part supply to the assembly lines in manufacturing companies (Schmid et al., 2021). In traditional assembly systems, single-level assembly lines were used to produce standardized products. However, due to the multiple variants and low demand of customized products, multiple products can be assigned to the same assembly line (Lopes et al., 2020). According to Caputo et al. (2015b), kitting supports high mix and low volume production by providing the necessary parts to the work station depending on the assembly planning. This reduces the space needed at a work station for materials. Kitting can be defined as gathering all parts into a package or cart and feeding them to assembly lines on the right time with the right quantities (Vujosevic et al., 2012). Two types of kit carts are available. Stationary kit carts contain parts for one workstation and each workstation has their own kit cart(s). Traveling kit carts contain parts for multiple workstations and travel together with the product along the assembly line (Wijnant et al., 2018). In high mix and low volume industries, kitting makes it possible to produce more products on the same line without a lot of parts at the workstation. Employees in the warehouse, also called kitters, collect all the materials in the kit warehouse in a box or cart. This pre-sorted kit which contains parts for a specific assembly process, is delivered at the assembly work station or assembly line at the right time. Kitting comes with several advantages and disadvantages. Kitting improves the efficiency and quality of assembly by eliminating the need for the operators to walk to the warehouse to find the products. Furthermore, training a new operator takes less time than without the kitting process. However, defect components during the assembly process takes a lot of time to solve, because the defect parts are not available at the workstation. As a consequence, the operators have to walk to the warehouse to replace their defect part (Fansuri et al. (2017), Schmid et al. (2021)). Finally, when the warehouse is not near the assembly line, kit carts have to be transported manually or with the use of an Automatic Guided Vehicle (AGV) (Hanson and Medbo, 2011). Although less assembly operators are needed, the major disadvantage of kitting are the kitters needed to kit all the carts in the warehouse (Khajavi et al., 2018).

1.2 Company information

During this research, a case study is conducted at Canon Production Printing (CPP) who develops and manufactures digital printing equipment operating in the global market with multiple sites around the world. CPP is founded and headquartered in Venlo, before known as the Dutch printing company Océ till the end of 2019 (CPP, 2021a). Factories are located in Europe and Asia to be able to operate in more than 80 countries. CPP offers a wide variation of products, from wide format poster printers to large-format high quality inkjet printers. The main activities of CPP in Venlo are R&D and manufacturing and logistics of large format, high end production printers. An example of a printer produced at CPP in Canon can be found in Figure 1.1.

Figure 1.1: VarioPRINT iX-series (CPP, 2021b)

CPP is already using kitting to control the material flow to the assembly process in combination with mixed model assembly lines. However, CPP experience a lot of variation in workload when kitting all the materials for the assembly.

1.3 Problem statement and Research objective

In the complex world, changes in consumer's preferences and production technology bring more uncertainties into the manufacturing process. These uncertain factors make production planning for the assembly line very difficult (Li, 2022). Example of an external uncertainty factor is customer demand which have influence on the production planning. Low volume, high complexity companies often use a Make To Order (MTO) approach where their production is based on customer demand instead of forecasting. To produce according to the customer demand, takt time can help to maintain continuous flow by matching the demand rate of the customers with the output rate in a pull system. Takt time can also be used in Make To Stock (MTS) environments where the production amount is varying. Takt time can be defined as the amount of time within a product has to be produced in order to meet the customer demand or planned production amount (Frandson et al., 2013). Takt time can be calculated dividing the available time by the production amount per time period.

$$\text{Takt time} = \frac{\text{time available}}{\text{production amount per time period}} \tag{1.1}$$

Furthermore, varying processing times is an example of an internal uncertainty factor and have also influence on the production planning. Theoretically, it is assumed that the processing times on the assembly working stations are operating deterministically (Fathi et al., 2019). However, in real life assembly, different sources of variation could have impact on the assembly performance and processing times. Different types of variation makes it very difficult to predict the processing times. Human and environmental factors have the greatest impact on the assembly processing time. Examples of human and environmental factors are workers' tiredness, illness, lack of skills, complex operations, part shortages and machine breakdown. According to Ayough et al. (2020) human factors can have a positive or a negative impact on the operators' actual processing times depending on the operator. The processing times are necessary to make an appropriate production planning. Considering human and environmental factors are necessary to obtain optimal production schedules and workforce schedules.

Based on the takt time, a certain amount of time is available to deliver the parts to the assembly line. Kitting is a labor intensive task which take a certain amount of time. The available time to kit is dependent on the takt time and the assembly processing times. The available time to kit can be calculated by subtracting the assembly time and transportation time from the takt time as shown in Figure 1.2. The takt time of a specific assembly line is dependent on the customer demand. The more products that have to be made, the lower the takt time, the lower the time to kit the necessary parts (Bastos et al., 2021). Short takt times cause problems regarding variability and lead to a demand peak at the kitting warehouse. These short takt times emerge to be able to deal with higher market driven product demand (Dlouhy et al., 2018). In addition, every workstation has a specific processing time to complete their assembly depending on the task (Gardarsson et al., 2019)). The processing time can be defined as the time a operator spends on assembling a product at a working station (Sotskov et al., 2006). So, the planning of the kitting activities is connected with the assembly planning. In the literature, different part feeding policies are compared with each other in terms of costs (Limère et al., 2012). However, there is lack of knowledge about the alignment between assembly planning and kitting planning in the literature.

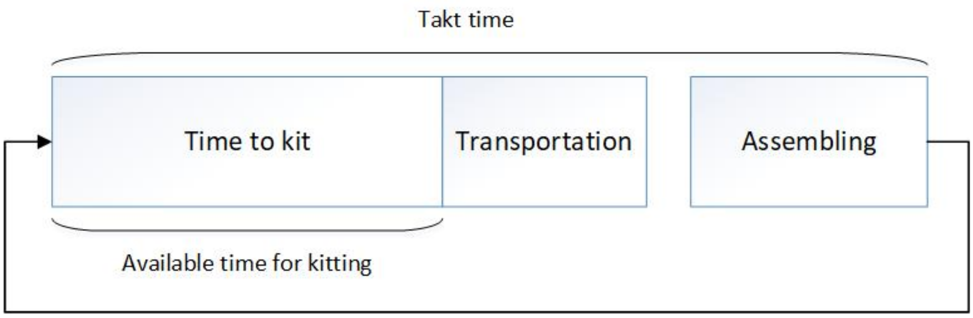


Figure 1.2: Description of takt time

Besides that, it is possible that working stations are operating parallel. Furthermore, there may be multiple assembly lines. The parallel working stations and the multiple assembly lines are causing variability in the kitting warehouse based on the different processing times. A difficulty with mixed-model assembly lines is that the demand of parts are not steady and there arise a high variability of required part quantities at various stations (Golz et al., 2010).

As described above, kitting is related to assembly to get the right materials at the right place on the right time. So, the workforce planning of the kitting process is related to the assembly planning. The assembly activities are affected by human factors and production related factors such as material problems and changing demand. As a consequence, the assembly planning is hard to predict and therefore the planning of the kitting activities is also hard to predict. The short takt times can cause problems in the daily planning, especially in the hourly planning. This results in the following research objective:

To develop a prediction model to predict the required hourly manpower to fulfill the kitting requirements affected by the assembly process

1.4 Research questions and contributions

The research gap addressed in this thesis is two fold. First, literature on kitting specific planning and decision making is limited. The literature focuses mainly on comparing line stocking with kitting based on costs. However, factors like human resources which have impact on the performance, are neglected (Caputo et al., 2015a). The use of machine learning or simulation has not been applied in kitting specific planning. However, machine learning and simulation are already successfully applied in assembly planning. The first research gap is the need for techniques to support the kitting planning including human factors and production related factors. Secondly, there is lack of knowledge regarding the alignment between kitting and assembly. In the literature, there is a lot of research about the benefits of kitting based on costs, quality and performance (Limère et al., 2012). Caputo et al. (2015a) developed a mathematical model for kitting operations planning, but context-specific decision factors like assembly performance were not included. Furthermore, Choobineh and Mohebbi (2004) did research in material planning within the kitting context where procurement lead times are variable. However, the alignment with the assembly lines is missing. As a result, the second research gap identified is the need for alignment between the kitting process and the assembly lines.

This research will address these research gaps by aligning the assembly planning and the kitting planning with the help of simulation or machine learning. As already mentioned, a case study is conducted at Canon Production Printing. In the literature, a few causes of the variation in the kitting and assembly processes are identified. However, every case is different. To be able to generate a solution for CPP, the current challenges regarding the alignment between assembly and kitting should be mapped. Furthermore, knowledge about the production process and variation of the company is required to include the right features in the model. These knowledge will be used in the machine learning model or simulation model to predict the kitting requirements. These predicted kitting requirements should be translated into manpower required per hour. The following sub research questions are formulated.

1. Which forecasting method can be used to predict kitting requirements according to the literature?
2. How is variation in the kitting process caused by human and production related factors?
3. Which data features are valuable to predict the kitting requirements and corresponding working hours?
4. Which prediction method performs best when predicting kitting requirements?

The deliverable of this thesis is a prediction model that predicts the kitting requirements of multiple production lines. Based on information about the kitting process, a translation is made to the hourly workforce to fulfill these kitting requirements. Based on the possible causes of variation in workload in the kit warehouse, advice is given on how to balance the workforce in the kit warehouse.

1.5 Research design

The research design starts with a literature search to investigate manufacturing uncertainties and prediction methods. After the literature review, a case study is conducted at Canon Production Printing. This project is a data mining project and uses the CRoss-Industry Standard Process for Data Mining (CRISP-DM). CRISP-DM is a standard process model to guide the most common steps in data mining projects. It is useful to extract knowledge from data to solve business problems (Martinez-Plumed et al., 2021). This methodology consists of 6 phases: business understanding, data understanding, data preparation, modeling, evaluation and deployment. Deployment is not performed in this research because it is beyond of time constraints and scope. Only advice about deployment and implementation of the prediction model are included in this research. The full research approach that is adopted in this research is shown in Figure 1.3. Each of the steps will be explained in this section.

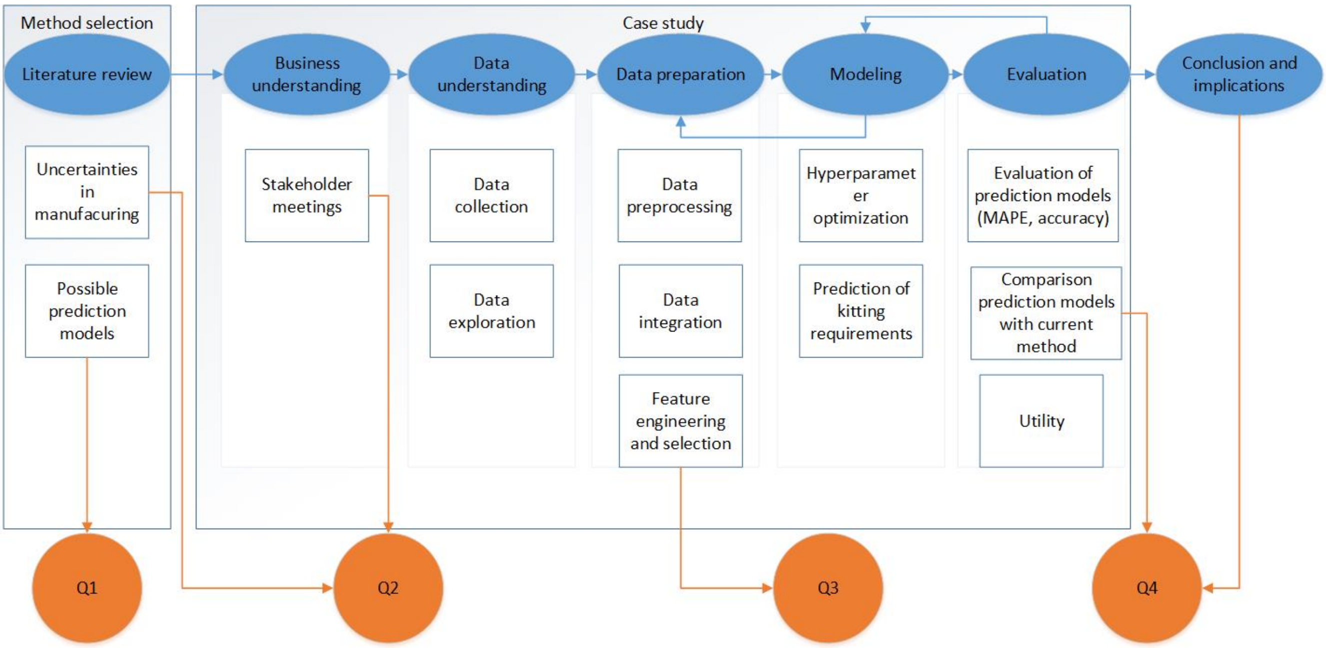


Figure 1.3: Research design

1.5.1 Literature review

The literature review starts with the explanation of different time concepts used throughout this thesis. To predict the kit requirements affected by the assembly process, more information is needed about the factors that cause variation in the assembly process. In this phase, research about uncertainties in manufacturing processes are investigated. Furthermore, relevant techniques and applications to develop a prediction model to predict the kitting requirements are researched. Because literature about the alignment between assembly and kitting is lacking, the literature review focuses on finding prediction models in production processes including manufacturing uncertainties and stochastic demand. Hence, with this result the 1^{st} research question can be answered. The output of this step are the selected prediction techniques, which will later be used as input during the Modeling phase. Furthermore, possible causes of variation in kitting and assembly processes are identified

1.5.2 Business understanding

In the Business Understanding, information is gathered about the company to get familiar with the business processes. Furthermore, factors creating variation in the kitting and assembly process are identified at the company. This information in combination with the uncertainties in the literature answers the 2^{nd} research question. With the identified factors creating variation in the production process, the right features can be chosen to include uncertainties in the model. This knowledge about the company helps to define a detailed problem. Eventually, a specific solution can be found to the problem of the company. To gain more understanding about the processes, meetings with the supervisors, assembly operators and employees of the kitting warehouse are planned.

1.5.3 Data Understanding

In this phase, the data is collected, explored and the quality of the data is evaluated (Larose and Larose, 2014). The raw data is collected and explored to get more understanding about the strengths and limitations of the data. For this project, the data consists of data about the kitting process, assembly process and production amounts. Data about the kitting process consist of the Kit history and the Kit cart events. The data set about the kit cart events also contains the estimated assembly time on the working station. Finally, production amounts can be obtained from the supervisors of the various assembly lines. The available data can be used to gain more knowledge about the production processes.

1.5.4 Data preparation

In this phase, the final data set is being prepared to use in the modeling phase. Examples of tasks are attribute selection, data cleaning and construction of new attributes (Larose and Larose, 2014). Different models might require different data preparation. The preparation step is repeated for every model that is developed in the modeling phase. First, data preprocessing is applied. The data preprocessing step consists of data filtering, data cleaning and data transformation, such as changing the format of the data set and dealing with missing values. The data sets are then combined with each other. After the data integration, feature engineering is applied. In this step, relevant feature are selected for the prediction models. With this result, the 3^{rd} research question can be answered. The output of the data preparation step is the final data set for each production line used in the modeling step.

1.5.5 Modeling

In the modeling phase, the appropriate modeling techniques are selected. During the modeling phase, it is possible that the data has to be prepared in a different way than implemented before. So, an iteration between data preparation and modeling could take place. Furthermore, the data preparation is repeated for every model that is developed, because every model needs a different data preparation. The modeling techniques are chosen based on the method selection in Chapter 2. The parameters needed for a model are also determined and explained in this phase (Schröer et al., 2021). Hyperparameter optimization is used to find the optimal parameters for the selected models. The prediction models with the optimal parameters are used to predict the kitting requirements in the kitting warehouse.

1.5.6 Evaluation and conclusion

This step helps to ensure that the research goals are met. Each model developed in the previous phase will be evaluated using evaluation metrics such as MAPE and MAE. The performance metrics are defined and explained in Section 2. After this step, improvements can be made to iterate back to the modeling phase. The prediction model will be compared with the current forecasting method of CPP. With this result, the last research question can be answered. During all the phases, discussions with employees of the company are performed when needed. This is done by discussing the questions per phase with the industrial engineers, planners and employees of the kit warehouse. These people have knowledge about the processes within CPP. Based on this evaluation, feedback and improvements are used to iterate the process of modeling and evaluation. At the end, the conclusion and implications are formulated to finalize the project. Besides that, advice about the implementation is given. The result will be delivered to the case company in a thesis report. Furthermore, a final presentation will be held to present the outcome of the project to all involved and interested parties

1.6 Research Outline

This master thesis consists of eight chapters. Chapter 2 discusses the background and literature relevant to this project. This includes the time concepts used throughout this thesis, uncertainties in manufacturing processes and the analysis of prediction methods in production processes. Chapter 3 details the Business Understanding phase and elaborates Canon Production Printing where the research is conducted. The datasets including data preparation and feature engineering are described Chapter 4. The processes related to the Modeling and Evaluation phase based on Time Between Calls (TBC) such as the hyperparameter optimization, the walk forward validation and results are presented in Chapter 5. To be able to predict the kitting requirements of multiple lines, the results of the prediction models are merged in Chapter 6. For CPP, it is more beneficial when the time between requests (TBR) to refill the same kit cart is predicted. In Chapter 7, the prediction model is also applied to predict the time between two requests of the same kit cart (TBR). Lastly the conclusions, consisting of answers to research questions, scientific and company relevance, limitations and future research directions, are shared in Chapter 8.

Chapter 2

Background and Related Work

This chapter presents the work and background which is relevant for this research. First, important time concepts in manufacturing are explained. These time concepts are used throughout this research. Subsequently, production uncertainties and factors affecting production planning and control (PPC) of mixed model assembly lines are described. Finally, applications of forecasting methods in manufacturing context are examined.

PPC refers to the organization and planning of the manufacturing process. Example of tasks are loading, scheduling, sequencing, monitoring and controlling the use of resources during production (Oluyisola et al., 2022). Production planning has to consider uncertainty in production systems (Graves, 2011). The uncertainty causes problems in either stabilizing the system or predicting and reacting to events and changes in the system.

2.1 Time concepts in manufacturing context

In material warehouses, delivering parts to assembly lines on time is necessary to avoid time delays. Due dates are determined for each part request order (Henn, 2015). The due date of a part request order depends on the composition of the part request order, processing time to pick this order and the schedule determining which orders are processed by the different pickers. Efficient assignment of parts request orders to pickers can improve the performance of the order picking system (Henn, 2015). However, the part supply system should be adjusted to the assembly line to optimize the performance. With the help of lean manufacturing, the material feeding flow will determine the ability of the organization to satisfy the customer demand (Fansuri et al., 2017). Lean focuses on minimizing the waste by implementing value-added activities and eliminating non-value added activities (Sundar et al., 2014). Lean manufacturing strives to maximize the value of the product for the customer. Different time concepts are used in lean manufacturing. As already explained in Section 1, takt time can be defined as the amount of time available to produce a product in order to meet the customer demand. The cycle time is the average time needed to do one repetition of a specific task or production process (Davies, 2009). For example, the cycle time of a machine is the time between the starting point of one product on a machine and the starting point of similar product on the same machine. The cycle time has to be lower than the takt time. If the takt time is lower than the cycle time, the customer demand will not be satisfied. The lead time is the required time to complete the process from start to end (Deshkar et al., 2018). The lead time starts with the order of customer and ends with the delivery to the customer. The processing time depends on the production type, the operation, the machine and the operator itself (Karnok and Monostori, 2011). An overview of the terms is given in Table 2.1.

Table 2.1: Definitions of time concepts in manufacturing context

Time concept	Definition
Takt time	The amount of time available to produce a product in order to meet the customer demand
Cycle time	The average time needed to do one repetition of a specific task or production process.
Lead time	The required time to complete the process from start to end. The lead time starts with the order of customer and ends with the delivery to the customer.
Processing time	The time a operator spends on assembling a product at a working station.

2.2 Uncertainties of mixed-model assembly lines

To predict the kit requirements affected by the assembly process, more information is needed about the factors that cause variation in the assembly process. Mixed-model assembly lines are used to produce a variety of products on the same assembly line. When product variety is limited, JIT delivery of parts allows companies to deliver parts to the assembly line within a very short time. Increasing product variety create reduction of the production rate due to shortened leadtimes and lack of human resources (Loveland et al., 2007). According to Golz et al. (2012), mixed-model assembly lines create the following planning problems:

- Line balancing. Processing times at work station are non-identical at different workstations. The processing time is dependent on the person and the task creating imbalances on the assembly lines (Shaaban et al., 2014).

- Master production scheduling (MPS). The MPS assign all individual customer orders to production periods in order fulfill the due dates while keeping the inventory costs low (Krueger et al., 2022).

- Production sequencing. To determine the production sequence, the MPS is necessary to know which products will be built (Krueger et al., 2022). However, stabilized production sequence limit production areas in their decision making because responding to changes are limited. Another issue with a production sequence is dealing with machine breakdown, quality issues and part shortages resulting in a changing production sequence. At any time during the production process, unforeseen events can occur that disrupt the production sequence in the short term (Franz et al., 2014).

- Material flow control. Material flow control is the supply of parts to the assembly lines. According to Golz et al. (2012), the high variability of part quantities is a difficulty regarding high variant mixed model assembly lines. This high variability is mostly caused by the ever changing daily production sequences.

- Resequencing. The sequence of the production process can change due to varying lead times, part shortages, machine breakdown and quality issues (Müller et al., 2020).

These planning problems are related to the PPC process. Besides the difficulties regarding line balancing and production sequences, human factors are also playing a role regarding PPC.

Human factors

A high amount of manual human work is still involved in operation processes, especially in material handling and assembly. Most planning models introduced to reduce costs ignored the human-related aspects which leads to unrealistic planning outcomes (Sgarbossa et al., 2020). An adjustment to the planning system is mainly based on personal experience and judgement of the production managers (Wang and Abubakar, 2017). Humans are more flexible than machines and are able to react to rapid and unexpected changes (Vijayakumar et al., 2022). Job rotation is often used to ensure a flexible workforce. However, human performance is also unpredictable due to their abilities and limitations (Abubakar and Wang, 2018). Including human factors is necessary to guarantee a high level of productivity and efficiency and providing a realistic planning model (Sgarbossa et al., 2020). Several factors affect the operator at the workstation in an assembly line. A high amount of product variants increase the complexity of the manufacturing process. Furthermore, increased product variation has a negative influence on the operator's performance in terms of quality and productivity (Hu et al., 2008). Besides the increased product variation, physical layout of the working station and the way of information sharing have impact on the operator's performance. Finally, the material flow is highly connected with to the operator's performance (Limère et al., 2012). The time to search for materials affect the operator's processing time. Kitting can improve productivity and reduce learning times when the kit cart is designed in the right way. Finally, personal aspects of an operators also have influence on the operating time. According to Wang and Abubakar (2017), experience and age significantly affects the processing time to complete a task. The varying processing times have influence on the alignment between kitting and assembly.

2.3 Prediction methods

In the following section, simulation and machine learning techniques are researched. Because literature about the alignment between assembly and kitting is lacking, the literature review focuses on finding prediction models in production processes including manufacturing uncertainties and stochastic demand. Simulation can be used to integrate uncertainties like machine breakdowns, quality issues and processing time fluctuation in the product (Yang et al., 2016). Machine learning is also able to take uncertainties into account with the use of artificial intelligence (Das et al., 2015).

Different prediction methods can be used to predict resources or dynamic parameters in a production process. In order to predict the kitting requirements affected by the assembly activities, the Production Planning and Control (PPC) process has to be controlled. The PPC experiences stochastic manufacturing nature and uncertainties. According to Kang et al. (2020) and Fahle et al. (2020), the majority of machine learning methods used in manufacturing are based on supervised learning. As shown in Figure 2.1, tree-based models and neural networks are most commonly used supervised machine learning techniques (Cadavid et al., 2019). So, decision tree, random forest, support vector machine and artificial neural network are selected as machine learning techniques. Furthermore, simulation can also model a PPC process which give the possibility to predict the required resources.

2.3.1 Simulation

Simulation models give the possibility to model the production planning and control (PPC) process. As described in Figure 2.2, simulation models predict future behavior based on models. The biggest issue in creating models for manufacturing applications is collecting the right data and figuring out the interrelationships (Langer et al., 2021). It is very time consuming to build a good simulation model. Furthermore, it is very difficult to mimic the reality including all human behaviors (van der Aalst (2018), Collins et al. (2021)). Process models are often different than the reality. Process mining can offer data for simulation by analyzing process-specific data (Langer et al., 2021).

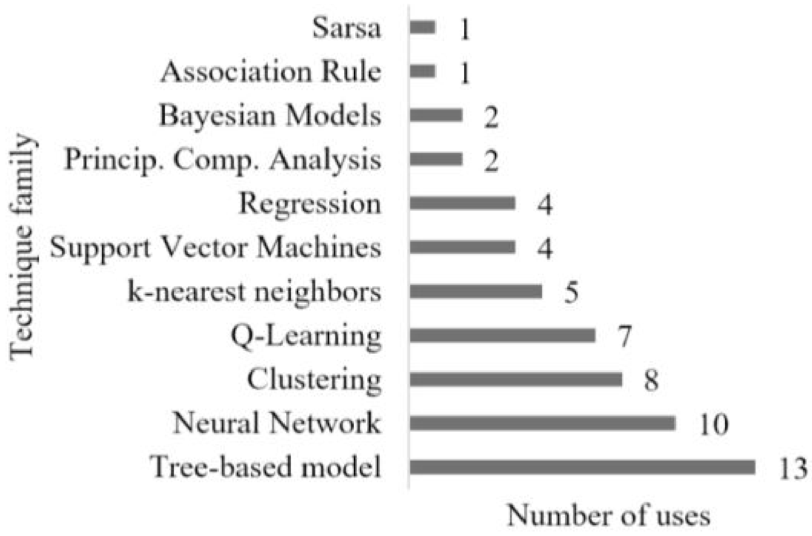


Figure 2.1: Usage of machine learning techniques in PPC (Cadavid et al., 2019)

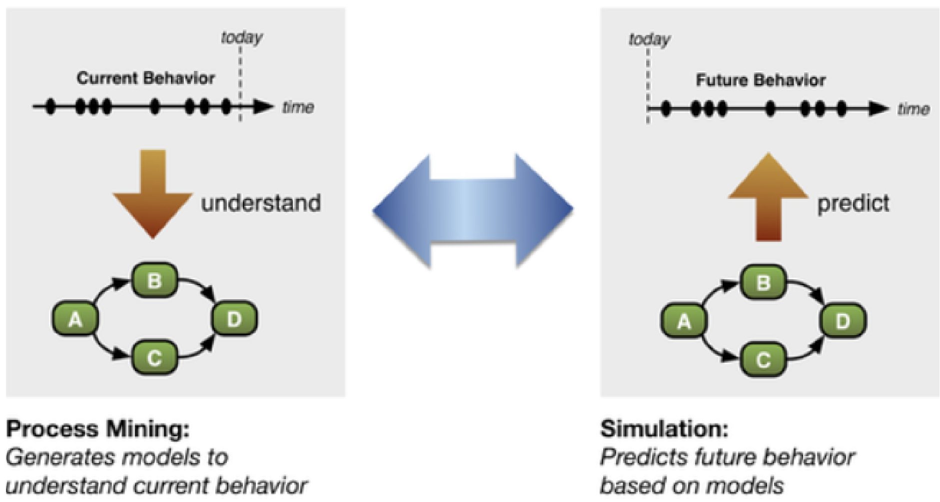


Figure 2.2: Connection between process mining and simulation

Simulation is a model that describes the behaviour of an existing or proposed system. The resulting model can be used to test how the performance of the existing system differ with different scenarios or process changes (Baines et al., 2004). Discrete Event Simulation (DES) has been widely used for process improvement and decision making (Machado et al., 2019). In manufacturing context, simulation is recommended due to complex factors like numerous manufacturing steps, batch processing and complex equipment (Fowler and Rose, 2004). DES can model the variation within manufacturing systems with the use of probability distributions (Prajapat and Tiwari, 2017). Planning and scheduling problems can also be solved with DES. Scheduling problems with more than two machines can't be solved by existing optimization algorithms because they are not able to find a solution in a reasonable time (Varela et al., 2017). All existing optimization algorithms handle specific types of production system but these algorithms are less efficient when the system gets larger and include more uncertainties (Kaylani and Atieh, 2016). Using DES in combination with flexible parameters facilitate modifications to the schedule quickly and with minimal effort.

Evaluation metrics

Different key performance indicators can be used to evaluate the simulation model in a manufacturing context. First, the product cycle time can be defined as the total manufacturing cycle time. The time spent at each individual working station can also be measured. Secondly, when optimizing a production schedule, delay can be measured as the difference between the due date and the actual end time in the simulation. The results of the simulation also have to be compared with the output of the real system. Furthermore, very busy time periods can be identified which could cause delays in the schedule (Kaylani and Atieh, 2016). Finally, resource optimization like operator utilization and machine utilization, can be measured.

Digital twin

A digital twin is a digital copy of a physical object and its process (Segovia and Garcia-Alfaro, 2022). The data flow between the physical object and the digital copy are integrated in both ways. A change in the physical object cause a change in the digital object and in the other way around (Kritzinger et al., 2018). Simulation and the digital twin are both designed to replicate existing processes. The main difference between a digital twin and simulation is that the data twin have a data connection between the physical object and digital object. The digital twin reacts on real time data while simulation is static and often need manual adaption of the parameters (Kritzinger et al., 2018). According to the the level of data integration between the physical object and digital object, three subcategories are considered. In a digital model, the data is exchanged manually (Singh et al., 2021). Most offline simulation models belong to this category (Segovia and Garcia-Alfaro, 2022). Secondly, a digital shadow contains an automated data flow from the physical to the digital object. From the digital object to the physical object is still manual. A simulation using real-time data as input is an example of a digital shadow. Finally, the digital twin contains an automatic bi-directional data flow between the physical and data object. An example is a simulation that uses real-time data and updates parameters of the manufacturing process (Segovia and Garcia-Alfaro, 2022). The differences between the digital model, digital shadow and digital object are showed in Figure 2.3 (Singh et al., 2021). According to Zhuang et al. (2021), the digital twin is a way to tackle high complexity processes. Characteristics of high complexity are strong randomness, process instability and strict data management. Furthermore, a digital twin can be used to optimize production planning and scheduling by collecting data from production equipment and enterprise resource planning systems. With the collected data, the current status of the production systems can be analyzed including fluctuations in customer demand, inventory and resources (Shao and Helu, 2020).

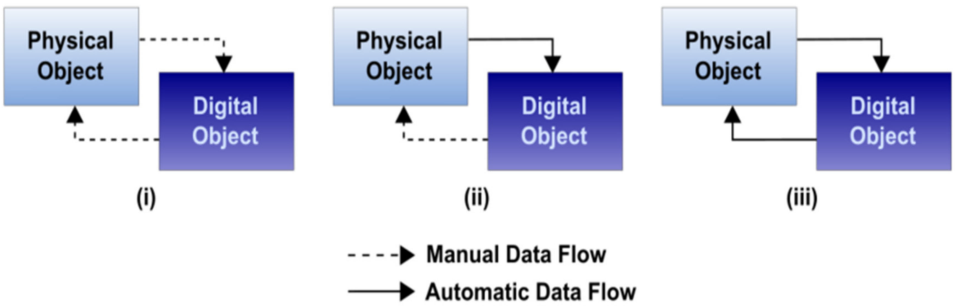


Figure 2.3: Difference between digital model, digital shadow and digital twin

Simulation in manufacturing context

Simulation models are already used in several applications in the manufacturing domain. According to Ali and Seifoddini (2006), a number of factors are critical in effective production lines, such as product time, human resources and material handling capacity. High mix and low volume production lines encounter more difficulties due the combination of changing needs and the complicated constraints such as unpredictable machine breakdowns, unavailability of human resources, parts shortages. Most of commercial simulation software does not provide the functionalities to include unexpected variation. The biggest challenge in the literature regarding planning are including the uncertainties to create a more realistic model. In this paragraph, simulation models including production related uncertainties and human factors are explained.

Yang et al. (2016) developed a flexible simulation support for production planning. In this simulation, forecast and different scheduling policies are included. With the simulation, the impact of different uncertainties like machine breakdown, quality uncertainties and processing time fluctuations, are analyzed very fast in a specific situation. The authors indicated as limitation that input parameters as batch size and parts per arrival are in reality variable. Jung et al. (2022) applied discrete event simulation to assess the real-time productivity of the garment production line. With the use of dynamic task time, the simulation was able to predict hour-by-hour production more accurately. As future research, the study indicated that the simulation can be further improved by including work difficulty and experience. Ali and Seifoddini (2006) applied simulation to model manufacturing behaviour considering labor uncertainty, machine uncertainty and logistics uncertainty. The goal of this study was to solve real-life problems such as manufacturing scheduling. The authors proposed real-time integration of data on the factory floor and the inclusion of more features to deal with uncertainties. Finally, Negri et al. (2021) used a digital shadow by proposing a dynamic production scheduling framework. The goal of this study is to use real time data for scheduling instead of optimal solution calculated from historical data. In this framework, uncertainties in the form of failure probabilities are included. The authors choose to make the framework not fully autonomous. There is still a degree of flexibility for human decision-makers. Further improvements are proposed by also predicting the future trend of the failure probabilities instead of only detecting the failure. Most of the literature research include manufacturing uncertainties. However, Lazarova-Molnar and Mizouni (2010) applied proxel-based simulation using a discrete-time Markov chain to model human behavior. The human behavior is modeled by including resource allocation and on-the-fly human decisions. Future research indicated by this study is to include value, effort and cost parameters. An overview of the application of simulation models is summarized in Table 2.2. As a conclusion, simulation already applied human factors and production related factors in manufacturing context. Usually these applications are done on the assembly planning where the alignment with kitting is missing. Tetik et al. (2021) emphasized the importance of a planning to make the product flow more efficient, but the study itself is focusing on the benefits of kitting on assembly.

Table 2.2: Application of simulation models in the manufacturing

Study	Model	Application	Limitation
(Yang et al., 2016)	Discrete Event Simulation	PPC simulation system including forecast and different scheduling policies considering uncertainties	In reality, input parameters such as batch size and parts per arrival can vary.
(Jung et al., 2022)	Discrete Event Simulation / Digital shadow	Real-time productivity assessment of garment production line	Work difficulty and experience is not included.
(Ali and Seifoddini, 2006)	Simulation	Simulation for manufacturing uncertainties. Fuzzy logics are used to measure the flexibility of the uncertainties.	Real-time integration of the factory floor is missing
(Negri et al., 2021)	Digital shadow / Discrete event simulation	DES model of the production system with real time computation of failure probability	Only detects the failure including failure probability instead of predicting for the future.
(Lazarova-Molnar and Mizouni, 2010)	Proxel-based simulation	Model human behavior by including resource allocation and on-the-fly human decisions.	value, effort and cost parameters are not included.

2.3.2 Machine learning

Machine learning methods are able to include dynamic factors like human factors in production planning in the manufacturing environment (Ryback et al., 2019). Including these factors in the production planning is important to make the production planning as realistic as possible. In this section, machine learning algorithms which are applicable in Production Planning and Control PPC are explained. Machine learning is considered as a subset of Artificial Intelligence (AI). The goal of AI is to develop human intelligence in machines. Machine learning is how the system develops human intelligence (Das et al., 2015). The focus of machine learning is to learn from data without being explicitly programmed (Dijkstra and Luijten, 2021). Machine learning make predictions by finding patterns and trends in data and adapt to new data. The accuracy of the machine learning models can be increased by using high quality data and large data sizes (Kang et al., 2020). According to Kang et al. (2020) and Fahle et al. (2020), the majority of ML methods used in manufacturing are based on supervised learning. Supervised learning requires a labeled data set to derive a function between the input and output. Unsupervised learning does not require labeled data and is used when relationships among input variables are not known (Kang et al., 2020). Finally, reinforcement learning is a machine learning method based on rewarding desired behavior and punishing negative behavior. According to the systematic literature reviews of Fahle et al. (2020), Kang et al. (2020) and Cadavid et al. (2020), the machine learning algorithms neural networks, support vector machines, random forest and decision trees are mostly used in manufacturing process planning. The different machine learning algorithms are further explained in the subsections.

Decision tree

According to (Tso and Yau, 2007), the decision tree can be used as an efficient decision support for a production system. A decision tree is presented as a tree with decision nodes and leaf nodes, as shown in Figure 2.4. The root node represent the whole population which have to be analyzed. The decision nodes are the input variables. The leave nodes are the terminal

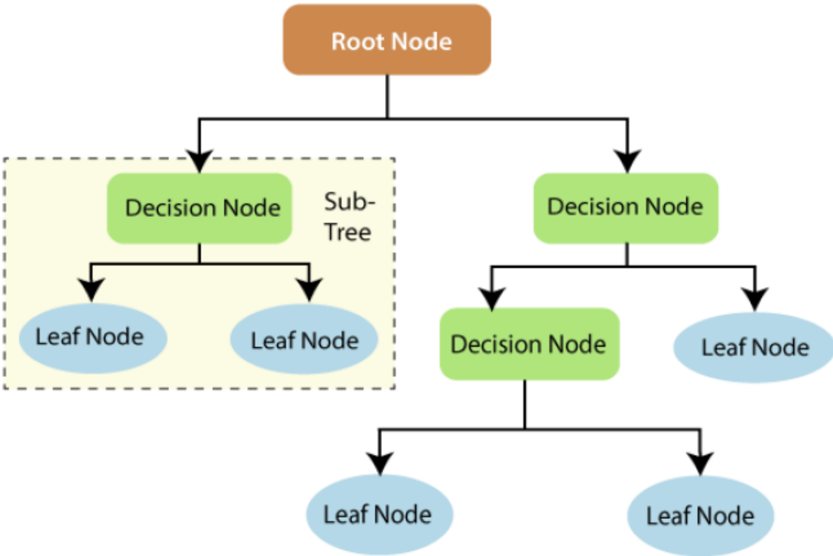


Figure 2.4: Structure of a decision tree

nodes with the possible outcome.The decision tree algorithm is a supervised machine learning algorithm where labeled data is needed to create a training model (Charbuty and Abdulazeez, 2021). Czajkowski and Kretowski (2016) distinguish two types of decision trees. A classification tree assigns a categorical label to each leaf node. A regression tree assigns a continuous value to each leaf node. At each decision point, the error between the predicted value and the actual value is calculated. The quality of the split in the decision node can be validated by statistical tests (Pekel, 2020). As a result, decision tree regression is seen as a reliable model. Furthermore, the structure of a decision tree is very easy to understand. However, the chance of overfitting is high because of the creation of over-complex decision trees. Overfitting of an machine learning algorithm means that the model is learning too many details and noise. Furthermore, a small variation in the data can result in a completely different decision tree. The parameters of the decision tree have to be tuned to deal with these problems (Pekel, 2020).

Random Forest

Random forest is a supervised machine learning algorithm and can be used both for classification and regression. Random forest is an ensemble learning method by combining the prediction of multiple decision trees (Zhang and Ma, 2012). The output of classification is a categorical variable while the output of a regression is a continuous variable. Each decision tree apply a different and randomly selected set of predictor variables (Zermane, 2021). These different decisions trees can deal with different sources of uncertainty and variability (Cheng et al., 2019). Because of multiple trees with different sets of input variables, random forest algorithms prevents overfitting and support generalization. When the model is overfitted, the model is too complex and can't generalize the new data. However, random forest is a black box method using multiple decision trees. In addition, the multiple decisions trees require more time and computation power than a single decision tree (Prasad et al., 2006).

Support vector regression

Support vector regression is based on support vector machine which is a supervised classification algorithm (Han and Chi, 2016). Support vector regression (SVR) is a regression model that estimates a continuous-valued multivariate function. This method tries to find a function that not deviates more than a pre-defined threshold. There is flexibility to define how much error is acceptable to fit the data. By using kernels, SVR is able to deal with nonlinearity (Lenz and Barak, 2013).

Artificial neural network

Artificial neural networks (ANNs), or simply neural networks, are more and more often used in manufacturing context. ANNs can be used to control production processes. Modelling the dynamics of a production process are important to identify the variability of its physical quantities or states (Burduk, 2013). According to Yuldoshev et al. (2018), artificial intelligent methods like neural networks will improve operational planning systems. The production planning can react quickly on changes and corrections in the original data, e.g. in case of random events. In the context of a production system, ANN is able find a relationship between many input variables and the output variable without the need to build a mathematical model. The different planning problems described in section 2.2 make it very difficult to create a mathematical model of a production system. Another aspect which have influence on production processes are human factors. According to Abiodun et al. (2018), neural network models are performing better in its application to human problems. An ANN can act in the same way as the human brain performs a particular task of interest. Recurrent Neural Network (RNN) is a class of ANN developed to process time based behaviors or sequential data (Tran et al., 2021). RNNs remember previous data. The next decision is made using the current input and the input learned from previous steps. Long short-term memory (LSTM) is a sub-class of RNN and has a longer memory than RNN. LSTM is used to model patterns in time sequence. The long memory makes it possible to learn from inputs that are separated from each other by long time lags (Yadav et al., 2020). Furthermore, this type is able to predict the next most probable element in the pattern (Morariu and Borangiu, 2018).

Evaluation measures

The quality of machine learning algorithms can be measured with different performance measures. Decision trees, random forests and neural networks are supervised learning methods. The most commonly used performance measures for supervised regression methods are rooted mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE and the mean squared error (MSE) (Seçkin et al. (2019), Botchkarev (2018)). The RMSE is a scale dependent measure. The RMSE is preferred over the mean squared error because the error is measured in the same unit as the data (Saigal and Mehrotra, 2012). Low values of MSE and RMSE are preferred. The MAE measures the average distance between the observed and predicted variable. Like the RMSE, the MAE is also measured in the same unit as the data. Furthermore, the MAE tend to be smaller than RMSE, because the RMSE give higher penalties to large errors while MAE gives the same weight to all errors (de Myttenaere et al., 2016). A low value of RMSE and MAE is preferred which means low prediction error. The MAPE is a performance measure based on percentage errors. The MAPE is often used when the value to predict is above zero (de Myttenaere et al., 2016). A low MAPE value is preferred which is equal to a low percentage error. This performance measure is valuable for the case study because the kitting requirements are very high resulting in working hours needed to kit the carts. The value of the predicted kitting requirements will be above zero. The formulas of the evaluation measures can be found in Table 2.3.

Table 2.3: Formulas of the evaluation measures

Evaluation Measure	Mathematical formula
Root mean squared error (RMSE)	$\text{RMSE} = \sqrt{\left(\frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{n}\right)}$
Mean squared error (MSE)	$\text{MSE} = \left(\frac{1}{n}\right)\sum_{i=1}^{n}(y_i - \hat{y_i})^2$
Mean absolute error (MAE)	$\text{MAE} = \left(\frac{1}{n}\right)\sum_{i=1}^{n}\lvert y_i - \hat{y_i}\rvert$
Mean absolute percentage (MAPE)	$\text{MAPE} = \left(\frac{1}{n}\right)\sum_{i=1}^{n}\left\lvert\frac{y_i - \hat{y_i}}{y_i}\right\rvert$

y_i = Observed value in period i
$\hat{y_i}$ = Predicted value for period i
$\bar{y_i}$ = Average of observed values y_i
i = Time period
n = Total number of time periods

Machine learning in manufacturing context

Machine learning models are already used in several applications in the manufacturing domain. The end goal of machine learning in the manufacturing is to recognize patterns in the data. With these patterns, future behaviour can be predicted (Bajic et al., 2018). Machine learning in manufacturing focuses the most on challenges related to complexity and dynamic behaviours. Parallel and high complex tasks, different skills and constraints regarding workload is rising complexity in the planning system (Hao et al., 2004). Furthermore, the manufacturing is also affected by production related uncertainties like part shortages and machine breakdowns. With machine learning, parameter values of unknown information can be predicted with the use of historical values. Future information can be predicted to make appropriate decisions regarding planning activities (Chen et al., 2021). Production uncertainties can change the production sequence, forcing the production schedule to be changed. (Wu et al., 2020). Existing scheduling algorithms require very long computational times to solve the changing production sequences. (Wu et al., 2020). This paragraph focuses on the prediction of human and production related factors affecting the manufacturing. In addition, this part explains applications of machine learning algorithms that have succeeded in reducing computation time.

Müller and Wiederhold (2002) applied decision trees to provide online decision support of human centered production processes. The results showed that one decision tree was not enough to derive knowledge about operators. The random forest algorithm is already successfully applied to predict the operator workload based on operator behavior and task demands (Borghetti et al., 2017). However, random forest is a supervised learning method. The authors indicated as limitation that a highly dynamic task which is not experienced before is difficult to predict. For companies with new dynamic activities, unsupervised learning could be a better solution Gyulai et al. (2018) applied a random forest to predict lead times using real-time streamed production data. The prediction model was able to react to dynamic changes of the production environment, while still providing accurate predictions. In this study, the inclusion of control parameters such as the Overall Equipment Effectiveness (OEE) is suggested.

In addition, neural networks can be used to model human behavior and is applied to personnel scheduling (Xie et al. (2003), Hao et al. (2004)). This study highlights the low computational costs of neural networks compared to mixed integer programming. In the study of Hao et al. (2004), a limitation is indicated that the neural network applied for personnel scheduling requires more extensive tests to confirm its reliability and general applicability. An artificial neural network (ANN) is also used to predict dynamic lead times based on flow time forecasting (Schneckenreither et al., 2021). In this study, exponential smoothing and ANN are compared based on the forecast accuracy. ANN outperforms exponential smoothing in cases of high processing time variability and in cases with high utilization. A limitation indicated in this study that the results are limited to the simulated case. Furthermore, inclusion of machine failure and different scheduling rules are proposed for future research. Sagheer and Kotb (2019) used Long Short-Term Memory to predict the production of petroleum with time series data. In this study, LSTM has been compared with traditional statistical methods like ARIMA. The data contains a lot of noise and defects. Furthermore, the production petroleum is dependent on several dynamic factors which are not always available. As a result, LSTM outperforms the statistical model ARIMA and is able to describe the nonlinear relationship between the systems inputs and outputs. Future research is suggested to apply LSTM in other forecasting problems with multivariate time series data. Finally, (Han and Chi, 2016) applied Support Vector Regression (SVR) to predict the periodically changed parameter. The results show that pre-processing the data is very important to get the right predictions. A difficulty in this study was that the machine data was collected in a relatively short period of time, while the product inspection data was collected in a relatively long period of time. In addition, the predicted value cannot be applied in real time because the machine must be restored to its original value. Applications of machine learning in manufacturing context are summarized in Table 2.4.

Table 2.4: Applications of machine learning techniques in manufacturing context

Study	Model	ML Method	Application	Limitation
(Müller and Wiederhold, 2002)	Decision tree	Supervised	Generate a physical model including action of human operators	One decision tree is not enough
(Borghetti et al., 2017)	Random forest	Supervised	Predict lead times using real-time streamed production data	Inclusion of OEE is proposed
(Gyulai et al., 2018)	Random forest	Supervised	Scheduling production tasks on a production line with short computation time	It has to be trained on a large number of well distributed instances
(Hao et al., 2004)	Artificial neural network	Supervised	Personnel scheduling with low computational costs	Requires more tests to confirm its reliability and general applicability.
(Schneckenreither et al., 2021)	Artifical neural network	Supervised	Predict dynamic lead times based on the flow time forecast	Results are limited to the simulated case. Inclusion of machine failures and different scheduling policies are proposed
(Sagheer and Kotb, 2019)	Long Short-Term Memory	Supervised	Forecasting of petroleum production with a lot of dynamic factors which are not always available.	Only tested on production data, future research including problems with multivariate time series data is suggested.
(Han and Chi, 2016)	Support vector regression	Supervised	To predict the periodic changed machine parameter	Different data gathering periods are used

2.4 Conclusions

Based on the literature review, different prediction methods can be used to predict parameters in a production process. In order to predict the kitting requirements affected by the assembly activities, the Production Planning and Control (PPC) process have to be controlled. The PPC includes the stochastic manufacturing nature and uncertainties. The selection of the techniques focuses on methods predicting variables in the manufacturing considering uncertainties and stochastic demands. Decision Tree, random forest, support vector regression, artificial neural network are the most commonly used machine learning methods in the literature. Because random forest algorithms prevents overfitting and support generalization compared to a decision tree, only random forest is selected. So, random forest, support vector regression and artificial neural network are selected for this thesis. Furthermore, simulation can also model a PPC process which give the possibility to predict the resources. In this thesis, simulation is not used, because a connection between the production order and kit cart is missing. When using simulation, each kit cart would have to be simulated individually rather than a production order.

Chapter 3

Business understanding

As mentioned in Section 1.2, this thesis project is conducted at Canon Production Printing in Venlo. Knowledge about the production process is required to be able to build a prediction model. First, the kitting process performed at CPP is described. To be able to make a connection between kitting and assembly, the characteristics of the different production lines are collected. Additional to influencing factors generated from the literature review, influencing factors on the kitting and assembly process identified at CPP are presented. These factors are necessary to predict the kitting requirements including the variation of the production process. Finally, the solution requirements specific for CPP are defined.

3.1 Current kitting process

In this section, the current kitting process of CPP is described. CPP uses a JIT kitting process where assembly operators request their parts by notifying the warehouse. To make the communication between the operators and the warehouse easier, they are using a so-called "pizza tool" described in Figure 3.1. This 'pizza tool' is a dashboard which can be compared with the Pizza tracker used by Domino's pizza to communicate the progress of making the pizza with the customer. In case of CPP, the 'pizza tool' indicates where the kit cart is located. This dashboard is visible both in the kitting warehouse and at every work station in the assembly lines. The kitting warehouse can see the status of all kit carts. The dashboard at the working stations only shows the necessary kit carts for that particular working station.

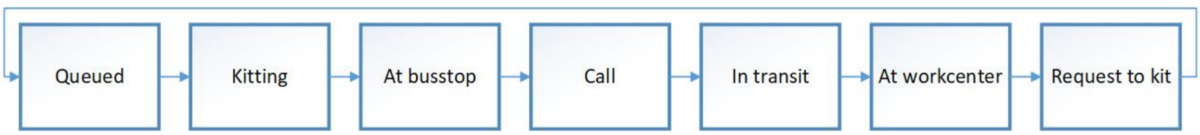


Figure 3.1: Pizza tool process

The process starts when the assembly operator requests a new kit cart. SAP checks if there is an production order open where this kit cart is needed. All production orders are connected with the required kit carts. SAP returns a message to the assembly operator if the kit cart is requested or not. Then, the kit cart is placed in a queue based on latest start date. The latest possible start date is the time at which a kit cart can be kitted without causing a delay in the assembly process as shown in Figure 1.2 and Figure 3.2. Furthermore, an example of the queue is given in Figure 3.2. The kit carts appear on the scanners of the kitters according the queue based on the latest possible start date.

In the kit warehouse, the kit carts are kitted by the kitters with the help of a bar code scanner. The kit warehouse is also called the 'supermarket' containing most of the parts needed for the

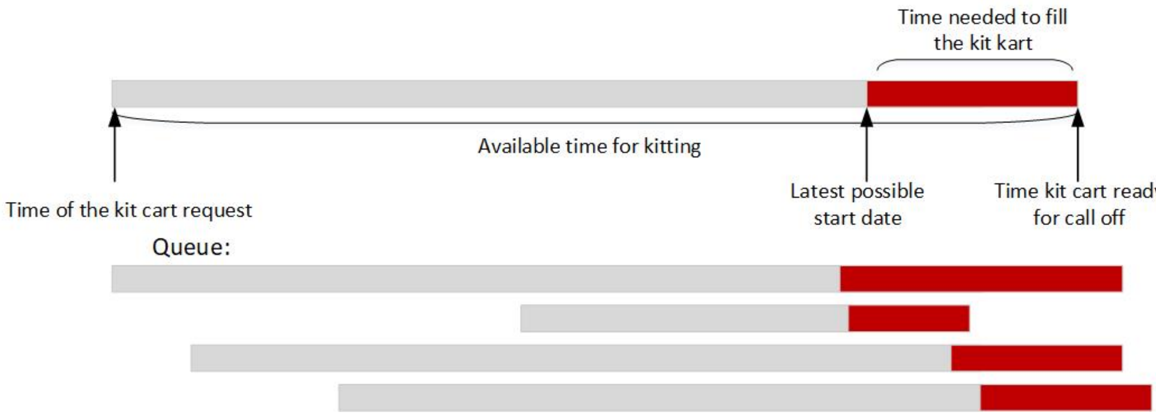


Figure 3.2: Latest possible start date

assembly lines. After finishing the kit cart, the kit cart is placed at the full busstop, a place where all full kit carts are collected. The kitter scans the location at the full busstop after which the materials of kit cart are deducted systematically from the inventory. The assembly operators are able to call the kit cart when they need the kit cart for assembly. After a call from the assembly operator, the kit cart is connected to an Automatic Guided Vehicle (AGV) and will be sent to the assembly operator. The AGV with the kit cart needs about 2 to 5 minutes to reach the assembly operator, depending on the distance between the kit warehouse and the production line. The assembly operator receives the kit cart and starts assembling. When the kit cart is empty, the assembly operator can request to refill the kit cart and returns the empty kit cart to the supermarket with an AGV. An extensive explanation of the kitting process is described in Appendix A.

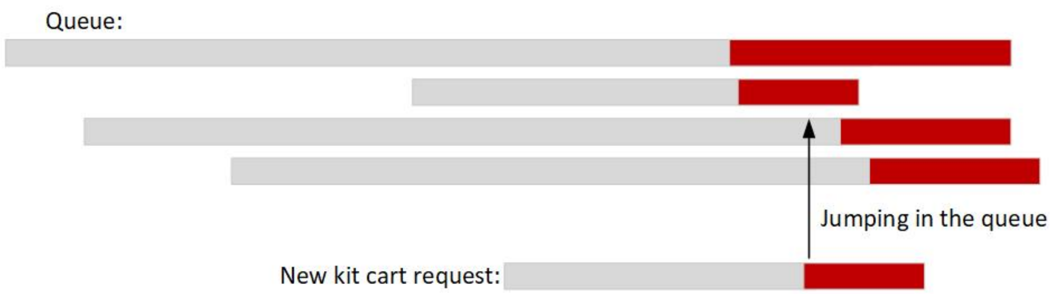


Figure 3.3: Prioritization of new kit cart requests

The kit carts only appear in the kit planning when the kit car is empty and requested. The products produced on different assembly lines have their own specific takt times. However, the kit carts are only scheduled based on the latest possible start date. The time availabe for kitting and time needed to fill a kit cart are predefined based on the minimum takt of the production line. The kit carts appear in this order on the barcode scanners (SAP WM mobile terminals). The barcode scanners are connected with SAP. Kit carts from production lines with short takt times can change the order of the kit carts from hour to hour by requesting kit carts which have to be kitted very quickly. An example is shown in Figure 3.3. Furthermore, the extra kit carts make workload planning very difficult because of the varying amount of requests from hour to hour. An example of the kitting requests per hour during a week is shown in Figure 3.4. Although CPP is using flexible workers to be responsive to swings, it cannot anticipate on changes in the next one or two hours. These short term changes causes problems in predicting the capacity of manpower to fulfill the demand and causes high costs because of overstaffing or delays. CPP is looking for a prediction model to respond to the varying kitting requirements to be able to predict the required workload.

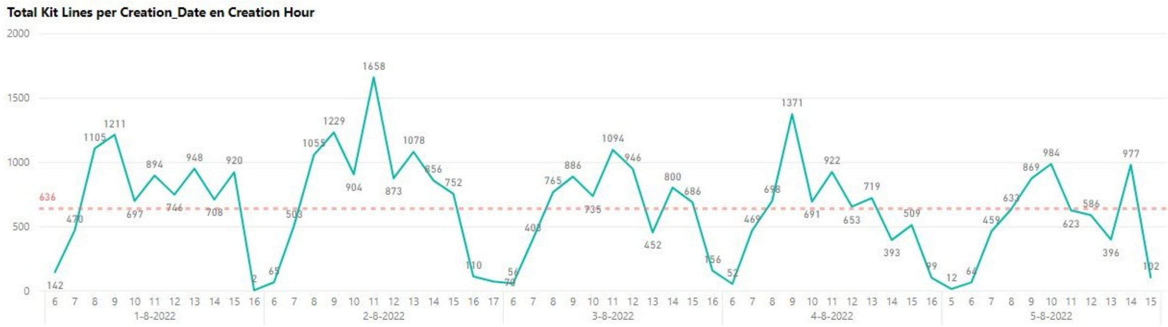


Figure 3.4: Variation of kitting requests per hour

3.2 Variation of the kitting requirements

This research attempts to develop a prediction model to predict hourly kitting requirements and associated work hours. During the literature review, factors influencing the alignment between kitting and assembly are identified. Furthermore, CPP employees who have knowledge of the processes are asked which factors could influence the alignment between assembly and kitting. The group of CPP employees consisted of industrial engineers, planners, assembly operators and kitters. Based on Section 2.2 and conversation with the employees of CPP, multiple factors are found to have influence on the relation between kitting and assembly.

Kitting. Multiple factors have influence on the kitting process. Human factors and human errors could have influence on the kitting process, because the kitting is done manually (Caputo et al., 2017).

- *Variance in kitting performance.* The kitting performance can vary depending on the age and experience of the kitter.
- *Inventory shortages.* Inventory shortages results in incomplete kit carts. The suppliers can't deliver the parts on time.
- *Human error.* Kitting is done manually which may cause human errors. Examples of human errors regarding kitting are wrong parts or missing parts. This affects the assembly operations due to incomplete kits and station downtime (Caputo et al., 2017).

Assembly. Furthermore, the assembly planning can also be influenced by multiple factors. These variation in assembly are obtained from Section 2.2 and derived from conversations with the employees of CPP.

- *Variance in processing times.* Comparable with the variance in kitting performance, differences in age and experience can cause variances between assembly operators (Wang and Abubakar, 2017). Furthermore, product variation and task complexity have influence on the productivity of the operator (Hu et al., 2008).
- *Part shortages.* Parts shortages can be errors in the kitting warehouse like damaged , missing or wrong parts. It is also possible that the kit cart is arriving too late causing delays in the assembly operations.
- *Human errors.* Assembly operations are also performed manually which may cause human errors. Incomplete assemblies or wrong placement of components are common errors in assembly. This could change the assembly planning. Requesting a kit cart too early can also affect the alignment between kitting and assembly.

Alignment between assembly planning and kitting. In order to predict the kitting requirements considering the assembly process, a connection between the kitting process and the assembly planning is required.

- *Multiple assembly lines.* In a warehouse, multiple assembly lines operate. These assembly lines have different takt times. In order to schedule these multiple assembly lines, knowledge about the production process is necessary (Choueiri and Santos, 2021). These takt times cause variation in kit cart requests per hour, as shown in Figure 3.5

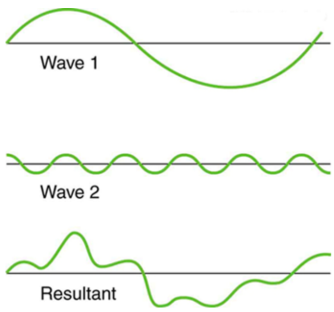


Figure 3.5: Variation created by multiple assembly lines

- *Start moment of production.* A possible reason of extra variance in the kitting requests is the starting moment of the production. If every production line is starting on Monday morning with a new machine, this could lead to peaks during the week. Shifting the production schedule of a production line could balance the workload.

- *Wrong prioritization of kit carts.* The available time for kitting for a specific kit cart is predefined and always the same regardless of production amount. Based on these times and the requests from the production, a queue is created. With this way of creating a queue, it is possible that a certain kit cart is not needed after the predefined time, because the production amount of that line is lower that week. A kit cart of another line may be needed in time to prevent delays in production of that specific line.

The relation between kitting and assembly with the influencing factors are shown in Figure 3.6.

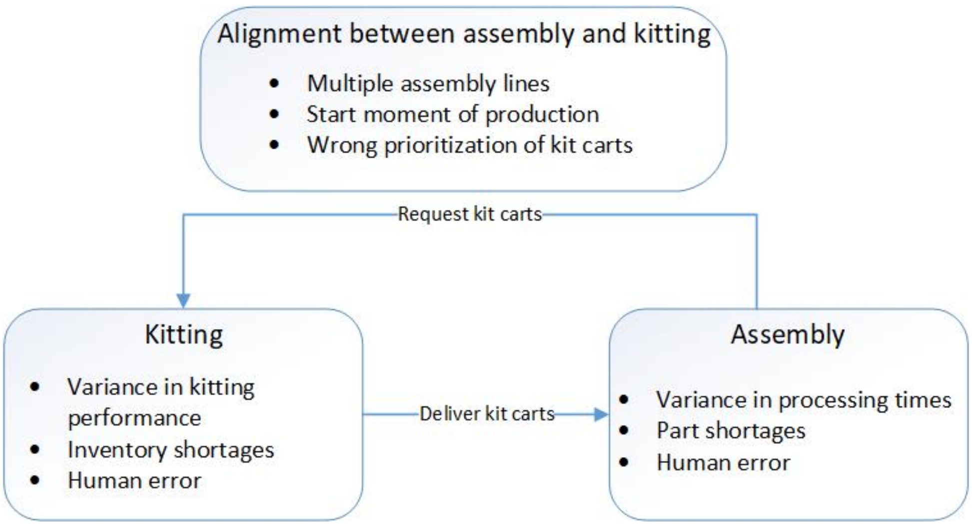


Figure 3.6: Relation between kitting and assembly

Additionally to the influencing factors described above, the layout of a kit cart has also influence on the kitting process. The number of common parts and type of parts has influence on the time needed to kit a kit cart. Besides that, the workplace layout of an assembly operator also has influence on processing times. In this research, changing the layout of the kit carts and workplace of assembly operators are out of scope.

3.3 Production lines

This thesis is conducted at the Manufacturing and Logistics department of Canon Production Printing in Venlo. Within the Manufacturing and Logistics department, multiple production lines are operating with different characteristics. For this research, the three biggest production lines are chosen, because 89% of the unique kit carts belong to these three production lines. The characteristics of the production lines are described below.

3.3.1 HCS

HCS is a mixed model assembly line where multiple models are produced on one production line. The HCS production line can be split into 2 separate lines, HCS3 and HCS2. On the HCS3 line, two models are produced, J1 and N1. Each model has their own set of kit carts. Based on a quota system, the right kit kart depending on the requested model, appears on the scanner of the kitters in the kit warehouse. On the HCS2 line, one model is produced for which the same kit trolleys are always used. The set of kit carts specific for each model is described in Appendix B.1.

The average time to produce one product on the HCS3 production line is about 1.5 hour. In 2021 and 2022, the production of HCS3 is around 20 per week and the production of HCS2 is around 12 per week. However, the production amount per week is depending on manpower capacity and parts availability. To produce one machine, multiple kit carts are needed. When the assembly time of a kit cart is close to the takt of the production line, the time available to fill a kit cart becomes almost zero. To cope with short takt times and long assembly times, a Two-Bin system is used where an A and a B version of a kit cart exist. When the A version is used for assembly, the identical B version is already filled in the kit warehouse. The available time to kit a kit cart is depending on the minimum time to build a product. In case of HCS, the available time for kitting is mostly 75 minutes. Although the A and B versions of the kit kart give more time for kitting in the kit warehouse, the takt time in the kit warehouse is still between 75 and 90 minutes. After requesting these kit carts, the kit carts show up late in the queue, as described in Figure 3.3. The kitting queue gives priority to kit carts that have little time available to kit and allows kit carts with more time to kit and longer takt times to wait. The short takt time causes last minute changes to the kitting queue.

3.3.2 VP6000

The VP6000 production line also produces multiple models on the same production line. The assembly operators are using generic kit carts necessary for every model and specific kit carts specific to a model. There are 45 kit carts for VP6000, but for every model only 31 kit carts are used to build an engine. Every model has their own set of kit carts. The set of kit carts per model is described in Appendix B.2. The average time to build one engine on the VP6000 production line is around 4 hours. The production of VP6000 engines is around 10 engines a week. Similar to the HCS, kit karts of the VP6000 have an A and B version to make it easier to cope with the short takt times and long assembly times.

3.3.3 Niagara

Niagara is the production line building largest product. The Niagara production line is divided into 8 different teams. One team of Niagara does not use kitting. The other 7 teams have their own kit karts. The time to build one product on Niagara production line is on average 16 hours. The available time to kit these kit karts are long compared to the other two production lines. Last minute changes to the kit schedule due to HCS and VP6000 may prevent Niagara kit carts from being filled on time. Compared with the other two production lines, Niagara is a low volume production line. The kit carts of Niagara are also used around every 16 hours. Less data about each kit cart is available due to the low volume. The overview of the most important characteristics of the production lines is described in Table 3.1.

Table 3.1: Important characteristics of the production line

Production line	Models	Sub Model	Number of kit carts	Year volume 2022
Niagara	varioPRINT iX-series		606	120/year
HCS	HCS 3	H1(old model)/J1	13	600/year
		N1	13	141/year
	HCS 2		10	511/year
VP6000	VP6000 Titan		31	297/year
	VP6000 MICR		31	14/year
	VP6000 TP		31	67/year

3.4 Solution requirements

In this section, the solution requirements specific to the case study are defined. The requirements are based on the the analysis of the current kitting process. Furthermore, supervisors of the kitting warehouse were asked what they expect from the prediction model. Throughout the research, the solution requirements are evaluated in an iterative way to assure that the prediction model addresses the research objective. First, the objective of the prediction model is to make predictions of the kitting requirements. In order to make realistic planning, the inclusion of human factors is necessary (Sgarbossa et al., 2020). As described in the previous section, human factors such as age and experience could have influence on the kitting and assembly process. Furthermore, human behaviour discovered from the data could have influence as well. This results in the following objective.

R1: The prediction method should predict the required kitting requirements per hour considering human factors.

First, a model has to be developed to predict the kitting requirements aligned with the assembly planning. This assembly planning contains multiple assembly lines with specific processing times. These assembly lines encounter human errors, missing parts and varying customer demand. The workforce in the kitting warehouse is related to the kitting requirements. The higher the kitting requirements, the more people are needed. In order to determine the required workforce, the predicted kitting requirements have to be translated in working hours. This results in the following requirement:

R2: The predicted kitting requirements should be translated in working hours

Furthermore, the prediction model should be useful and understandable. The employees of the kitting warehouse and assembly operators should be able to interpret the results of the prediction method. Understanding of the prediction model and the corresponding results is necessary to take the right actions. This is defined in the following objective.

R3: The prediction model should be easy to use and understandable for its users

Changes in the production schedule also cause changes in the required workforce. In order to respond in a timely manner to changes in production schedules, the prediction model should be able to make timely predictions of the required manpower. The manpower prediction have to be available one day in advance. Time is necessary to rearrange the workforce in the kitting warehouse, because people are not always available to work. This is defined in the following objective:

R4: The prediction model should be able to make predictions of the required manpower one day in advance.

Finally, the production schedule of a low volume, high complexity manufacturing company can vary every week. Furthermore, a huge amount of process data is collected every week. For this reason, it is essential that the artifact is able to incorporate new process data over time. With this new process data, the estimation accuracy can increase. This is defined in the following objective:

R5: The prediction model should possess the ability to incorporate new process data over time to increase the accuracy of the predictions.

Chapter 4

Data Understanding & Data Preparation

This chapter contains elaboration of the data understanding and data preparation, as described in the research design shown in Figure 1.3. During this research, case data from CPP is used. First, the datasets used in this research are described. In Section 4.2, data integration including data preparation steps are described. Finally, feature engineering with additional data preparation steps are detailed in Section 4.3.

4.1 Datasets

In this thesis, case data from CPP is used to build a prediction model. The main datasets used in this research are the kitting events data, zscankitlog data and AGK data. These datasets are related to each other based on kit cart information. The datasets were retrieved from databases from CPP with the use of SQL. In order to use these data to build a prediction model, the data must be prepared. All the datasets including general data preparation will be in explained in the subsections.

4.1.1 Kitting events data

CPP is using a 'pizza tool' to make the communication between the assembly operators and the kitting warehouse easier. The 'pizza tool' indicates where the kit cart is located, as shown in Figure 3.1. The data set about the kitting events contains timestamps from the pizza tool. The following timestamps are available in this dataset:

- Request: timestamp when the assembly operator request to refill kit cart.
- Start kitting: timestamp when the kitter starts filling the kit cart with materials.
- End kitting: timestamp when the kitter scans the barcode at the full busstop where all the finished kit carts are collected.
- Called: timestamp when the assembler presses the button to indicate that he needs the kit car for his assembly job. The assembly worker has to press the button manually on the computer.
- In transit: timestamp when the kit cart is connected to an AGV and is in transit to the assembly operator. The employee of the kitting warehouse has to press the button manually on the computer.
- Next request: timestamp when the assembly operator request to refill the same kit cart.

In addition to these timestamps, the minutes between all timestamps have been calculated taking into account evenings, weekends and holidays. For example, the actual time needed for kitting is calculated by taking the difference between start kitting and end kitting. The visualization of the kitting events data set is showed in Figure 4.1. All the columns of the data set are described in Table 4.1. A few example rows of the kitting events are showed in Figure 4.2

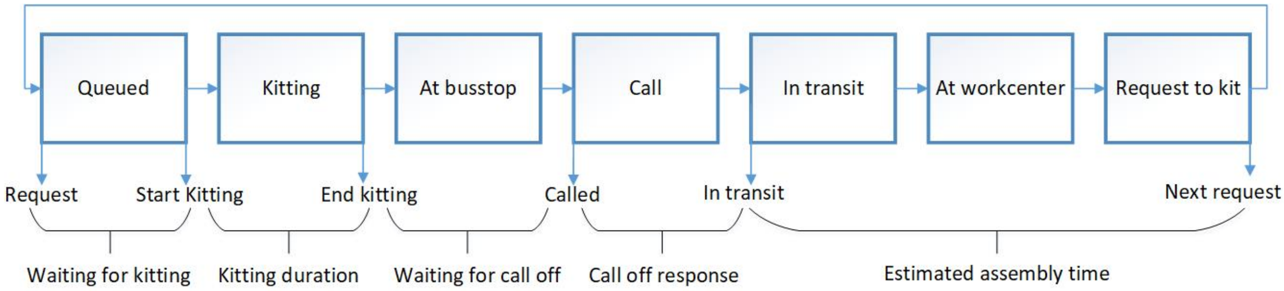


Figure 4.1: Visualization of the kitting events dataset

Table 4.1: Columns of kitting events data set

Column	Type	Description
Kit cart	String	Number of the kit cart
Request	Datetime	Timestamp when the assembly operator request to refill kit cart.
Start kitting	Datetime	Timestamp when the kitter starts filling the kit cart with materials.
End kitting	Datetime	Timestamp when the kitter scans the barcode at the full busstop where all the finished kit carts are collected.
Called	Datetime	Timestamp when the assembler presses the button to indicate that he needs the kit car for his assembly job. The assembly worker has to press the button manually on the computer.
In transit	Datetime	Timestamp when the kit cart is connected to an AGV and is in transit to the assembly operator. The employee of the kitting warehouse has to press the button manually on the computer.
Next request	Datetime	Timestamp when the assembly operator request to refill the same kit cart.
Date ID	String	Date ID based on in transit timestamp
Waiting for kitting	Float	Time between the request timestamp and start kitting timestamp in minutes
Kitting duration	Float	Time between the start kitting timestamp and end kitting timestamp in minutes
Waiting for call off	Float	Time between the end kitting timestamp and called timestamp in minutes
Call off response	Float	Time between the called timestamp and in transit timestamp in minutes
Estimated assembly time	Float	Time between the in transit timestamp and next request timestamp in minutes

Kit cart	Request_DTM	StartKitting_DTM	EndKitting_DTM	Called_DTM	InTransit_DTM	NextRequest_DTM
N578	2022-12-22 09:23:58	2022-12-22 10:01:13	2022-12-22 10:45:43	2022-12-22 12:00:55	2022-12-22 12:02:07	2023-01-06 10:10:13
V20B	2022-12-22 07:59:42	2022-12-22 08:12:28	2022-12-22 08:47:58	2022-12-22 10:43:52	2022-12-22 10:45:41	2022-12-22 10:57:12

DateID	WaitingForKitting_MIN	KittingDuration_MIN	WaitingForCalloff_MIN	CalloffResponse_MIN	EntireKittingProcess_MIN
20221222	37,25	44,5	75,19999695	1,200000048	158,149993
20221222	12,75	35,5	115,9166641	1,799999952	165,966659

Figure 4.2: Example rows of kitting event data set

Data preparation

The kitting event dataset does not need much data pre-processing. From the timestamp when the kit cart is called by the assembler, the year, month, week, day, and hour are extracted and added as a new column. An example is shown in Figure 4.3. This makes it easier to filter the desired dates by specific years and months.

Kit cart	Called_DTM
H10B	2022-12-19 11:25:57

hours	day	month	year
11	19	12	2022

Figure 4.3: Extracting year, month, day and hour from the Called timestamp

In the same way, the year, month, day and hour are also extracted from the timestamp when the kitting ends. This makes it possible to merge the kitting events dataset with other data sets related to kitting which is further elaborated in Section 4.2.

4.1.2 Zscankitlog data

CPP is using customized modules in SAP where the kit carts are added as separate production orders. When a production order of a module or engine is released, separate production orders are created for each kit cart needed to complete that production order. The numbers of these kit cart production orders are noted in this dataset and is unique for every data point. With these customized modules, the materials of the kit cart are automatically deducted from the inventory when the kit cart is filled instead of at the end of the production order. If the materials are deducted from the inventory at the end of the production order (after the last kit cart), there will be differences in the inventory while assembling the production order. When a kit cart is requested to refill, the requested kit cart is added to the queue based on the latest possible start date of a kit cart. This dataset contains all historical data points of kit carts that have appeared in the kit cart queue, including the planned end kitting timestamp and the actual end kitting timestamp. The most important columns in the zscankitlog dataset are described below:

- Available time to kit (VGW03): available time to fill the corresponding kit cart. The available time to kit for a specific kit cart is defined and always the same independent of the production amount.
- Duration: time needed to refill the corresponding kit cart. The time needed to fill the specific kit cart is also predefined for each kit cart.
- Pln_date and Pln_ time: date and time when the kit cart should be filled based on the timestamp of requesting to refill the kit cart and the available time to kit. Based on the planned date and time and duration to refill a kit cart, the latest possible start date can be calculated.
- Act_date and Act_time: date and time when filling the kit cart actually ends.

- Boolean columns whether the kit cart was filled on time or late and whether the kit cart is complete or incomplete.
  - CO_INTM: Complete, in time.
  - CO_LATE: Complete, late.
  - NC_INTM: Not Complete, in time.
  - NC_LATE: Not Complete, late.

With the planned date and time and actual date and time, delays can be calculated. On the other hand, it can be calculated how much too early a kit cart has been filled. The connection between the planned date and time and the queue to refill the kit carts is shown in Figure 4.4.

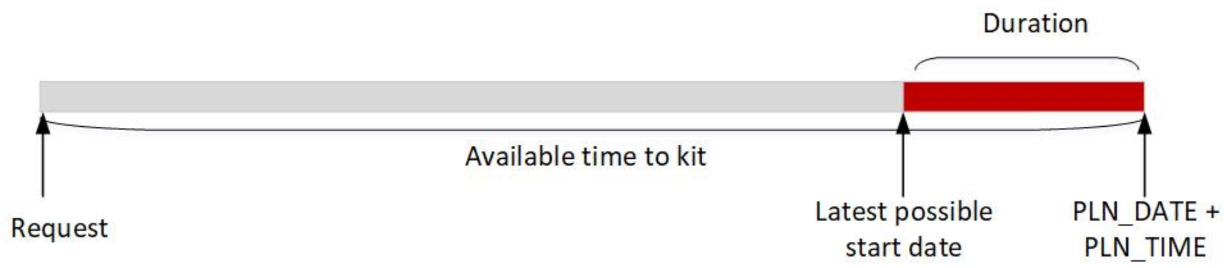


Figure 4.4: Connection between queue of kit carts and planned date and time

Furthermore, the workplace where the kit cart is requested is connected to the SAP transaction and visible in the dataset. The material number of a kit cart is also stated in the dataset. The A and B versions of a kit cart have the same material number, because they consist of the same materials. Personal information such as the kitter's name has been removed for privacy. The columns of the zscankitlog dataset are summarized in Table 4.2. A few example rows of the kitting events are showed in Figure 4.5.

Data preparation

Comparable to the kitting events data set, the year, month, day and hour are extracted from the Actual time when the kitting was ended. All the columns in zscankitlog have the type string. The types of the columns are set to be equal among the datasets so that values can be compared. Planned and actual date and time are converted to type datetime. Furthermore, the dates and timestamps are combined making it easier to compare with other datetime objects. The string of duration and the time available to kit (VGW03) are transformed to type integer and calculated in minutes. The transformation is shown in Figure 4.5

Table 4.2: Columns of zscankitlog dataset

Column	Type	Description
Kit cart	String	Number of the kit cart
Workplace	String	Workplace where the kit cart is requested
MATNR	String	Number for each set of kit carts with the same materials.
Time available to kit (VGW03)	String	Available time to fill a kit cart. The string has to be translated to a timestamp in the form %H%M%S (023000 = 02:30:00).
AUFNR	String	Production order number of a kit cart. This number is unique for every data point.
PLN_DAT	String	Date when the kit cart should be filled based on the timestamp of requesting to refill the kit cart and VGW03 (time available to kit). The string has to be translated to a date in the form of %Y%m%d (20220217 = 2022-02-17).
PLN_TIM	String	Time when the kit cart should be filled based on the timestamp of requesting to refill the kit cart, VGW03 and duration. The string has to be translated to a timestamp in the form %H%M%S (095323 = 09:53:23).
ACT_DAT	String	Date when filling the kit cart actually ends. The string has to be translated to a date in the form of %Y%m%d (20220217 = 2022-02-17).
ACT_TIM	String	Time when filling the kit cart actually ends. The string has to be translated to a timestamp in the form %H%M%S (095323 = 09:53:23).
CO_INTM	Boolean	Complete, in time. The corresponding kit cart is complete and in time.
CO_LATE	Boolean	Comlete, late. The corresponding kit cart is complete but late.
NC_INTM	Boolean	Not complete, in time. The corresponding kit cart is not complete but in time.
NC_LATE	Boolean	Not complete, late. The corresponding kit cart is not complete and late.
CALC_LATE_HRS	Float	How many hours the actual date and time is later than the planned date and time.
CALC_EARLY_HRS	Float	How many hours the actual date and time is earlier than the planned date and time.
Duration	String	Time needed to refill the corresponding kit cart. The string has to be translated to a timestamp in the form %H%M%S.

Kit cart	ARBPL	MATNR	VGW03	AUFNR	PLN_DAT	PLN_TIM	ACT_DAT	ACT_TIM
H06B	7085	0003950819	011500	000044480475	20220218	125259	20220218	121855
H06A	7085	0003950819	011500	000044479982	20220217	093150	20220217	085009

CO_INTM	CO_LATE	NC_INTM	NC_LATE	CALC_LATE_HRS	CALC_EARLY_HRS	DURATION
1	0	0	0		-0,6	002900
1	0	0	0		-0,7	002700

Kit cart	ARBPL	MATNR	VGW03_new	AUFNR	PLN_DAT	PLN_TIM	ACT_DAT	ACT_TIM
H06B	7085	0003950819	75	000044480475	2022-02-18	125259	2022-02-18	121855
H06A	7085	0003950819	75	000044479982	2022-02-17	093150	2022-02-17	085009

CO_INTM	CO_LATE	NC_INTM	NC_LATE	CALC_LATE_HRS	CALC_EARLY_HRS
1	0	0	0		-0,6
1	0	0	0		-0,7

DURATION_new	year	month	day	hour	PLN	ACT
29	2022	02	18	12	2022-02-18 12:52:59	2022-02-18 12:18:55
27	2022	02	17	8	2022-02-17 09:31:50	2022-02-17 08:50:09

Figure 4.5: Transformation of zscankitlog data

4.1.3 AGK data

At the start and end of an assembly job, the assembly worker must scan a barcode from a travel ticket or shop floor paper. The data generated by these barcode scanners is timestamps of the start and end of each assembly job. For Niagara team 2 only, the start and end of an assembly task are connected to a single kit cart. For another master thesis project, the timestamp when the kit cart is in transit and the next request of the kit cart are already connected with the barcode data. The barcode scanners are used from April 21 and further on. So, The registration of these timestamps started from April 2022. These kit trolleys are linked to a production order, which makes it possible to determine the production sequence. Unfortunately, the kit carts of other Niagara teams and the kit carts of HCS and VP6000 are not connected to a production order. Due to the parallel work on assembly tasks and the possibility to work in advance, it is difficult to determine a fixed production sequence. For example, a certain assembly task can already be worked in advance if the assembly operator has a day off during the week. Because the kit cart is not connected to a production order, it is not clear for which production order this task was intended. As a result, only for Niagara team 2 it is possible to use the production sequence and calculate the time between different orders. All the columns of the data set are described in Table 4.3. A few example rows of the kitting events are showed in Figure 4.6.

ScanID	WorkstationID	TimestampStart	TimestampEnd	Order_Number	Start_Operation_Description	Kitkar_InTransit	KitKar_NextRequest
1	3	8-8-2022 12:33	9-8-2022 07:25	000044512842	NI_IM2_MAIN_FRAME_UM_N210_START	8-8-2022 13:12	9-8-2022 12:13
3	3	11-8-2022 07:46	11-8-2022 10:46	000044512842	NI_IM2_INTEGRATIE_UM_N262_START	11-8-2022 07:49	11-8-2022 12:25
4	9	9-8-2022 11:29	9-8-2022 13:39	000044512842	NI_IM2_PRP_VM_N212_START	9-8-2022 11:22	9-8-2022 13:40

Figure 4.6: Example rows of AGK data

Data preparation

In this dataset, the kitkart number of a specific assembly task is available in the operator description. Deriving the kit cart from the operator description is showed in Figure 4.7. This dataset can be connected with the kitting events dataset based on the kit cart number derived from the operator description and the timestamp when the kit cart is in transit.

Table 4.3: Columns of AGK dataset

Column	Type	Description
ScanID	Integer	Unique number of a scan.
WorkstationID	Integer	Workstation where assembly is executed.
TimestampStart	Datetime	Start of assembly task based on agk scan.
TimestampEnd	Datetime	End of assembly task based on agk scan.
Order number	String	Order number of the end product to which the assembly task belongs
Start operation description	String	Description of the assembly task.
Kitkar_inTransit	Datetime	Timestamp when the corresponding kit cart is in transit to the assembly operator.
Kitkar_NextRequest	Datetime	Timestamp when the corresponding kit cart is requested to refill by the assembly operator.

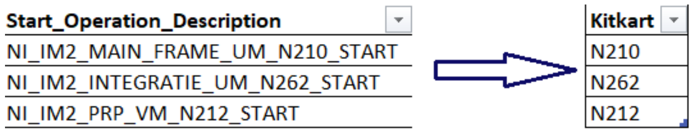


Figure 4.7: Transformation of AGK data

4.1.4 Kitlines and Production Amounts

In addition to the three major datasets, extra information about the kit carts and production is collected. Based on the history of the SAP transaction, the number of kit lines per kit cart can be derived. The kitlines are the total number of parts on a kit cart. Each time the kit cart is picked, the number of picked parts is stored in the SAP dataset. For each kit cart, the median number of parts has been taken over the past six months, because this value corresponds to a complete kit cart. Furthermore, the actual production amounts of the production lines can be retrieved from SAP. This information will be used to calculate the takt of the production line during a specific week.

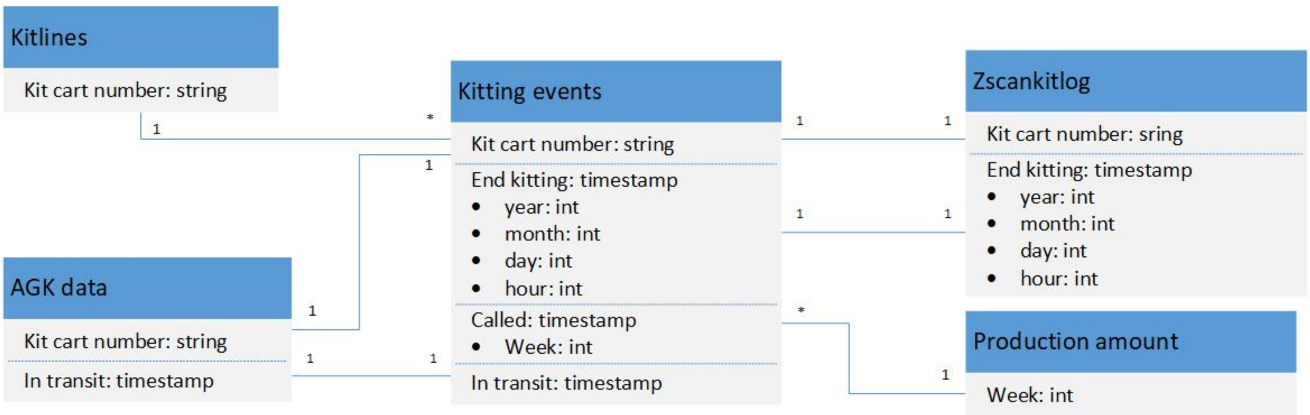


Figure 4.8: Overview of datasets and connections

4.2 Data Integration and data preparation

CPP stores the datasets separately and therefore the datasets are integrated for modeling. The characteristics of the most important tables are shown in Table 4.4.

Table 4.4: Characteristics of the databases

Database	Records	Start	End
Kitting events	62354	14-3-2019	6-3-2023
Zscankitlog	353906	4-2-2019	23-2-2023
AGK	3274	21-4-2022	7-3-2023

The zscankitlog dataset and kitting events dataset both contain a timestamp when the kitting is ended. The zscankitlog dataset is connected to the kitting events dataset based on the 'end kitting' timestamp, when the kit cart is filled. The actual timestamp of zscankitlog almost matches the 'end kitting' timestamp of the kitting event dataset due to a slow lag in SAP. Taking the year, month, day and hours is enough to match these two data sets, because the lag is only a few seconds.

The AGK dataset and the kitting events dataset both contain the 'in transit' timestamp of a specific kit cart. The AGK dataset can be combined with the kitting events dataset based on the kit cart number and the 'in transit' timestamp, when the kit cart is on its way to the assembly operator. Thereafter, the kitlines are added to the aggregated dataset based on the kit cart number. An overview of the datasets including the connections is shown in Figure 4.8. The production amounts are added per production line after the feature selection.

4.2.1 Data preparation

The integrated dataset still need some data preparation to create the final dataset. Data filtering, missing values, outlier detection and feature engineering are described in the following subsections.

Data filtering

For this study, case data from CPP will be used from 2021 and 2022, because production has grown strongly over the years, which means that kit trolleys have been added and changed. So, the final data set is filtered on 2021 and 2022. After integration and filtering, the final dataset contains 51485 records.

Missing values

The second data preparation step is removing NaN values. The time between two calls of the same (combined) kit cart can be estimated by looking at the difference between two called timestamps of the same (combined) kit cart. Whenever a called timestamp is missing, the row is deleted from the dataset. After removing missing values, the final dataset contains 50212 records.

4.3 Feature engineering

During this section, new features will be introduced. After introducing new features, additional data preprocessing is executed. Finally, the input variables for the model are described.

4.3.1 Feature engineering

As mentioned in earlier, the connection between the kit carts and the production order is missing. When a kit cart is requested to refill, a kit cart production order is created. As soon as the kit cart production order is created, the connection between the production order and kit cart is removed. Because the assembly operators are working parallel and sometimes they are working in advance, it is impossible to obtain an actual production sequence. To be able to predict the kitting requirements without knowing a clear production sequence, some additional features are added. The following features are added to the final dataset:

- **Production line**: The production line can be added based on the first two characters of a kit car. The dataset can be easily filtered for each production line. For this research, , the three largest production lines are used to predict the kitting requirements of multiple production lines.
- **Kit cart combined**: HCS and VP6000 are mixed model production lines. Multiple models are produced on these lines with a different set of kit carts depending on the model. The kit carts which replace each other when switching to another model can be combined to get a flow of kit carts.
- **Timestamp of the next call of a kit cart**: The kitting events dataset is grouped by the combined kit carts and a new column is added with the timestamp of the next call of the same combined kit cart.
- **Time between calls (TBC) of the same kit cart**. The difference between the call of a specific kit cart and the next call of the same kit cart. The calculation of the time between two calls of the same kit cart has to be corrected with days off, weekend days and evenings. The assembly operators calls the kit warehouse when they need a kit cart from the kit warehouse. A typical workday at CPP is starting at 7:30 and ends at 16:00. After observing, assembly operators arrive and leave work at different times. It is therefore assumed that operators do not work for 15.5 hours per day and that the kit cart is not called in these 15.5 hours.

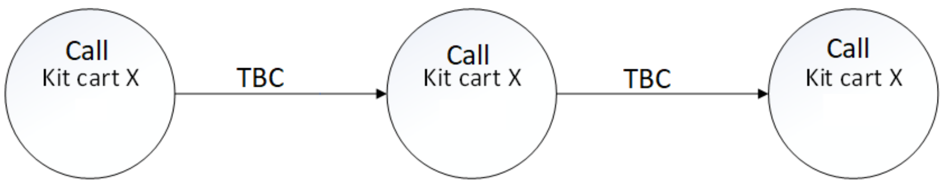


Figure 4.9: Time between the calls of the same kit cart

- **Time-Request-Call**. The time between the request to refill the kit cart and the moment the kit cart is called up for production by the technician. With this function the priority of the kit carts in the queue can be examined.

4.3.2 Data splitting

The three largest production lines have completely different characteristics as described in the business understanding. That is why a separate dataset is used for each production line. Based on the added variable 'team', the final dataset is split into three separate datasets. Then, the production amounts per week are added for the VP6000 and HCS line. For the HCS line, the amounts are splitted in HCS3 and HCS2, because these two models can be modelled in parallel.

For Niagara, the accumulated production amounts of the last 4 weeks are added to the dataset. An additional variable is added to each separate data set:

- **Takt of the production line** Based on the production amounts, the takt of the production line is calculated and added to the dataset. For HCS and Niagara, the takt per week is calculated by dividing 40 hours by the production amount per week assuming a working week of 40 hours. Niagara is a low volume production line that produces a product every 16 hours. So the production amount per week is 2 or 3 per week, but in reality the production amount is approximately 2.5 per week. So for Niagara, the takt is calculated by dividing 160 hours by the production amount of the last 4 weeks, assuming working weeks of 40 hours.

Outliers

Finally, the outliers are removed from the dataset. For each kit cart separately, the outliers are detected per takt time. The outliers are identified by making a boxplot of the time between the calls (TBC) using the approach explained in Figure 4.10. In addition, the time between requesting and calling a kit cart is always longer than 30 minutes if all timestamps are available. So if the same kit cart is called again within 30 minutes, the row will be removed from the dataset because the records likely represent the same kit cart.

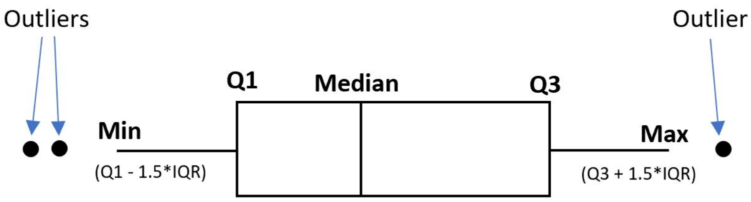


Figure 4.10: Approach of detecting outliers

Table 4.5: Characteristics of the dataset per production line

Production line	Records before removing outliers	Records after removing outliers
VP6000	19916	12289
HCS	16158	13536
Niagara	13641	11934
Total	**49715**	**43318**

4.3.3 Input variables

In the literature, there is no model available to predict the kitting planning according to the assembly process. The feature importance function of the random forest regressor is used to select the most important features. According to the feature importance function, the data features that are valuable and can be used to forecast kitting requirements are the production amount, takt, kitlines, median value of past assembly times, median value of target variable and the kit cart number. From the integrated data set, the following features are added to the model.

- **Kit cart.** Each kit cart event is connected to a kit cart number. The kit cart numbers are used as input for the kit cart.

- **Kitlines.** Total number of parts on a kit cart.

- **Workplace.** Workplace where the kit cart is requested.

This research is focusing on predicting the kitting planning considering assembly factors. Hiller et al. (2022) uses a regression model to predict the throughput of an order. According to Hiller et al. (2022), mean or median values of processing times based on the material number can increase the accuracy of the prediction of throughput time. Based on this research, past values of assembly times are added to the model to increase the accuracy. Additionally past values of the time between the calls (target variable) can be added to the model. For this research, the models have been kept as simple as possible. Additional to the features of the integrated dataset, aggregated features ared added to the model:

- **Production amount.** The production amount is added to each kitting event separately. This is dependent on:
  - Production line for which the kit cart was needed.
  - Production amount for the specific line where the kitting event has been performed. Every week, the production amount of VP6000 and HCS are determined based on capacity and parts availability. For Niagara, the production amount per 4 weeks is added, because the production amount is determined every month.
- **Takt.** The takt is calculated and added to each kitting event separately based on:
  - Production amount. The takt is calculated by dividing the weekly demand by 40 hours. Working weeks of 40 hours are assumed.

  By including the takt, the assembly and kitting will be aligned based on the production amounts of multiple production lines.
- **Changing assembly times.** The time between calling and requesting to refill a kit cart could be seen as the estimated assembly time from a kit cart. The time between calling and requesting to refill a kit cart is the time a kit cart is located at the working station including travelling time. The estimated assembly time is visualized in Figure 4.1. The changing assembly times are calculated based on:
  - Kit cart number. Based on the kit cart number of the kitting event, previous values of the same kit cart can be derived.

  With the median value of the assembly times, varying processing times which could have influence on the kitting process are included in the model. The median is used, because this value is less sensitive to outliers.
- **Last value of Time between two calls (target variable).** The target variable is the time between two calls of the same kit cart. The last value of TBC is based on:
  - Kit cart number. Based on the kit cart number of the kitting event, previous values of the same kit cart can be derived.
  - Takt. Previous values of a kit cart are added when a production line is operating with a certain takt.
  - Time between calls (target variable). The median value of the time between two calls of the same kit cart is calculated from the historical data.

  The last value of the target value provides information about previous value of a kit cart used when working with a certain takt.

These variables are typically available in all manufacturing environments where kit carts are used to feed material to the assembly lines. Additional features as the day of previous call and hour of previous call were tested to include in the model. However, the influence of these variables were too low. Kitting can be used in different ways. Like CPP where the assembly operator gives a call when the kit cart is needed. However, kitting can also be connected to the assembly planning (Erickson and Dragonas, 2022). The takt of the assembly lines support the alignment between assembly and kitting when multiple production lines are operating with different takt time. The assembly planning contains values about the production amounts and varying assembly times. Additionally, the impact of human behavior of the assembly operators can be researched by comparing the requests to refill a kit cart with the call of the kit cart when the kit cart is needed in production. However, human factors related to kitting performance were not included due to privacy reasons.

Chapter 5

Modeling & Evaluation based on Time between Calls

This chapter shows the modeling and evaluation steps taken to predict the time between calls of the same kit cart. Based on the literature review in Section 2, random forest, support vector regression and neural network are compared to each other. To obtain the optimal prediction model, a hyperparameter optimization is conducted. For the hyperparameter optimization, the time between two calls is used because this time should be less sensitive to human behavior. Besides that, manufacturing companies using an assembly schedule can track when the material is needed in the assembly line.

5.1 Hyperparameter optimization

The hyperparameters of each of the chosen machine learning algorithms should be optimized. To optimize these hyperparameters, grid search is used. Grid search builds a model for every combination of hyperparameters and evaluates each model by storing the MAPE. The MAPE metric is used in the grid search, because this metric is not scale dependent and can be used to compare different machine learning techniques. The combination with the lowest MAPE is deemed as the optimal hyperparameters. Furthermore, percentages are easy to understand for other users. The range of hyperparameters for random forest are determined by first doing a random search. After the random search, the values close to the best result of the random search are used to determine a range for the grid search. Due to time constraints, only a grid search in conducted for the neural network and support vector machines. The following hyper parameters per machine learning algorithm are taken into account:

Random forest

- Number of trees. this parameter refers to the number of trees used.
  Random search: range between 200 and 2000 with steps of 200 is used.
- Max depth. This parameter refers to the maximum depth of the trees reducing the complexity of the model.
  Random search: range between 10 and 110 with steps of 10 is used including None.
- Min samples leaf. This parameter refers to the minimum number of data points required to be at the leaf node.
  Random search: values 2, 5 and 10 are tried.
- Min samples split. This parameter refers to the minimum number of data points required to split an internal node.
  Random search: values 1, 2 and 4 are tried.

- Max features. This parameter refers to the number of features to consider when looking for the best split.
  Random search: sqrt(number of features) and number of features are tested.

- Bootstrapping. Type of resampling. If true, smaller samples of the dataset are used to build the trees. If false, the whole dataset is used to build each tree.
  Random search: True and False are tested.

The values tested for the grid search are based on the results of the random search. The values tested for the grid search can be found in Appendix C. The final optimal hyperparameters are summarized in Table 5.1.

Table 5.1: Optimal hyperparameters of the Random Forest model for every production line

Production line	Bootstrap	Max depth	Max features	Min samples leaf	Min samples split	Number of trees (n_estimators)
VP6000	TRUE	10	40	3	5	200
HCS	TRUE	20	40	5	6	100
Niagara	TRUE	10	40	3	4	300

Support vector regression

- Kernel. A kernel function is used to take data as input and transform it into the required form of processing data.
  Grid search: values 'linear', 'rbf' and 'poly are tested.

- Gamma. Kernel coefficient for 'rbf', 'poly', 'sigmoid'.
  Grid search: 1e-7 and 1e-4 are tested.

- C. Regularization parameter for the support vector regression. A high value of C gives a higher priority to avoid mistakes.
  Grid search: 1.5 and 10 are tested.

- Epsilon.
  This parameter defines a margin of tolerance where no penalty is given to errors. With an epsilon of 0, every error is penalized. Grid search: 0.1, 0.2, 0.3 and 0.5 are tested.

To use support vector regression for modeling, scaling of the input features is necessary. Support vector regression uses distances between observation points, so unscaled data generates a different model. Min-max scaling is used to scale the input features. The optimal support vector regression hyperparameters per production line are described in Table 5.2.

Table 5.2: Optimal hyperparameters of the Support Vector Regression model for every production line

Production line	Kernel	C	Gamma	Epsilon
VP6000	linear	10	1,00E-07	0.1
HCS	linear	10	1,00E-07	0.5
Niagara	linear	10	1,00E-07	0.2

Neural network

- Activation. The activation function defines the output of that node given an input or set of inputs.
  Grid search: 'identity', 'tanh', 'relu' are tested,

- Solver. This parameter specifies the algorithm for weight optimization across the nodes. Grid search: 'lbfgs', 'sgd' and 'adam' are tested.

- Alpha. A parameter for regularization term, also called a penalty term that avoids overfitting by penalizing weights with large magnitudes.
Grid search: 0.00005, 0.0005, 0.005 and 0.05 are tested.

- Hidden layer sizes. Number of neurons in the hidden layer. The number of hidden neurons should be between the size of the input layer and the size of the output layer.
Grid search: 4, 16 and 32 are tested.

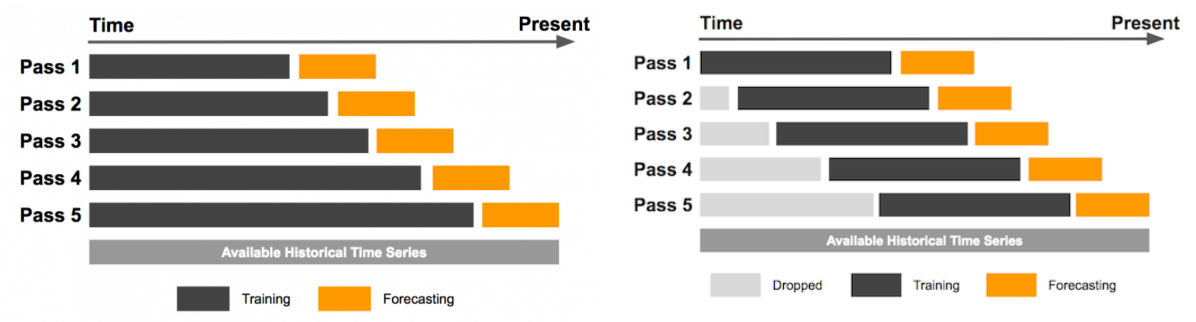
Neural networks also benefit from scaling so that all features contribute equally to the model. Min-max scaling is used to scale the input features. The optimal neural network hyperparameters per production line are described in Table 5.3.

Table 5.3: Optimal hyperparameters of Neural Network model for every production line

Production line	Activation	Solver	Alpha	Hidden layer sizes
VP6000	identity	Adam	0.005	16
HCS	tanh	Adam	0.05	4
Niagara	tanh	Adam	0.00005	64

5.2 Walk-forward validation

During this case study, the walk-forward validation method is applied. Walk forward validation is often used in time series models or demand forecasting. There are two approaches for walk forward validation. The expanding window approach trains a model on all available historic data and uses that to make a forecast. The expanding window approach is showed in Figure 5.1a. Secondly, a rolling window with a certain amount of data points is chosen to train the model. The rolling window approach uses the most recent data points, as shown in Figure 5.1b.



(a) Expanding window approach

(b) Rolling window approach

Figure 5.1: Walk forward validation

5.3 Results

Based on the results of the hyperparameter optimization, the accuracy metrics are calculated for each production line for three machine learning algorithms. The accuracy metrics are calculated for the time between two calls of the same kit cart. To find the best model, multiple timestamps are tested to include easy predictable timestamps and difficult predictable timestamps. For example, when a prediction is made at the end of the day, the kit cart can be requested the same day or the next day depending on the behavior of the assembly operator. The same goes for predicting around a break of the assembly operators. An expanding walking forward validation is used where all the data available until the timestamp of the prediction is used for training. The accuracy metrics are calculated by averaging the accuracy metrics of 19 different timestamps between 30-08-2022 and 15-11-2022. These timestamps can be found in Appendix F.3. The accuracy metrics are calculated for each production line seperately and can be found in the subsections. Only for the 1-MAPE, a high value is preferred. For the other accuracy metrics, a low value is preferred.

5.3.1 VP6000

For production line VP6000, the accuracy for the time between the calls of the same combined kit cart is presented in Table 5.4. Based on Table 5.4, support vector regression gives the best results for VP6000. The MAE, MSE, RMSE and MAPE are the lowest for support vector regression compared to the other models. Based on the accuracy metrics of the time between two calls of the same kit cart, support vector regression is the best model. When merging the production lines, support vector regression is used for the VP6000 production line.

Table 5.4: VP6000 - Accuracy metrics of time between two calls

ML model	MAE	MSE	RMSE	MAPE	1-MAPE
Random forest	93.3	13604.95	116.63	0.59	0.41
SVM	92.00	13575.62	116.51	0.56	0.44
NN	94.00	13763.38	117.32	0.60	0.40

5.3.2 HCS

For production line HCS, the accuracy for the time between the calls of the same combined kit cart is presented in Table 5.5. Based on Table 5.5, the majority of the accuracy metrics of support vector regression gives the best results for HCS. The MAE, MSE and RMSE has the best values for support vector regression compared to the other models. When merging the production lines, support vector regression is used for the HCS production line.

Table 5.5: HCS - Accuracy metrics of time between two calls

ML model	MAE	MSE	RMSE	MAPE	1-MAPE
Random forest	69.60	8563.00	92.49	0.542	0.458
SVM	66.20	8028.60	89.56	0.491	0.507
NN	71.45	11181.67	105.66	0.392	0.608

5.3.3 Niagara

For production line Niagara, the accuracy for the time between the calls of the same combined kit cart is presented in Table 5.6. Based on Table 5.6, random forest gives the best results for Niagara. The MAE, MSE and RMSE are the lowest for random forest compared to the other models. When merging the production lines, random forest is used for the Niagara production line.

Table 5.6: Niagara - Accuracy metrics of time between two calls.

ML model	MAE	MSE	RMSE	MAPE	1-MAPE
Random forest	291.55	134052.70	365.88	0.355	0.645
SVM	300.10	145077.78	379.97	0.353	0.647
NN	296.65	142209.34	376.09	0.353	0.647

The highest performing model for each production line are summarized in 5.7. In the next chapter, the results of the prediction model per production line are merged.

Table 5.7: Highest performing model for each production line

Production line	ML model
VP6000	Support vector regression
HCS	Support vector regression
Niagara	Random Forest

Chapter 6

Results of merging multiple production lines

In previous chapter, the best prediction model for each production line is obtained. The best performing prediction model of each production line predicts the time between two calls of the same kit cart. To make a prediction of the required kitting requirements, a translation has to be made from the time between two calls to the required kitting requirements. Furthermore, the results of the prediction model per production line are merged to predict the kitting requirements of all the production lines together.

6.1 Translation to kitting requirements

The goal of this research is to predict the kitting requirements. With the prediction model, the time between two calls of the same kit cart is calculated, because each kit cart has a certain rhythm based on the production amounts and assembly times.

To translate the prediction to the required kitting requirements, the timestamp of the next kit cart has to be calculated. With these timestamps, the kitlines of all production lines can be summed. As already mentioned in Section 4.3, assembly operators tend to arrive and leave at different times. Assembly operators are working 8 hours a day excluding a lunch break of half an hour. Some assembly operators end their day at 4:00 PM while other assembly operators prefer to start a little later and leave at 4:30 PM. Because assembly operator work at different times during the day, it is impossible to give a specific timestamp when a kit cart is used for production because this is dependent on when the assembly operator started to work. To compare actual times and predicted times, a start point is chosen which could be seen as point 0. An hour after the start point could be seen as point 60. The data of 2021 and 2022 is used, therefore 01-01-2021 07:00:00 is chosen as start point.

6.2 Results

For each production line, it is exactly known how many kit carts are needed to build a product. Based on the takt of the production line, the part demand of the production line is constant. A problem arise when production lines operate on a different takt each week based on the planned production and capacity. The part demand per takt is constant, but with different takt times every week, the part demand per hour is varying. The difficulty is predicting the parts demand across all production lines combined when operating with different takt times and varying processing times.

In Section 5.3, the best prediction model is selected for each production line. The prediction model per production line predicts the time between two calls of the same kit cart (TBC). This is the moment when the kit cart is needed for production and is called by the assembly operator. The results of the prediction models per production line are combined into one dataset. The merged dataset includes the prediction when the next same kit cart is called by the assembly operator. The records are grouped based on the predicted time point (minute level) when the same kit cart is called again. Thereafter, the number of kitlines per time bucket is calculated, because there are large and small kit carts. As a result, it makes more sense to predict the kitlines rather than the number of kit carts. Finally, the predicted number kitlines is compared to the actual number of kitlines. This process is done by trying different time buckets to see their effect on accuracy. This process is repeated to predict 19 different timestamps to represent easy predictable days and difficult predictable days. The timestamps can be found in Appendix F.3. The process of merging the production lines is described in Figure 6.1.

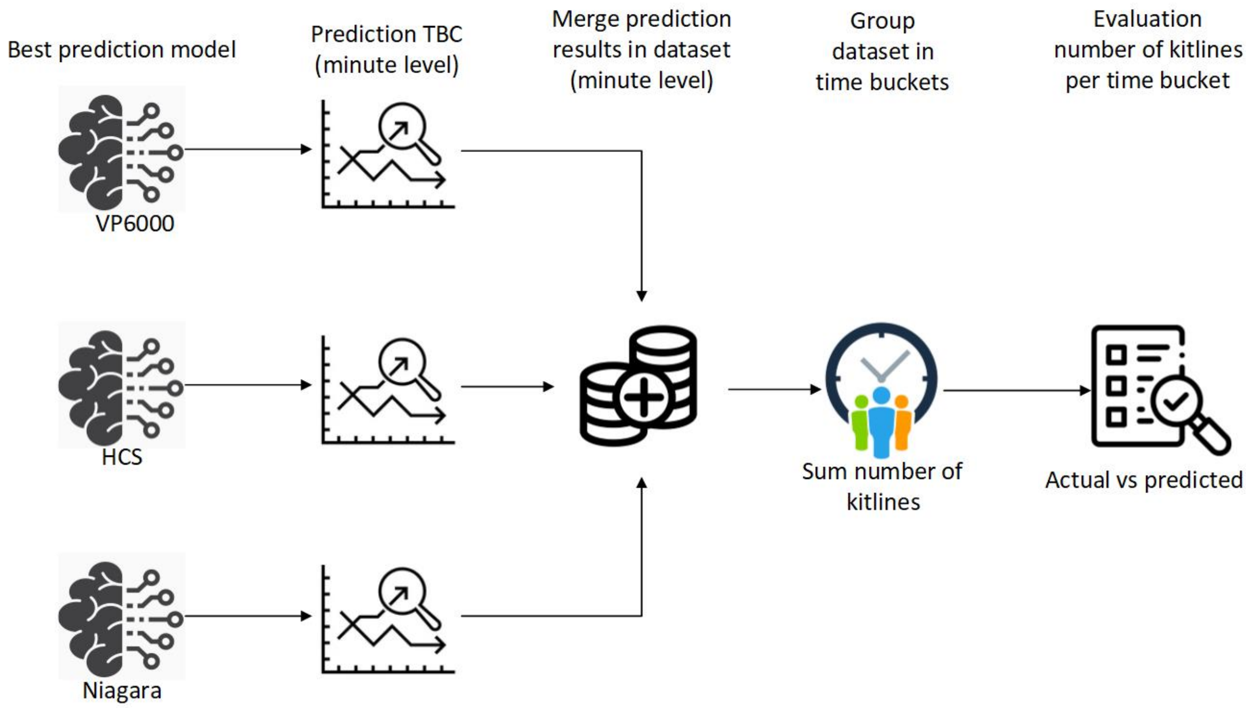


Figure 6.1: Process of merging the production lines

As accuracy metric, the inverse of the MAPE is used. The MAPE is not scale dependent, which means that different time buckets can be compared with each other. The time buckets are determined by looking at the most common takt times of the production line. The takt time of HCS is between 1 and 2 hours. VP6000 has a takt time of approximately 4 hours. Finally, Niagara has a takt time of around 16 hours. The time buckets are divisible by one of the takt times of the production lines. The accuracy of the called kitlines per 30, 60, 120, 240 and 480 minutes is shown in Figure 6.2. For example, for a time bucket of 30 minutes, the accuracy of called kitlines is calculated for the first 30 minutes, second 30 minutes and so on. The mean accuracy metrics of the called kitlines using different time buckets can be found in Appendix D.1.

As can be seen in the Figure 6.2, the mean accuracy of the number of kit lines is remarkably higher when a time bucket of 60 minutes is used. A larger the time bucket results in a higher accuracy. With a larger time bucket, there is a greater chance that the kit cart has been predicted in the correct time bucket. However, with a large time bucket is the variation within a time bucket not visible. It is not known whether there are more kitlines needed in the first part of the bucket or the last part. The part demand of a production line is constant during the takt of the production line. A larger time bucket ensures that a takt of the production line fits completely in the time bucket, which ensures a constant part demand. However, the takt of the production lines changes weekly due to customer demand or capacity, dependent on the company. Because the time bucket is not exactly equal to the size of the takt, some variation will always be visible. With a time bucket of 30 minutes, the variation is hardly to predict.

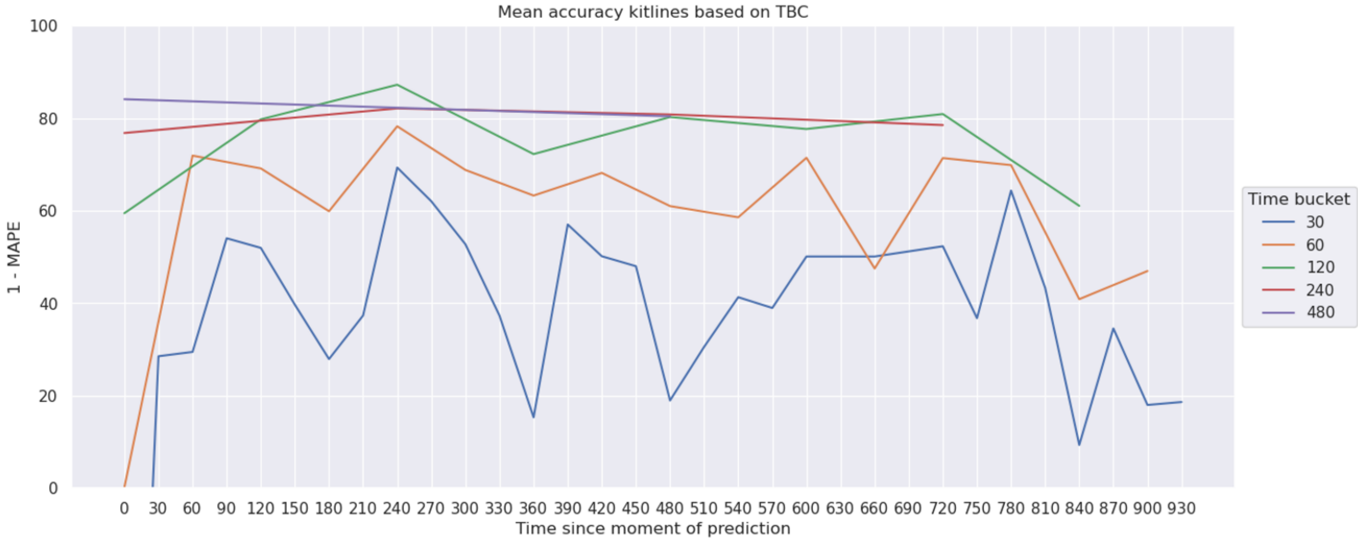


Figure 6.2: Mean accuracy called kitlines over time for every time bucket

The median accuracy of the number of called kitlines per time bucket is even higher, as shown in Figure 6.3. From these results it can be concluded that there are timestamps that are difficult to predict. The bad timestamps identified in the dataset are timestamps just before a break. The actual kitlines were lower than the predicted kitlines, because the prediction model does not include breaks of the assembly operators and kitting employees.

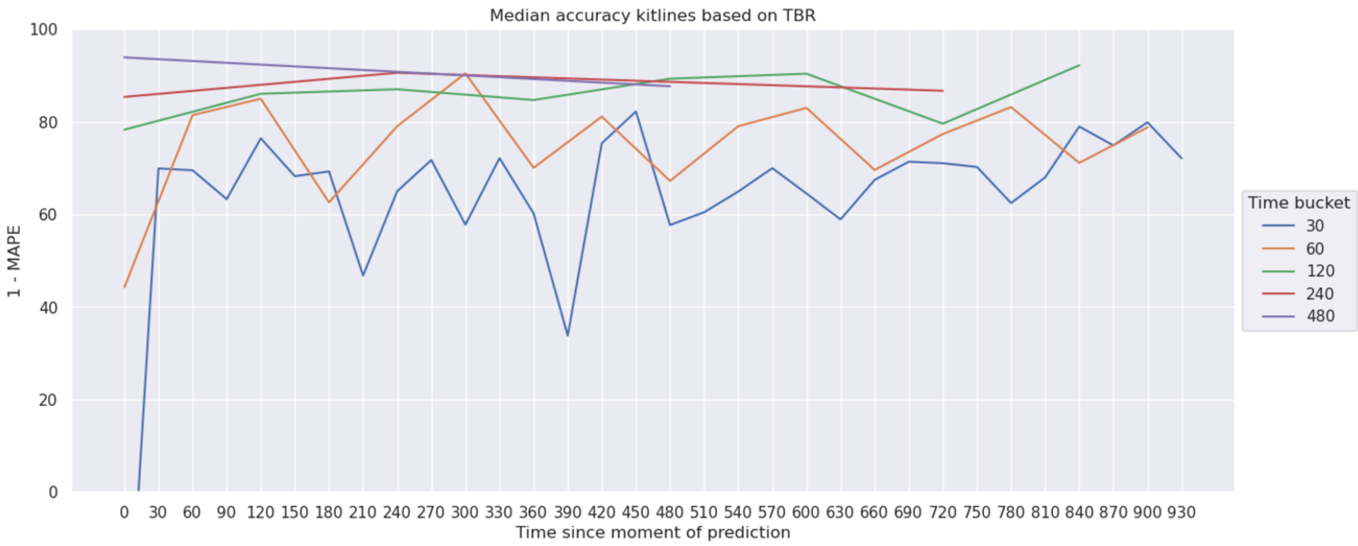


Figure 6.3: Median accuracy called kitlines over time for every time bucket

Chapter 7

Modeling & Evaluation based on Time between Requests

In the previous chapters, the time between the calls of the same kit cart was predicted to calculate the number of kitlines needed at the production lines. In case of CPP, TBC does not work well because the assembly operators give a signal to refill the empty kit cart. The workload in the kit warehouse is dependent on signals of the assembly operator. When the assembly operator requests to refill a kit cart, a queue is created based on the latest possible start date. A kit cart is requested to be refilled directly when the previous production is finished, but the assembly worker can sometimes be early or late with requests. Requesting to refill a kit cart could contain some extra human behavior. In addition, the kit cart cannot be refilled if the kit cart has not been returned to the kit warehouse. For CPP it is better to predict when the kit cart will be requested to refill. In this chapter, the number of kitlines per time bucket are generated based on the time between the requests of the same kit cart (TBR). Thereafter, a comparison is made between the time between the requests (TBR) and time between the calls (TBC), as shown in Figure 7.1. Finally, the workload in the kit warehouse based on the requests is calculated for CPP. Additionally, the results are compared to the current method of CPP.

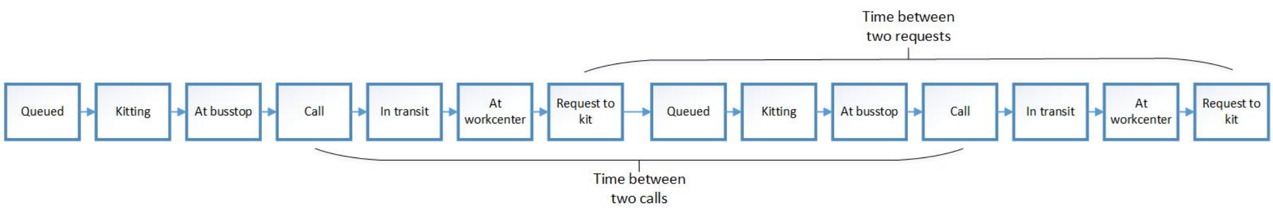


Figure 7.1: Comparison between TBC and TBR

7.1 Time between Requests (TBR)

In case of CPP, the assembly operator gives a signal for the kit cart to be refilled with materials. CPP uses the request timestamp to create a kit schedule based on the kit carts that are empty and need to be refilled. For CPP, it is more beneficial when the time between two requests to refill the same kit cart is predicted. The predicted timestamp can be used to make a kit schedule.

The same preprocessing steps are applied to predict the time between two requests. First, data is filtered on 2021 and 2022. Furthermore, missing values are removed. Whenever a called timestamp is missing, the row is deleted from the dataset. Thereafter, an additional feature is added to the dataset:

- **Time between requests of the same kit cart**. The difference between the request of a specific kit cart and the next request of the same kit cart, as shown in Figure 7.1. The time between two requests is corrected for weekend days and days off. A typical workday at CPP is starting at 7:30 and ends at 16:00. After observing, assembly operators arrive and leave work at different times. It is therefore assumed that operators do not work for 15.5 hours per day and that the kit cart is not requested in these 15.5 hours.

After splitting the datasets into three separate datasets, one for each production line, the outliers are detected per takt time for each kit cart separately. The outliers are identified by making a boxplot of the time between the Requests (TBR). Kit carts requested twice within 30 minutes are also removed from the dataset, because the records likely represent the same kit cart. The three final datasets for each production line are used for modeling with the same hyperparameters used in the method for TBC.

The prediction model predicts the time between two requests to refill the same kit cart (TBR). Based on the predicted time till the next same kit cart, the amount of requested kitlines per time bucket is predicted. As accuracy metric, the inverse of the MAPE is used. The accuracy of the kitlines per 30, 60, 120, 240 and 480 minutes is shown in Figure 7.2. Again, the accuracy metrics are calculated by averaging the accuracy metrics of 19 different timestamps between 30-08-2022 and 15-11-2022. The timestamps can be found in Appendix F.3. The mean accuracy metrics of the requested kitlines using different time buckets can be found in Appendix D.2. Comparable to the results of TBC, the median accuracy of the number of requested kitlines per time bucket is even higher, as shown in Figure 7.3.

7.2 Comparison between TBC and TBR

With the comparison between the time between calling a kit cart (TBC) and requesting to refill a kit cart (TBR), the impact of human factors can be identified. The kit cart is called when the kit cart is needed for production which is equal to the production flow. The request to refill the kit cart with materials is most of the time directly when the previous production is finished, but the assembly worker can sometimes be early or late with requests. The request to refill a kit cart is an additional manual task performed by humans. The time between two requests should follow the same rhythm as the time between two calls of a kit cart. Additional error is caused by human behavior by requesting a kit cart too early or too late. The comparison between Figure 6.2 and Figure 7.2 shows that the inverse of the MAPE is slightly lower when the number of kitlines is predicted with the time between requests (TBR) when using small time buckets. For example, with a time bucket of 60 minutes, TBR has an average accuracy of 63% and a median accuracy of around 70% where TBC has an average accuracy of 63% and a median accuracy of 73%. However, when predicting the kitlines requested or called for one day, the requested kitlines are more stable. In addition, the other accuracy metrics of TBR and TBC can be found in Appendix D. The prediction of the kitlines based on TBR is slightly worse than TBC which can be explained as human behavior of the assembly operators.

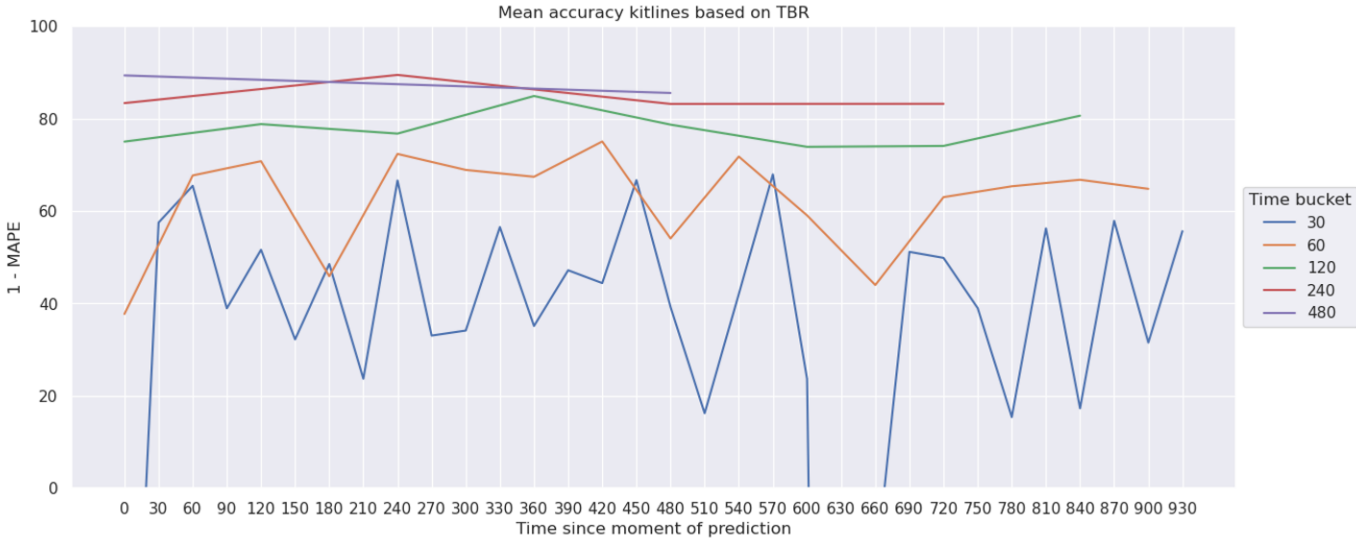


Figure 7.2: Mean accuracy requested kitlines over time calculated for every time bucket

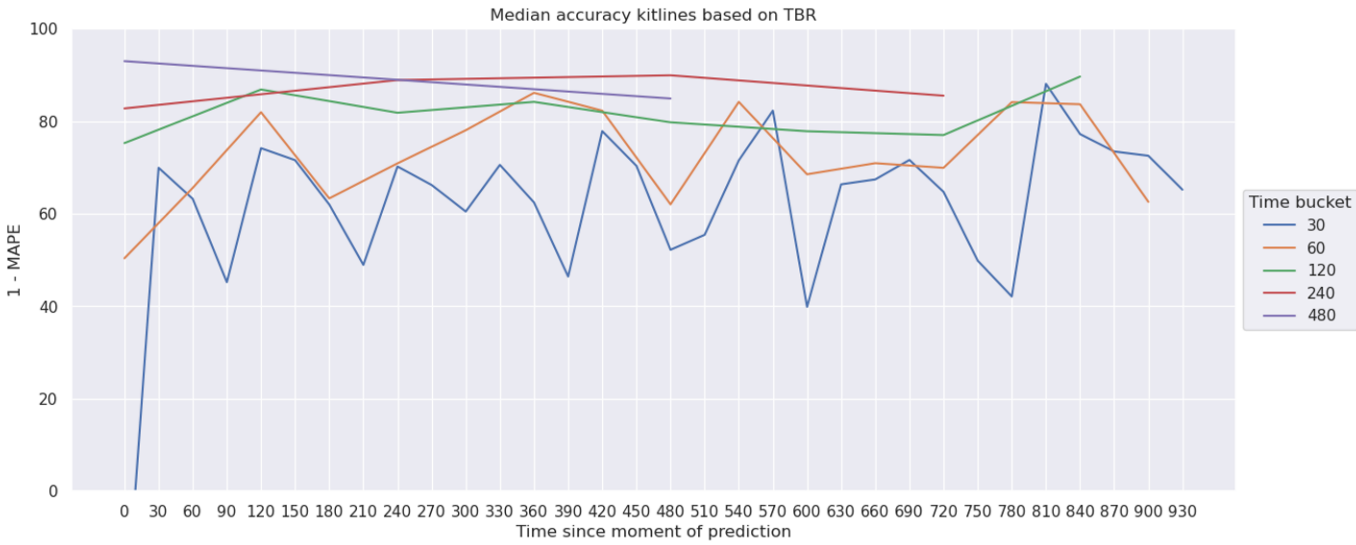


Figure 7.3: Median accuracy requested kitlines over time calculated for every time bucket

7.3 Translation to workload

The result of the prediction model based on TBR is the request timestamp of a kit cart. To make a translation to workload, an extra step is added in the process. After merging the prediction results of the production lines in one dataset, a step is added to calculate the predicted start and end kitting timestamp. The kit cart queue of CPP is created based on the request timestamp of a kit cart following the latest possible start date mechanism. The latest possible start date of a kit cart can be calculated with the predefined values of the available time to kit and duration. The start and end kitting can be calculated with Formula 7.1 and Formula 7.2. The visualization of the calculation is shown in Figure 7.4

$$\text{End kitting} = \text{Request timestamp (predicted)} + \text{Time available to kit (predefined)} \tag{7.1}$$

$$\text{Start kitting} = \text{End kitting} - \text{Duration (predefined)} \tag{7.2}$$

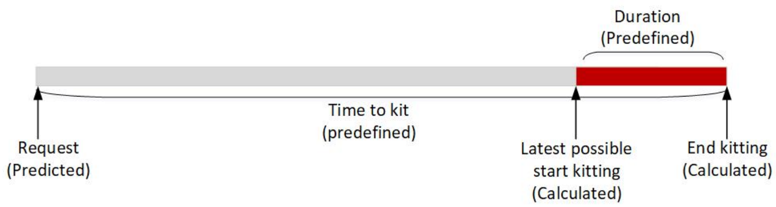


Figure 7.4: Calculation of the kit cart queue

The calculation of the start and end of the kitting activity in the process is made visible in Figure 7.5.

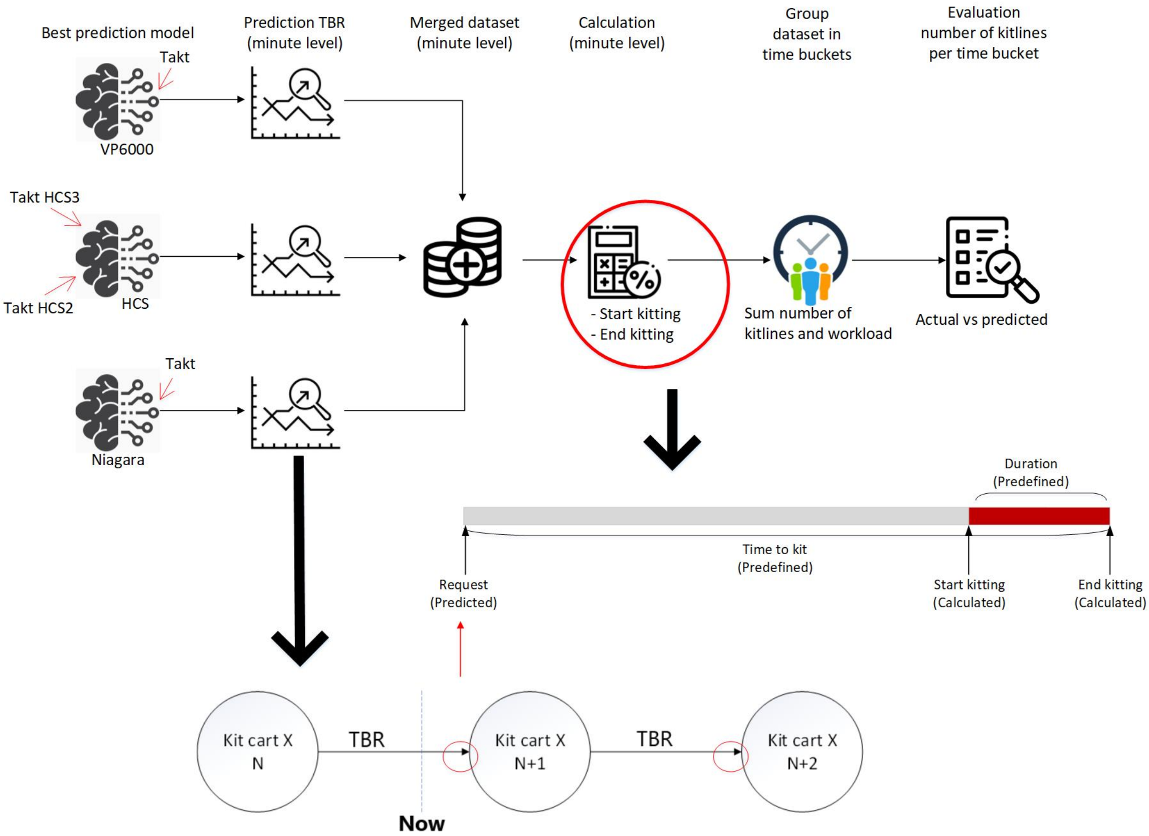


Figure 7.5: Calculation of Start kitting and End kitting in the process

Based on Figure 7.2, a time bucket of 60 minutes is chosen with an average accuracy of 63% and a median accuracy of around 70%. With the calculated start and end time of the kitting activity, the workload to pick the materials can be calculated for every hour separately, as shown in Figure 7.6. So the total workload is calculated for the first 60 minutes, then for the next 60 minutes, etc. In the same way, the number of kitlines to be picked can be calculated for each hour separately. During this calculation, it is assumed that the duration to kit a kit cart and the corresponding kitlines are evenly distributed. When a kit cart consists of many common parts, the picked kitlines per minute are higher than when a kit cart consists of many different or large parts.

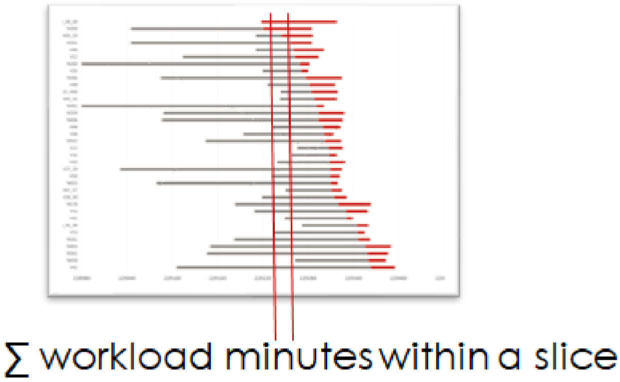


Figure 7.6: Calculation of workload per time block

The mean and median accuracy of kitting minutes calculated using time buckets of 60 minutes is shown in Figure 7.7. Additionally, the mean and median accuracy of the kitlines, assuming that the minutes and kitlines are evenly distributed, are shown in Figure 7.8. Additional accuracy metrics of the predicted workload and predicted kitlines can be found in Appendix F. The accuracy metrics for the number of kit lines are better than the accuracy metric of the workload. The drop in accuracy in the second hour an fourth hour can be explained by breaks. Most timestamps have a break for the assembly operators and kitting employees after about 2 hours and after about 4 hours. The connection between the timepoints used in this prediction and timestamps can be found in Appendix F.3. However, the workload per 60 minutes can be predicted with a mean accuracy of 70% and a median accuracy of 78%. The kitlines per 60 minutes can be predicted with a mean accuracy of 70% and a median accuracy of 79%.

Figure 7.7: Accuracy of minutes in workload planning of CPP (every 60 min)

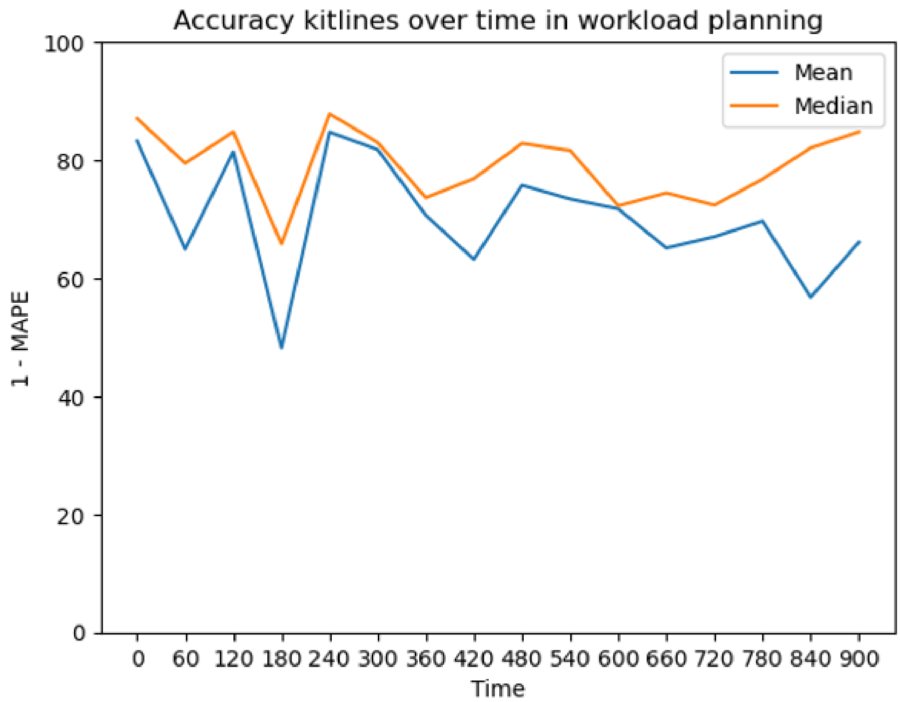


Figure 7.8: Accuracy of kitlines in workload planning of CPP (every 60 min)

7.4 Evaluation with current method of CPP

In the business understanding, a lot of variation in the kitting requests was visible in the number of requested kitlines per hour which may lead to peaks in the kit warehouse. Currently, CPP cannot forecast the workload or kitting requirements per hour in the future. People are scheduled on the shop floor based on a rough estimate of the kitlines to be picked per day. However, the variation of kitlines to be picked per hour cannot be predicted.

To show the differences between the current situation and new situation, the results of time point 229280 are presented. Time point 229280 is equal to the timestamp 17-10-2022 11:50. Figure 7.9 shows the number of requested kitlines per 60 minutes around time 229280. This is the moment that the assembly operator request to refill a kit cart. Based on calculation in Figure 7.4, the kit cart is placed in the kit cart queue. It can be concluded that the number of requested kitlines varies every 60 minutes.

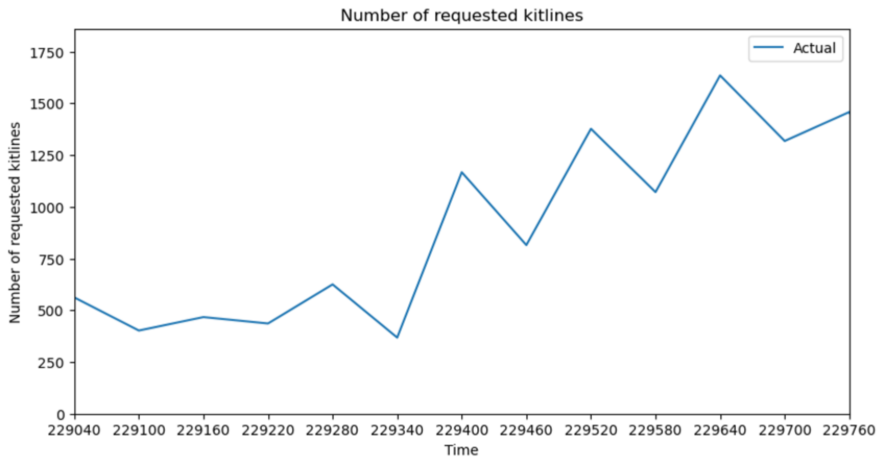


Figure 7.9: Requested number of kitlines per 60 minutes

In the current situation, only the already requested kit carts are visible in the kit cart queue of CPP. An example of the queue at timepoint 229280 is shown in Figure 7.10. As a consequence, the workload and number of kitlines can only be calculated for the kit carts already requested at timestamp 229280. In Figure 7.11b and Figure 7.12b, a snapshot of the workload and kitlines per 60 minutes from timepoint 229280 is shown. Both lines are declining, as the kit carts are not yet known in the future. In the current situation of CPP, the workload can increase quickly by requesting kit carts with short takt times. These new kit carts with short times will be requested and added to the queue in the coming hours.

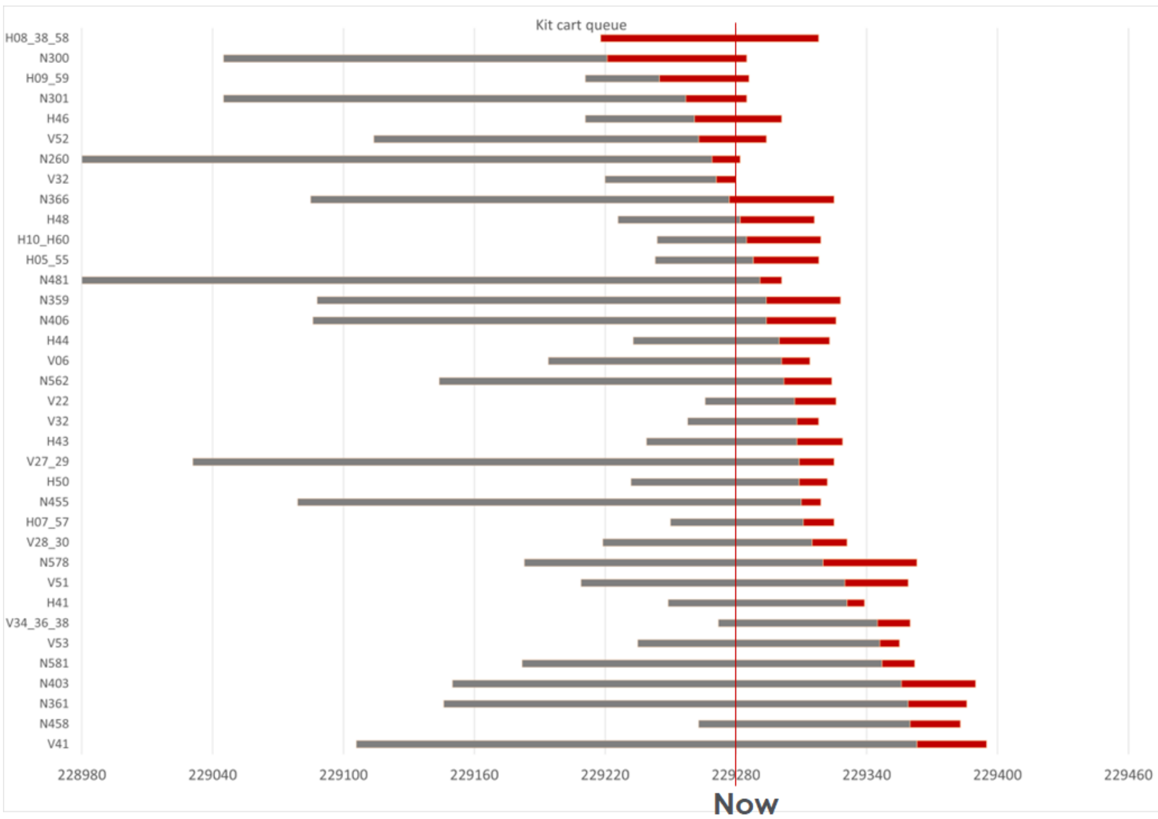
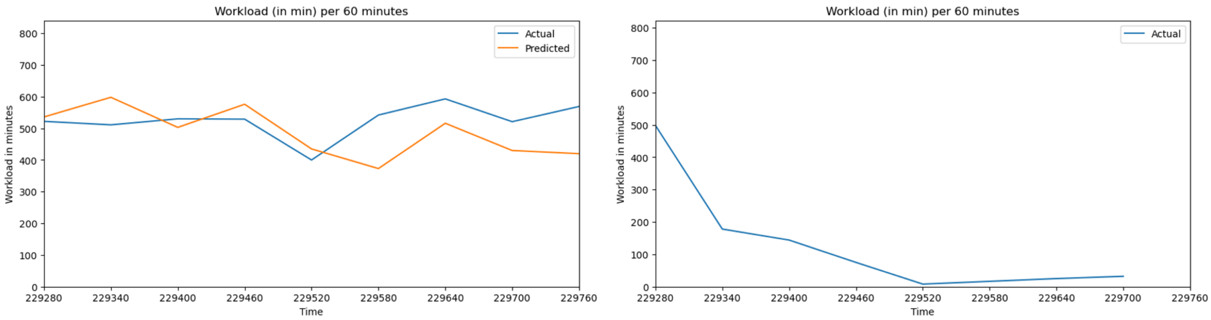


Figure 7.10: Current kit cart queue of CPP

Historical data has been used to train and test the models for the individual production lines.

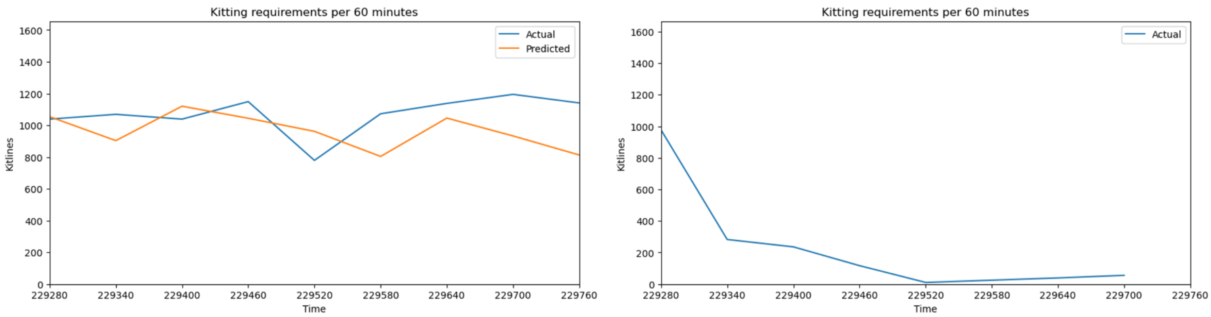
This allows to compare the predicted workload per hour with the actual workload per hour which was needed to fulfill all the kitlines in that particular hour. The current situation of Canon only shows a snapshot with the current calculation of the workload and kit lines at timestamp 229280 for the next few hours based on the already requested kit carts.

In the same way, the actual kitlines are the actual to be picked kitlines planned for that time window. So, the predicted workload and kitlines per 60 minutes are compared with the actual workload and kitlines per 60 minutes. The comparison between the prediction and the actual values of the workload and kitlines can be found in Figure 7.11a and Figure 7.12a respectively.



(a) Prediction vs Actuals (b) Current situation CPP (snapshot time 229280)

Figure 7.11: Workload in minutes where new situation is compared to current situation



(a) Prediction vs Actuals (b) Current situation CPP (snapshot time 229280)

Figure 7.12: Number of kitlines where new situation is compared to current situation

In the business understanding in Section 3.1, the current kitting process of CPP is explained. The order of the kit cart queue of CPP is determined based on the latest possible start date. As a consequence, new kit cart request with shorter available time to kit were allowed to get priority in the kit cart queue. In Figure 3.2 and Figure 3.3, the creation of the kit cart queue was presented. Based on the calculations of the new start kitting time point and end kitting time point explained in Figure 7.5, a new kit cart queue is generated. Figure 7.13 shows the new kit cart queue including predictions. The darker lines are the already requested kit carts while the light lines are the predictions of new kit carts. The new kit cart queue shows that a few kit carts will be requested from a production line with a shorter takt time in the coming hour. These kit carts change the order of the queue due to higher priority. With these extra kit carts, the workload in that particular hour is increased.

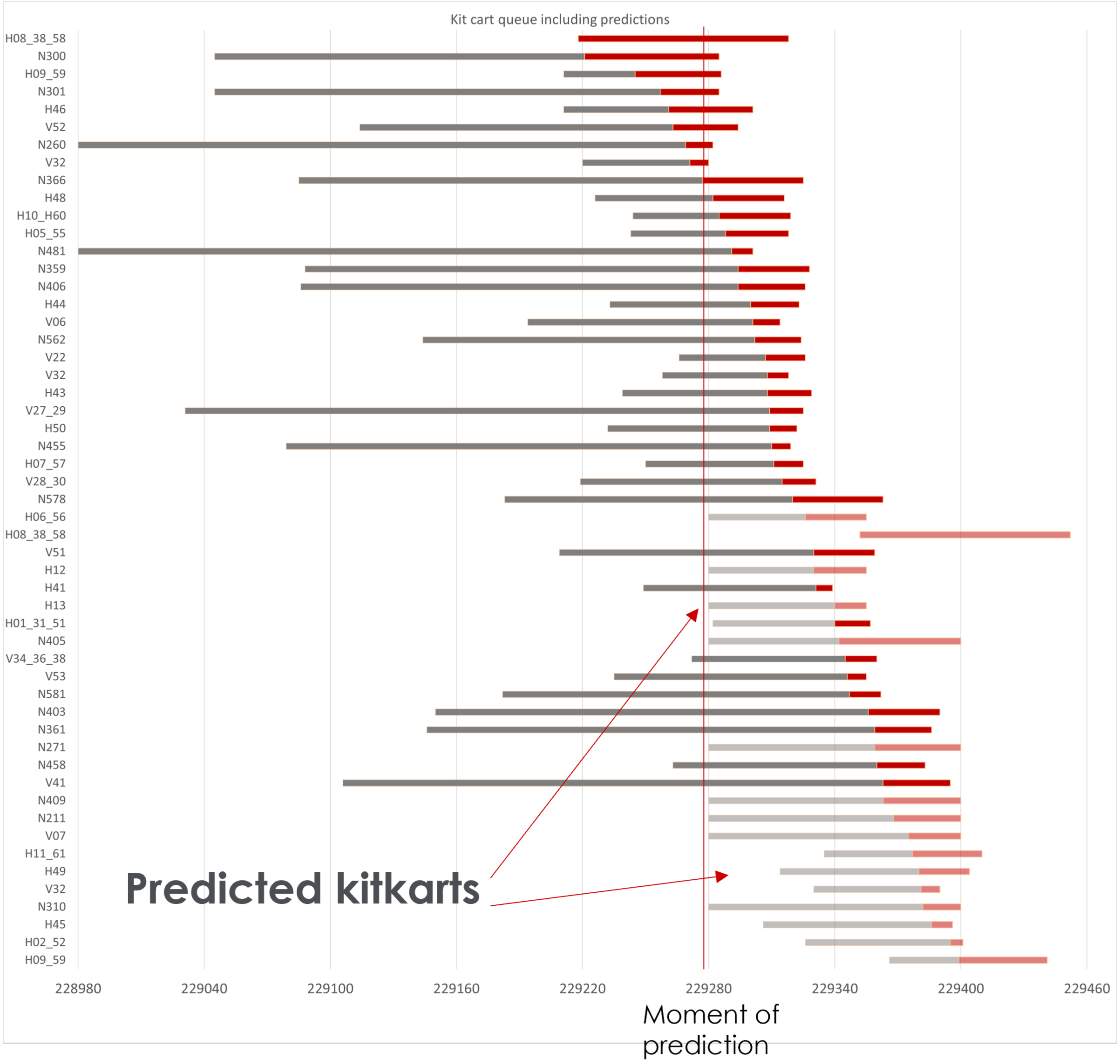


Figure 7.13: Kit cart queue including predictions

In case of CPP, the time available to kit a kit cart and the duration to gather all the materials of a kit cart is already predefined for each kit cart specific. These times are not dependent on the varying production amounts. When a kit cart is requested by the assembly operator, the kit cart is placed in the queue based on the calculated start kitting and end kitting timestamp of the specific kit cart. For this time point (229280), the number of kitlines to be kitted per 60 minutes in Figure 7.12a is more stable than the actual requested kitlines in Figure 7.9. Depending on which kit carts are requested and how much time is available for kitting, a completely different variation can arise for the workload and number of kitlines per 60 minutes. As a consequence, the variation of the requested kitlines is translated into a different variation of the kitlines to be picked per hour.

Furthermore, the kit cart is also waiting a lot in the full bus stop where the kit cart is stored between kitting and calling. In Appendix E, the time between calling and requesting a kit cart is compared with the available time to kit. Especially for production VP6000, the time between requesting and calling the kit cart is much longer than the available time to kit (VGW03). The kit carts wait for a long time in the full busstop, where all full kit carts are collected, before the kit cart is called by the assembly operator. This could lead to a wrong urgency of the kit carts. If a kit cart turns out to be kitted too late according to the predefined time, the kit cart is probably not late for production. This also applies to a few kit carts of HCS and about half of the kit carts of Niagara. As a result, a different variation arises when viewing the called kitlines per hour. Figure 7.14 shows the differences in variation of the requested kitlines, to be picked kitlines and the called kitlines.

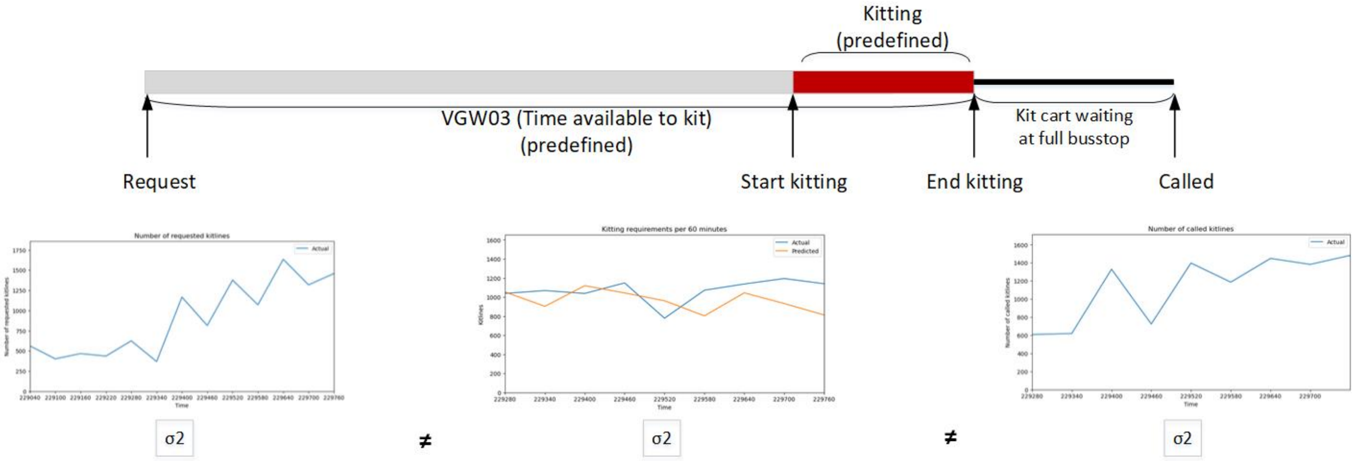


Figure 7.14: Visualization of differences in variation

7.5 Conclusion

There is a lot of variation in the requested kit lines per 60 minutes. Part of this variation arises from multiple production lines that work with a different takt times. The prediction model that predicts the time between two requests from the same kit cart can predict the requested kitting requirements per 60 minutes with a mean accuracy of 63% and a median accuracy around 70%. However, the variation of the kit lines to be picked in the kit warehouse is different from the variation of the requested kit lines due to the predefined time available to kit and the duration. The workload and the to be picked kitlines in the kit warehouse can therefore also differ from hour to hour. The workload per 60 minutes can be predicted with a mean accuracy of 70% and a median accuracy of 78%. The kitlines to be picked per 60 minutes can be predicted with a mean accuracy of 70% and a median accuracy of 79%. To properly respond to the variation of the workload, a recommendation is to balance the workload in the kit warehouse by considering a different scheduling mechanism.

Chapter 8

Conclusions

The last chapter contains the conclusion of this master thesis. First, the research questions are revisited and answered. Secondly, the scientific relevance and company relevance are described. Finally, the limitations of this master thesis and suggestions for future research are described.

8.1 Revisiting the Research Questions

At the beginning of this master thesis, the importance of the alignment between assembly and kitting is described. During this master thesis, a literature review is conducted where prediction models are selected to predict manufacturing behavior. After that, business understanding about the production processes is obtained and data is collected. After preparing this data, prediction models are created and evaluated. Finally, application of the prediction models is elaborated at the case company. The output of this thesis is a prediction model that predicts the kitting requirements of the production line including multiple production lines. With the information about the kitting process, a translation is made to the hourly workforce to fulfill these kitting requirements. Based on the possible causes of variation in workload in the kit warehouse, advice is given on how to balance the workforce in the kit warehouse.

As mentioned in Section 1.3, the main research objective is formulated as:

RO: To develop a prediction model to predict the required hourly manpower to fulfill the kitting requirements affected by the assembly process

To achieve research objective, four subquestions are formulated and answered in detail.

SQ1: Which forecasting method can be used to predict kitting requirements according to the literature?

To answer this research subquestion, a literature review is conducted. However, in the literature, not much attention is paid to the alignment between kitting and assembly. As a consequence, the focus of the literature review is on finding prediction models in production processes including manufacturing uncertainties, human behavior and stochastic demand. It is found that machine learning models and simulation are techniques which are used to predict dynamic lead times or manufacturing behaviour. The literature review contains three simulation techniques and five machine learning techniques that can be used to predict manufacturing behaviour. Simulation is not used, because a connection between the production order and kit cart was missing in the case study data. When using simulation, each kit cart would have to be simulated individually rather than a production order. As a consequence, three machine learning models were selected to use during this master thesis.

SQ2: How is variation in the kitting process caused by human and production related factors?

Influencing factors creating variation on the kitting and assembly process are identified during the literature review and business understanding. With the identified factors creating variation in the production process, the right features can be chosen to include uncertainties in the model. During this thesis a case study is conducted at Canon Production Printing. To be able to generate a solution for CPP, the current challenges regarding the alignment between assembly and kitting should be mapped. Various discussions were held with industrial engineers, planners, assembly operators and employees of the kit warehouse to get knowledge about the production processes of CPP. It was found that human factors have influence on kitting performance and assembly performance. Furthermore, inventory shortages and part shortages also create some deviating manufacturing behavior. The alignment between assembly and kitting could also be disturbed by multiple assembly lines operating with different takt times. Additionally, the start moment of the production and prioritization of the kit carts may create variation in the kit warehouse.

SQ3: Which data features are valuable to predict the kitting requirements and corresponding working hours

In the literature, there is no model available to align the kitting process with the assembly lines. For this research, the models have been kept as simple as possible. Based on the literature review and business understanding, multiple data features are added to the dataset. Additional features as day of previous call and hour of previous call are tried to add to the model. However, the influence of these variables were too low. The feature importance function of the random forest regressor is used to select the most important features. According to the feature importance function, the data features that are valuable and can be used to forecast kitting requirements are the production amount, takt, kitlines, median value of past assembly times, median value of target variable and the kit cart number.

SQ4: Which prediction method performs best when predicting kitting requirements?

After a detailed analysis and comparison of existing machine learning techniques, three machine learning techniques were selected. Due to the completely different characteristics of the production lines, each production line has their own prediction model. For each machine learning technique, hyperparameter optimization is conducted to find the optimal parameter settings of the model for each production line. For random forest, random search and grid search is combined. Due to time constraints, only grid search is used for support vector regression and artificial neural network.

For each production line, the three machine learning algorithms with their optimal hyperparameters are tested. Based on the accuracy metrics, the highest performing prediction model is chosen for each production line. For production lines VP6000 and HCS, the best performing model is support vector regression. For production line Niagara, random forest is the best performing model. To be able to predict the kitting requirements of multiple lines, the results of the prediction models are merged. The goal of this thesis is to predict the hourly manpower. However, when time buckets are used, variation is created if the kit cart is predicted a few minutes late and end up in the wrong time bucket. So, the accuracies using different time buckets based on the takt of average production are calculated. From the results with different time buckets it can be concluded that a larger time bucket leads to a more stable prediction of the required kit lines on the production lines.

Revisiting main research objective

With the research subquestions above, the main research objective is achieved:

RO: To develop a prediction model to predict the required hourly manpower to fulfill the kitting requirements affected by the assembly process

During this thesis the kitting requirements for the production lines are predicted based on Time Between Calls (TBC) and Time Between Requests (TBR). The average accuracy per 60 minutes is for both around the 63%. The median accuracy of TBC is slightly better. The differences can be explained by human behavior of the assembly operators. Based on information about the kitting process, a translation is made to the hourly workforce to fulfill the kitting requirements. The kitlines to be picked per 60 minutes can be predicted with a mean accuracy of 70% and a median accuracy of 79%. The workload per 60 min has an average accuracy of 70%. Based on the possible causes of variation, advice is given on how to balance the workforce.

8.2 Relevance

This section presents the relevance of this research. First, the scientific relevance is described. Secondly, the relevance to CPP is discussed.

8.2.1 Scientific Relevance

As stated in Section 1.4, based on literature two research gaps are identified. First, literature on kitting specific planning and decision making is limited. In the literature, comparisons between different methods to feed materials to production line are compared based on costs (Caputo et al., 2015a). So there is a lot of evidence that kitting has benefits as long as it is well organized. A technique to support kit planning was missing. The prediction model contributes to the literature by supporting decision making in kitting planning considering multiple production lines and varying processing times.

Secondly, there is lack of knowledge regarding the alignment between kitting and assembly. In the literature, there is a lot of research about the benefits of kitting based on costs, quality and performance (Limère et al., 2012). Caputo et al. (2015a) developed a mathematical model for kitting operations planning, but context-specific decision factors like assembly performance were not included. However, the alignment with the assembly lines is missing, especially when multiple production lines are operating. All the production lines have different characteristics with their own variation. This variation is also translated to the kitting process. The difficulty is predicting the parts demand across all production lines combined when operating with different takt times. Furthermore, human factors create a variation in the assembly process. By including information about production amounts and varying processing times, the prediction model contributes to the alignment between kitting and assembly.

8.2.2 Company relevance

The conclusions and outcomes of this master thesis research are relevant to Canon Production Printing. In Chapter 7, the application at the CPP is described. In Section 3.4, requirements specific to CPP are described. The requirements are answered in detail below.

R1: The prediction method should predict the required kitting requirements per hour considering human factors.

The general prediction model predicts the number of kitlines based on the time between the calls. With this prediction model, the number of kitlines per hour needed at the production lines can be calculated. In the prediction model, varying processing times are included. Besides that, the human behavior of assembly operators is researched. The prediction based on TBR are slightly worse than TBC which can be explained as human behavior of the assembly operators. However, human factors such as experience and age of the assembly operators and kitting employees is neglected due to privacy constraints. So, the prediction model indeed predicts the kitting requirements per hour but the human factors are limited.

R2: The predicted kitting requirements should be translated in working hours

Due to the large time differences between requesting and actually needing the kit cart, the prediction of the number of kit lines is also made based on the time between the requests of the same kit cart. Furthermore, the available time for kitting and the duration to kit a kit cart are pre defined. So, the workload of CPP is dependent on the available time for kitting, duration and the request timestamp. Based on the predicted request time point, the start and end kitting can be estimated. The queue can be estimated with the predicted request time point, start kitting and end kitting. With the created queue, the workload and kitlines per hour can be estimated.

R3: The prediction model should be easy to use and understandable for its users

The results of the prediction model are not explicitly tested with the users. However, the dashboard visible in the kit warehouse is constructed in the same way as the dashboard in the old situation. When implementing the results in the data flow of the company, the users have to be involved to assess if the prediction model is easy to use and understandable.

R4: The prediction model should be able to make predictions of the required manpower one day in advance.

The prediction model is able to make predictions a few days ahead. The workload per 60 minutes can be predicted with a mean accuracy of 70% and a median accuracy of 78%.

R5: The prediction model should possess the ability to incorporate new process data over time to increase the accuracy of the predictions.

Finally, the prediction model is able to incorporate new process data. The model is build in Jupyter notebook. The data in the model is immediately loaded from SQL which is updated regularly. The additional pre-processing step that needs to be done each year is to add the company's collective free days. These days are not considered working days. Furthermore, the new production amounts can be added to the model via Excel or SQL. When the prediction model is run again, historical records are automatically used as training set. The aggregated variables are also calculated immediately.

Based on the results of calculating the workload and kitlines per 60 minutes when using the time between two requests of a kit cart, some recommendations specific for CPP can be suggested. During this research, the difficulty was to merge all the production lines with different characteristics operating with different takt times. The requested kitting lines are varying from hour to hour due to different takt times and different behavior of production lines. A suggestion is to form a separate kit team for each production line with their own planning. The production lines are very different and splitting the lines with their own preferred time bucket size could be beneficial. The size of the time bucket to predict the workload can then be adjusted to the takt time of the production line.

Based on the planning mechanism of CPP, a kit cart queue is created based on the latest possible start date of a kit cart. However, the use of predefined available time to kit (VGW03) and duration to kit causes a variation in the number of kitlines and workload per hour in the kit cart queue. To properly respond to the kitting requirements of the production lines, the kitlines and corresponding workload in the kit warehouse have to be balanced. A suggestion to get a balanced workload is to change the priority of the production lines. For example, the kit trolleys of the production line can be kitted first with the highest probability. Then the production line with the second priority can be kitted and finally the holes are filled with kit carts from the production line with the lowest priority. Another suggestion is to use dynamic times for the time available to kit, but this can still lead to peaks in the kit warehouse. A next step for CPP could be research in different planning mechanism to balance the workload in the kit warehouse.

8.3 Limitations and future research directions

In the final section of this thesis, the limitations and recommendations for future research are presented. The main limitation of this research is the lack of human factors such as experience and age of the kiting employees and assembly operators. Experience and age could have influence on kitting performance and assembly performance. However, companies have to deal with privacy rules to protect their employees. Furthermore, requesting and calling up a kit cart is done via the pizza tool. This action is linked to an IP address and not to a specific person. Requesting and calling the kit cart can be done by different people. Only varying processing times are added to include some human behavior of the assembly operators.

A limitation in this thesis is that the same prediction model including the optimized hyperparameters is used for both time between calls (TBC) and time between request (TBR) prediction. Due to time constraints, the hyperparameter optimization steps are not repeated for time between requests (TBR). Another limitation regarding the model is that the outliers and missing values have been removed from the dataset. This can create gaps in the dataset. A suggestion is to replace the outliers with estimated values based on the remaining data.

In this thesis, the three biggest production lines are used to predict the kitting requirements. However, service kit carts also create variation in the requested kitlines and workload per hour in the kit warehouse. This group has to be included to get a more reliable prediction. All the production lines need preparation due to their own characteristics. So, due to time constraints, the three biggest production lines are chosen. Furthermore, the calculation of the workload and kit lines per hour assumes that the workload and kit lines are evenly distributed. In reality, it depends on the type of parts and the number of common parts.

Finally, three direction of further research are suggested. First, research to more input features is proposed. As already mentioned in the thesis, the link between the production order and the kit car is missing. When assembly workers work in parallel and in advance, it is not possible to obtain an actual production sequence. With a production sequence, the relationship between the kit carts could be determined. Based on probabilities, the next kit cart within a production order can be predicted. With the availability of a production sequence, other techniques like simulation could give better predictions. Due to lack of literature about the alignment between kitting and assembly, the model to predict the time between two calls of the same kit cart have been kept as simple as possible. More input features can lead to higher accuracy. Inclusion of more human factors can already give more information about different processing times and kitting performance. Furthermore, the inclusion of real time information about the process could give better predictions.

In this thesis, only machine learning models are used to predict the kitting requirements per hour. Simulation and time series forecasting could also be possibilities to predict future values. When there is no connection with the production order, a simulation for each kit cart separately has to be created. Time series forecasting including input factors like takt time can be used to predict either the required kitlines or required manpower. However, information about the kit carts is not available anymore. To include information about which kit cart is causing the kitlines in a given period, a time series prediction of each kit cart is required individually. An advantage of simulation and time series forecasting is the inclusion of breaks from the kitting employees and assembly operators. As future research, comparison between machine learning, time series forecasting and simulation is suggested.

Besides, validation for the generalization of the results is suggested. The results of this research are currently based on one case study executed in a high complex, low volume manufacturing environment with mixed-model assembly lines.

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Appendix A

Description of kitting process

During this research, a case study is conducted at Canon Production Printing (CPP) who develops and manufactures digital printing equipment operating in the global market with multiple sites around the world. CPP is founded and headquartered in Venlo, before known as the Dutch printing company Océ till the end of 2019 (CPP, 2021a). Factories are located in Europe and Asia to be able to operate in more than 80 countries. CPP offers a wide variation of products, from office printers to large-format high quality inkjet printers. The main activities of CPP in Venlo are R&D and manufacturing and logistics of large format, high end production printers. An example of a printer produced at CPP in Canon can be found in Figure A.1.

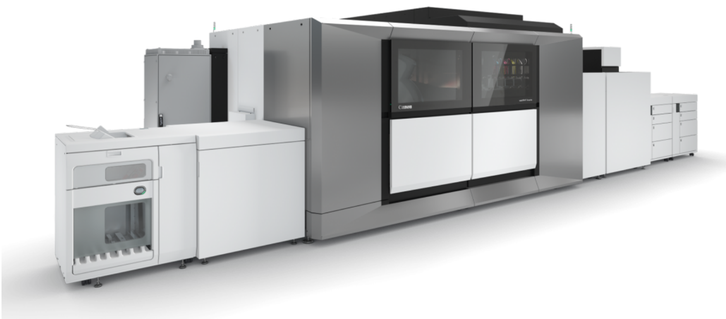

Figure A.1: VarioPRINT iX-series (CPP, 2021b)

CPP uses a JIT kitting process where assembly operators request their parts by notifying the warehouse. To make the communication between the operators and the warehouse easier, they are using a so-called "pizza tool" described in Figure A.2. This 'pizza tool' is a dashboard which can be compared with the Pizza tracker used by Domino's pizza to communicate the progress of making the pizza with the customer. In case of CPP, the 'pizza tool' indicates where the kit cart is located. This dashboard is visible both in the kitting warehouse and at every work station in the assembly line. The kitting warehouse can see the status of all kit carts. The dashboard at the working stations only shows the necessary kit carts for that particular working station.

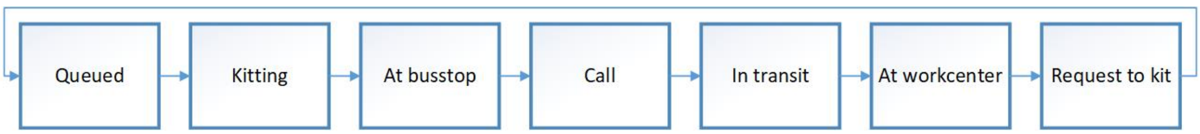

Figure A.2: Pizza tool process

The process starts when the assembly operator requests a new kit cart. SAP checks if there is an production open where this kit cart is needed. SAP returns a message to the assembly operator if the kit cart is requested or not. When the refill of a kit cart is requested, the kit cart status is turned on

"Empty". Based on the kit cart, multiple transfer requests in SAP WMS are created depending on the parts. After that, a kit cart production order is created to be able to backflush the materials when the kit cart is used instead of back flushing all the materials at the end of the production of one product. Back flushing all the materials at the end causes a lot of inventory differences throughout the week, because a product is using a lot of kit carts to finish all the assemblies and make the final product. These kit cart production order is different than the production order for a product which consist of multiple kit carts. Then, the kit carts are placed in a queue based on latest start date. The latest possible start date is the time at which a kit cart can be kitted without causing a delay in the assembly process as shown in Figure 1.2 and Figure A.3. Furthermore, an example of the queue is given in A.3.

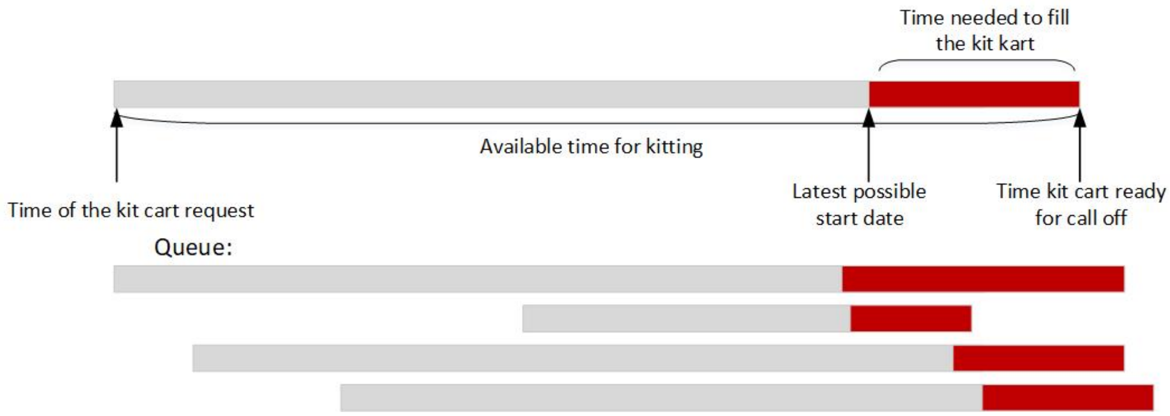

Figure A.3: Latest possible start date

The warehouse is also called the 'supermarket' containing most the parts needed for the assembly lines. In the supermarket, the kit carts are kitted by the kitters with the help of a bar code scanner. The kit carts appear on the scanners of the kitters according the queue based on the the latest possible start date. The status of the kit cart in SAP is "lock" when the kit car appears on the scanner of a kitter preventing showing up on multiple scanners. If the kit cart is accepted on a scanner by a kitter, the kit cart status turned into "WIP". After accepting the kit cart, the transfer requests (TR) changed to transfer orders (TO). The transfer orders connected to the kit cart are kitted by the kitter in the supermarket. In case of a break, for example going to the toilet, the status of the kit cart changes to "Stop". The kit cart status changes back to "WIP" when the kitter continues kitting the kit cart. After finishing the kit cart, the kit cart is placed at the full busstop, a place where all full kit carts are collected. The kitter scans the location at the full busstop after which the materials of kit cart are deducted systematically from the inventory. The status of the kit cart changes to "Full" and the assembly operators are able to call the kit cart when they need the kit cart for assembly. After a call from the assembly operator, the kit cart is connected to an AGV and will be sent to the assembly operator. The AGV with the kit cart needs about 2 to 5 minutes to reach the assembly operator. The assembly operator receives the kit cart and starts assembling. When the kit cart is empty, the assembly operator can request tp refill the kit cart again and returns the empty kit cart to the supermarket with an AGV.

With the use of JIT, the kit carts only appear in the kit planning when the kit car is empty and requested. The products produced on different assembly lines have their own specific takt times. Depending on the takt time and the latest possible start date, the different kit carts are placed in order. The kit carts appear in this order on the kit scanners. Short takt times can change the order of the kit carts from hour to hour by adding kit carts which have to be kitted very quickly. An example is shown in Figure A.4. Furthermore, the extra kit carts make workload planning very difficult because of the varying amount of requests from hour to hour. Although CPP is using flexible workers to be responsive to swings, it cannot anticipate on changes in the next one or two hours. These short term changes causes problems in predicting the capacity of manpower to fulfill the demand and causes high costs because of overstaffing or delays. CPP is looking for a prediction model to respond to the varying kitting requirements to be able to predict the required workload.

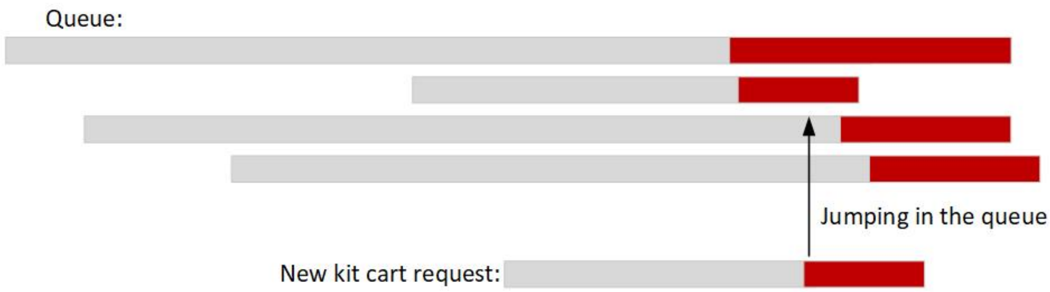

Figure A.4: Prioritization of new kit cart requests

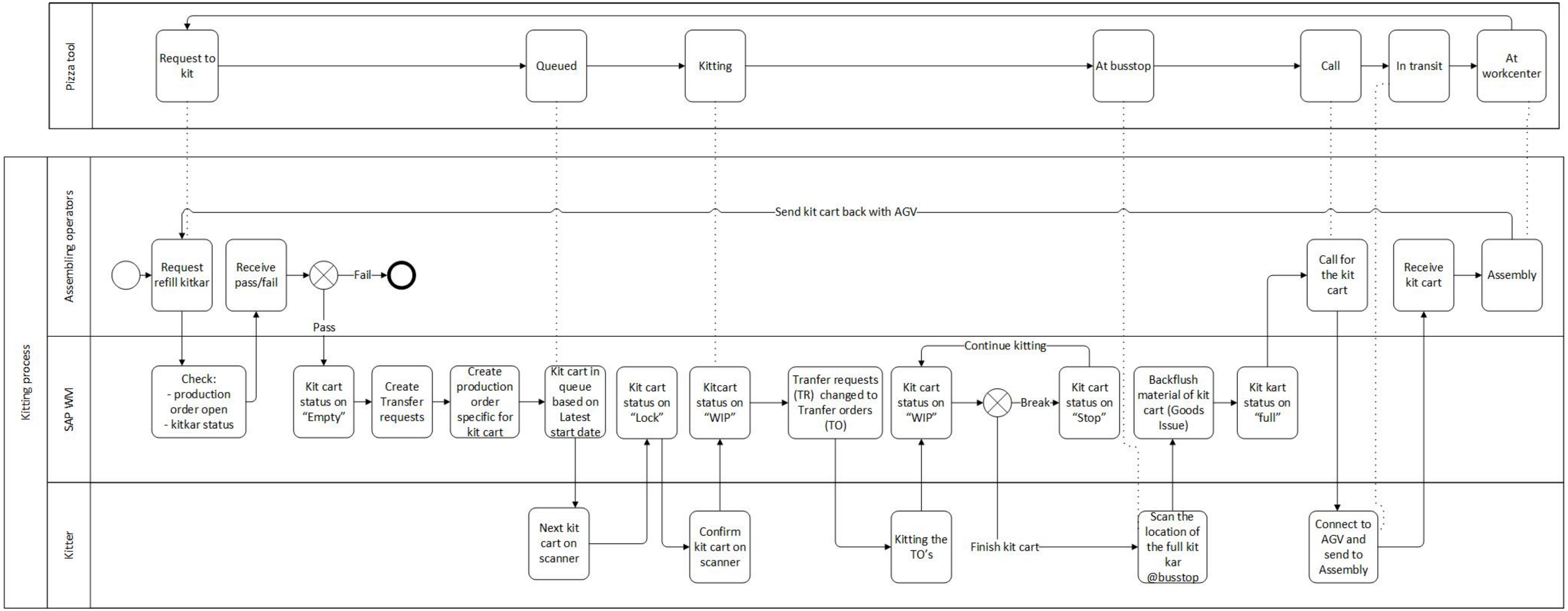

Figure A.5: Description of kitting process

Appendix B

Set of kit carts per model

B.1 HCS

Three different models are modelled at the HCS production line. Every model has their own selection of kit carts. The selection of kit carts per model is described in Table B.1.

Table B.1: HCS kit carts per model

HCS H1 (Older version of J1, HCS3)	HCS J1 (New model HCS3)	HCS NI (HCS3)	HCS2
H01	H02	H13	H41
H02	H03	H51	H42
H03	H04	H52	H43
H04	H05	H53	H44
H05	H07	H54	H45
H06	H09	H55	H46
H07	H10	H56	H47
H08	H11	H57	H48
H09	H12	H58	H49
H10	H13	H59	H50
H11	H31	H60	
H12	H38	H61	
H13	H56	H62	

B.2 VP6000

The VP6000 production line also produces multiple models on the same production line but the operators are using generic kit carts necessary for every model and specific kit carts specific to a model. There are 45 kit carts for VP6000, but for every model only 31 kit carts are used to build an engine. Every model has their own selection of kit carts. The selection of kit carts per model is described in B.2. The differences in kit carts are highlighted.

Table B.2: VP6000 kit carts per model

VP6000 Titan	VP6000 MICR	VP6000 TP
V01	V01	V01
V02	V03	V04
V05	V05	V05
V06	V06	V06
V07	V07	V07
V09	V09	V08
V10	V11	V09
V12	V12	V12
V13	V13	V13
V14	V14	V14
V15	V15	V15
V16	V16	V16
V19	V19	V19
V20	V20	V20
V21	V21	V21
V22	V22	V22
V23	V23	V23
V24	V24	V24
V25	V25	V25
V26	V26	V26
V27	V29	V29
V28	V30	V30
V31	V31	V31
V32	V32	V32
V33	V33	V33
V34	V36	V38
V35	V37	V39
V50	V50	V50
V51	V51	V51
V52	V52	V52
V53	V53	V53

Appendix C

Hyperparameter optimization Random Forest

For the hyperparameter optimization of random forest, random search is used. Based on the results of the random search, the values close to the best result of the random search are used to determine the range for the grid search. The values tested for the grid search and the final optimal hyperparameters are described in Table C.1.

Table C.1: Optimal hyperparameters of the Random Forest model for every production line

Production line	Grid search	Bootstrap	Max depth	Max features	Min samples leaf	Min samples split	Number of trees (n_estimators)
VP6000	bootstrap': [True], 'max_depth': [10, 20, 30], 'max_features': [40, 5, 'sqrt'], 'min_samples_leaf': [3, 4, 5], 'min_samples_split': [4, 5, 6], 'n_estimators': [100, 200, 300, 500]	TRUE	10	40	3	5	200
HCS	bootstrap': [True], 'max_depth': [10, 20, 30], 'max_features': [40, 5, 'sqrt'], 'min_samples_leaf': [3, 4, 5], 'min_samples_split': [4, 5, 6], 'n_estimators': [100, 200, 300, 500]	TRUE	20	40	5	6	100
Niagara	bootstrap': [True], 'max_depth': [10, 20, 30], 'max_features': [40, 5, 'sqrt'], 'min_samples_leaf': [3, 4, 5], 'min_samples_split': [4, 5, 6], 'n_estimators': [100, 200, 300, 500]	TRUE	10	40	3	4	300

Appendix D

Accuracy metrics TBC and TBR

D.1 Time between calls (TBC)

Table D.1: Mean accuracy metrics of predicted called kitlines based on Time Between Calls

Time bucket	Time	1-MAPE	MAPE	MAE	MSE	RMSE
30	0	-136.88	236.88	893.15	933293.80	893.15
30	30	21.74	78.26	200.00	57447.23	200.00
30	60	29.43	70.57	254.77	98342.62	254.77
30	90	50.70	49.30	161.69	38973.08	161.69
30	120	51.73	48.27	177.62	50608.23	177.62
30	150	42.93	57.07	148.31	39171.85	148.31
30	180	23.36	76.64	245.15	79081.46	245.15
30	210	32.84	67.16	205.08	60468.92	205.08
30	240	67.56	32.44	171.00	46130.85	171.00
30	270	61.10	38.90	160.00	39944.92	160.00
30	300	59.33	40.67	144.15	36241.69	144.15
30	330	33.51	66.49	222.92	67305.69	222.92
30	360	18.85	81.15	234.46	100277.80	234.46
30	390	49.69	50.31	205.62	64866.85	205.62
30	420	40.31	59.69	201.54	67358.31	201.54
30	450	43.24	56.76	260.15	96190.00	260.15
30	480	22.36	77.64	242.54	80190.38	242.54
30	510	37.48	62.52	153.77	41593.15	153.77
30	540	45.00	55.00	187.92	63573.46	187.92
30	570	23.94	76.06	280.38	103441.90	280.38
30	600	52.23	47.77	176.77	39943.23	176.77
30	630	36.35	63.65	258.33	82508.83	258.33
30	660	45.26	54.74	148.00	42847.85	148.00
30	690	9.55	90.45	228.33	93117.00	228.33
30	720	53.39	46.61	191.08	46439.23	191.08
30	750	38.01	61.99	213.15	64865.92	213.15
30	780	66.84	33.16	131.77	27165.31	131.77
30	810	49.14	50.86	215.15	74868.85	215.15
30	840	15.62	84.38	221.62	91998.54	221.62
30	870	27.95	72.05	175.77	61763.92	175.77
30	900	26.97	73.03	235.69	76511.08	235.69
30	930	29.43	70.57	209.00	68372.69	209.00
60	0	0.16	99.84	799.62	771363.50	799.62
60	60	71.60	28.40	264.46	102220.00	264.46
60	120	68.79	31.21	215.62	73921.92	215.62
60	180	55.59	44.41	343.46	188425.50	343.46
60	240	77.42	22.58	244.08	84302.38	244.08

Table D.1: Mean accuracy metrics of predicted called kitlines based on Time Between Calls

Time bucket	Time	1-MAPE	MAPE	MAE	MSE	RMSE
60	300	68.55	31.45	275.38	114247.40	275.38
60	360	64.18	35.82	297.15	154681.20	297.15
60	420	69.01	30.99	273.85	119854.60	273.85
60	480	61.04	38.96	290.15	123157.20	290.15
60	540	55.50	44.50	349.85	165002.30	349.85
60	600	71.00	29.00	233.62	84204.69	233.62
60	660	42.85	57.15	308.77	157488.80	308.77
60	720	69.26	30.74	241.46	95692.69	241.46
60	780	72.90	27.10	208.62	70372.77	208.62
60	840	40.92	59.08	351.38	206859.50	351.38
60	900	52.75	47.25	354.38	183671.30	354.38
120	0	59.25	40.75	686.38	660098.80	686.38
120	120	78.05	21.95	356.00	202924.50	356.00
120	240	85.68	14.32	293.77	127850.10	293.77
120	360	73.09	26.91	467.77	305594.10	467.77
120	480	77.97	22.03	335.23	187870.30	335.23
120	600	77.61	22.39	327.15	232715.90	327.15
120	720	81.79	18.21	324.54	166720.40	324.54
120	840	64.65	35.35	613.00	485625.90	613.00
240	0	76.44	23.56	811.00	1179536.00	811.00
240	240	81.58	18.42	686.62	583216.90	686.62
240	480	80.45	19.55	639.31	629042.10	639.31
240	720	79.54	20.46	728.77	775288.00	728.77
480	0	84.18	15.82	1134.38	2253208.00	1134.38
480	480	80.94	19.06	1348.54	2305024.00	1348.54

D.2 Time between requests (TBR)

Table D.2: Mean accuracy metrics of predicted requested kitlines based on Time Between Requests

Time bucket	Time	1-MAPE	MAPE	MAE	MSE	RMSE
30	0	-98.93	198.93	665.62	568121.20	665.62
30	30	57.52	42.48	213.69	87117.23	213.69
30	60	65.47	34.53	159.92	46880.85	159.92
30	90	38.95	61.05	233.15	70010.69	233.15
30	120	51.62	48.38	176.77	62988.15	176.77
30	150	32.22	67.78	173.92	51843.92	173.92
30	180	48.54	51.46	195.85	47110.77	195.85
30	210	23.70	76.30	261.00	100233.20	261.00
30	240	66.62	33.38	180.08	40715.31	180.08
30	270	33.05	66.95	200.85	61107.31	200.85
30	300	34.13	65.87	180.62	53291.85	180.62
30	330	56.54	43.46	181.23	55418.31	181.23
30	360	35.12	64.88	209.54	53198.00	209.54
30	390	47.18	52.82	219.38	74218.15	219.38
30	420	44.40	55.60	141.08	32493.08	141.08
30	450	66.69	33.31	139.62	25432.23	139.62
30	480	39.25	60.75	224.85	65007.46	224.85
30	510	16.24	83.76	224.77	63905.23	224.77
30	540	42.04	57.96	186.85	65364.54	186.85
30	570	67.94	32.06	115.46	24081.77	115.46
30	600	23.66	76.34	302.31	107897.50	302.31
30	630	-501.73	601.73	245.92	111598.10	245.92
30	660	-18.79	118.79	191.54	58047.38	191.54
30	690	51.17	48.83	153.50	32941.33	153.50
30	720	49.86	50.14	178.38	47432.23	178.38
30	750	38.99	61.01	234.08	78952.69	234.08
30	780	15.40	84.60	224.85	75985.15	224.85
30	810	56.25	43.75	145.85	56001.08	145.85
30	840	17.29	82.71	193.15	71355.46	193.15
30	870	57.88	42.12	163.38	42990.46	163.38
30	900	31.52	68.48	199.46	66195.46	199.46
30	930	55.65	44.35	195.92	47881.92	195.92
60	0	37.72	62.28	529.00	353470.10	529.00
60	60	67.71	32.29	284.92	101891.80	284.92
60	120	70.80	29.20	215.15	87686.85	215.15
60	180	45.90	54.10	420.54	223982.10	420.54
60	240	72.37	27.63	273.08	103971.70	273.08
60	300	68.90	31.10	203.23	64277.23	203.23
60	360	67.42	32.58	283.08	149503.50	283.08
60	420	75.06	24.94	183.46	57439.62	183.46
60	480	54.06	45.94	328.08	149544.20	328.08
60	540	71.80	28.20	214.00	78952.77	214.00
60	600	59.06	40.94	336.38	177688.70	336.38
60	660	43.99	56.01	329.46	141238.40	329.46
60	720	63.01	36.99	293.85	134216.50	293.85
60	780	65.36	34.64	256.38	136213.90	256.38
60	840	66.77	33.23	237.92	138730.80	237.92
60	900	64.81	35.19	289.08	119903.50	289.08
120	0	75.03	24.97	462.69	291841.80	462.69
120	120	78.82	21.18	364.00	201356.00	364.00
120	240	76.76	23.24	380.46	222295.40	380.46

Table D.2: Mean accuracy metrics of predicted requested kitlines based on Time Between Requests

Time bucket	Time	1-MAPE	MAPE	MAE	MSE	RMSE
120	360	84.89	15.11	273.77	94209.92	273.77
120	480	78.70	21.30	343.62	173356.10	343.62
120	600	73.90	26.10	426.00	249270.60	426.00
120	720	74.09	25.91	445.00	243998.50	445.00
120	840	80.64	19.36	321.00	184493.30	321.00
240	0	83.37	16.63	590.69	459846.20	590.69
240	240	89.46	10.54	388.54	260706.80	388.54
240	480	83.19	16.81	534.69	478569.80	534.69
240	720	83.21	16.79	589.38	480888.90	589.38
480	0	89.36	10.64	734.00	904078.00	734.00
480	480	85.56	14.44	998.69	1458766.00	998.69

Appendix E

Data analysis per production line

E.1 VP6000

Every time a kit cart is requested to refill by the assembly operator, the kit warehouse get an amount of time to refill the the kit cart. Per kit cart, a standard time to refill the kit cart is defined in SAP. In a continuous production, these times (VGW03) should be approximately equal to time between requesting the kit cart by the assembly operator and calling the kit cart by the assembly operator. The time between requesting to refill kit cart and calling the kit cart to use the kit cart is compared with the predefined amount of time to refill the kit kart in Figure E.1. The blue dot in Figure E.1 is the predefined time available to kit a kit cart. The boxplot shows the actual time between requesting the kit cart and calling the kit cart for production. For the kit carts of VP6000, the time between requesting and calling the kit cart is much longer than the predefined time (VGW03) to fill the kit cart. This leads to wrong urgency or the kit carts. If a kit cart turns out to be kitted too late according to the predefined time, the kit cart is probably not late for production. This also applies to a few kit carts of HCS and about half of the kit carts of Niagara. The same figures are made for HCS and Niagara in Figure E.2 and Figure E.3 respectively.

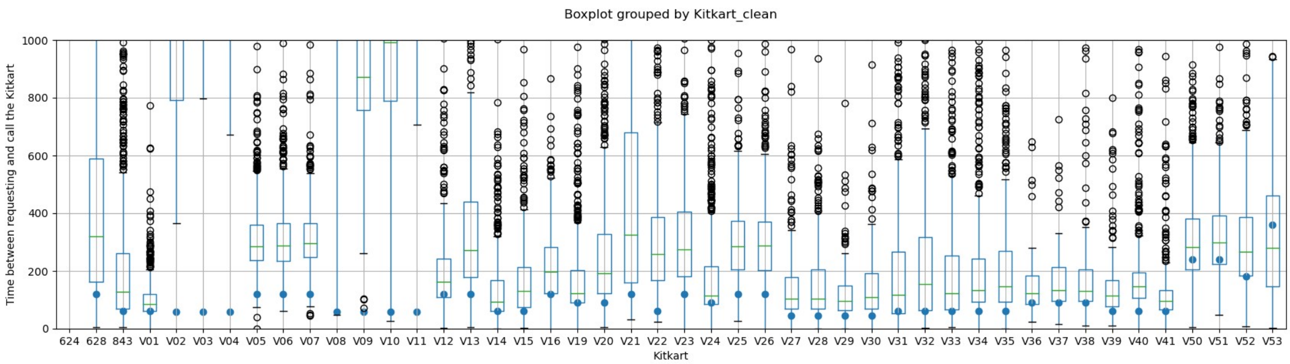

Figure E.1: Relation between VGW03 and the time between requesting and calling

E.2 HCS

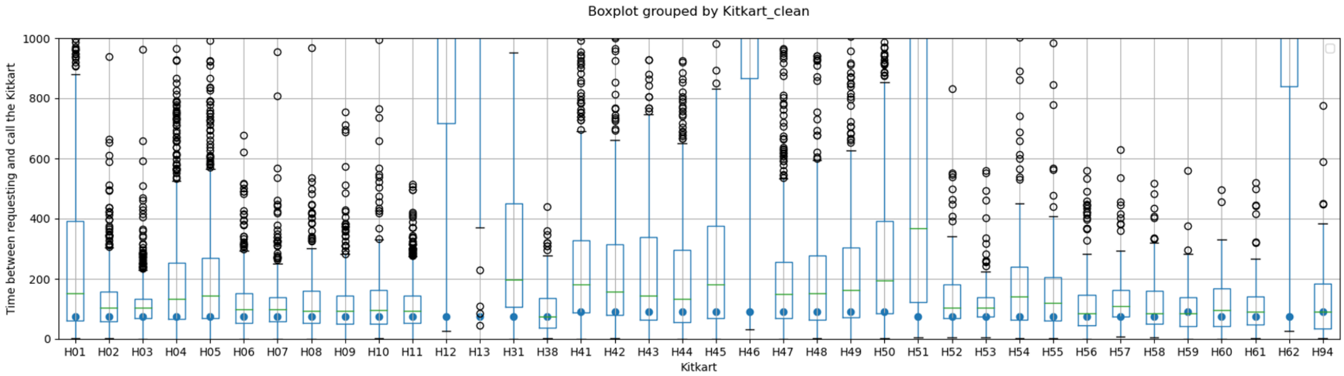

Figure E.2: Relation between VGW03 and the time between requesting and calling

E.3 Niagara

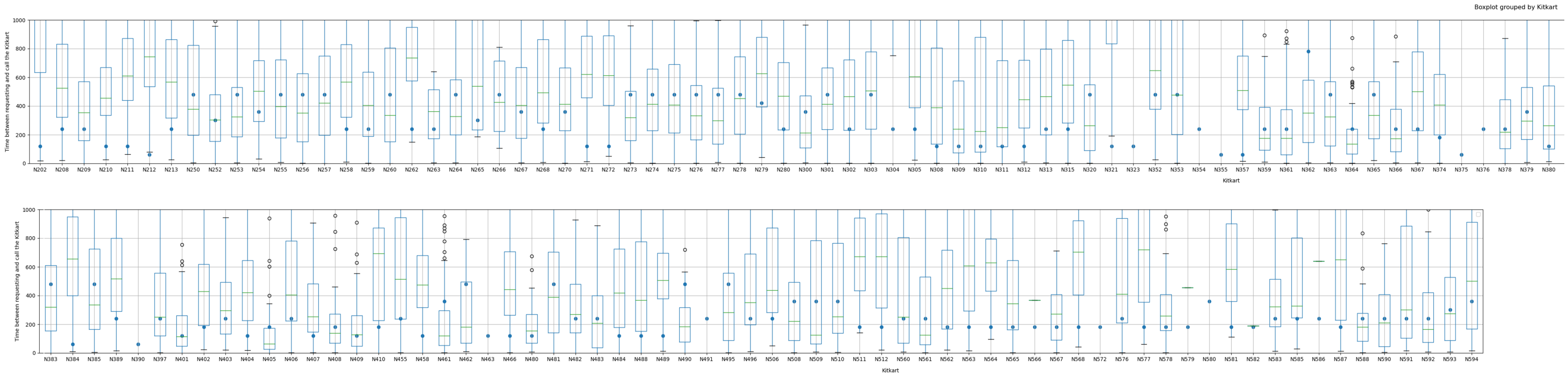

Figure E.3: Relation between VGW03 and the time between requesting and calling

Appendix F

Application at the company - accuracy metrics

F.1 Accuracy metrics workload per 60 minutes

Table F.1: Mean accuracy metrics workload every 60 minutes

Day	1-MAPE	Mape	1 - (sum error / sum actuals)	MAE	MSE	RMSE
0	84.42	15.58	84.42	55.85	4859.95	55.85
60	60.31	39.69	60.31	154.35	34176.90	154.37
120	84.89	15.11	84.89	63.35	7136.36	63.37
180	41.49	58.51	41.49	218.00	64226.12	218.02
240	82.43	17.57	82.43	73.20	8167.50	73.20
300	85.02	14.98	85.02	71.25	9090.19	71.25
360	70.95	29.05	70.95	129.05	22080.60	129.07
420	64.24	35.76	64.24	138.50	28719.31	138.52
480	76.55	23.45	76.55	94.90	14926.12	94.93
540	75.66	24.34	75.66	89.85	12872.17	89.87
600	74.81	25.19	74.81	111.45	17976.49	111.47
660	62.30	37.70	62.30	146.05	28761.55	146.05
720	74.29	25.71	74.29	103.95	20257.29	103.98
780	67.95	32.05	67.95	118.40	22888.78	118.45
840	54.63	45.37	54.63	128.25	28895.87	128.22
900	65.86	34.14	65.86	142.45	31448.89	142.42

Table F.2: Median accuracy metrics workload every 60 minutes

Day	1-MAPE	Mape	1 - (sum error / sum actuals)	MAE	MSE	RMSE
0	88.30	11.70	88.30	44.50	1982.50	44.50
60	71.10	28.90	71.10	137.00	18724.06	136.83
120	91.30	8.70	91.30	44.00	1937.00	44.00
180	50.69	49.31	50.69	223.50	50024.50	223.50
240	86.85	13.15	86.85	55.00	3026.00	55.00
300	90.15	9.85	90.15	46.50	2168.50	46.50
360	74.25	25.75	74.25	129.50	16770.50	129.50
420	72.59	27.41	72.59	129.00	17041.00	129.00
480	82.54	17.46	82.54	68.00	4625.00	68.00
540	82.89	17.11	82.89	76.50	5888.89	76.67
600	76.26	23.74	76.26	100.00	10000.00	100.00
660	73.85	26.15	73.85	124.00	15520.00	124.00
720	79.96	20.04	79.96	85.50	7322.50	85.50
780	78.27	21.73	78.27	96.50	9368.50	96.50
840	76.75	23.25	76.75	96.50	9291.22	96.33
900	72.56	27.44	72.56	116.50	13572.50	116.50

F.2 Accuracy metrics kitlines per 60 minutes

Table F.3: Mean accuracy metrics kitlines every 60 minutes

Day	1-MAPE	Mape	1 - (sum error / sum actuals)	MAE	MSE	RMSE
0	83.25	16.75	83.25	126.74	24829.40	126.74
60	64.92	35.08	64.92	270.85	112217.78	270.85
120	81.40	18.60	81.40	166.84	47889.33	166.84
180	48.18	51.82	48.18	362.09	188592.78	362.09
240	84.75	15.25	84.75	129.14	24628.51	129.14
300	81.81	18.19	81.81	162.37	42385.56	162.37
360	70.66	29.34	70.66	260.13	95315.32	260.13
420	63.19	36.81	63.19	291.79	120729.68	291.79
480	75.76	24.24	75.76	206.36	70931.51	206.36
540	73.42	26.58	73.42	201.11	62259.92	201.11
600	71.75	28.25	71.75	246.87	85008.12	246.87
660	65.12	34.88	65.12	290.68	120477.38	290.68
720	67.03	32.97	67.03	267.40	115605.49	267.40
780	69.67	30.33	69.67	232.54	82426.25	232.54
840	56.78	43.22	56.78	243.15	109368.96	243.15
900	66.09	33.91	66.09	275.53	135167.79	275.53

Table F.4: Median accuracy metrics kitlines every 60 minutes

Day	1-MAPE	Mape	1 - (sum error / sum actuals)	MAE	MSE	RMSE
0	87.07	12.93	87.07	115.22	13337.78	115.22
60	79.48	20.52	79.48	209.29	43830.53	209.29
120	84.80	15.20	84.80	114.77	13427.59	114.77
180	65.82	34.18	65.82	343.69	118589.39	343.69
240	87.85	12.15	87.85	113.49	12879.51	113.49
300	83.01	16.99	83.01	132.86	18247.02	132.85
360	73.65	26.35	73.65	228.93	52409.43	228.92
420	76.87	23.13	76.87	251.55	64400.94	251.55
480	82.86	17.14	82.86	197.15	38866.01	197.14
540	81.65	18.35	81.65	162.50	26405.50	162.50
600	72.26	27.74	72.26	233.65	54606.95	233.64
660	74.44	25.56	74.44	227.13	51616.46	227.13
720	72.39	27.61	72.39	243.02	59056.22	243.01
780	76.79	23.21	76.79	192.82	37850.18	192.82
840	82.09	17.91	82.09	171.12	29363.63	171.12
900	84.78	15.22	84.78	168.08	28372.39	168.07

F.3 Timepoints connected with timestamps

Table F.5: Timepoints connected with timestamp

Time point	Time stamp
212000	2022-08-30 12:50:00
213440	2022-09-02 11:20:00
214880	2022-09-06 11:40:00
216320	2022-09-12 08:20:00
219200	2022-09-19 13:50:00
220640	2022-09-22 12:20:00
222080	2022-09-27 10:50:00
223520	2022-09-30 09:20:00
224960	2022-10-05 07:50:00
226400	2022-10-07 14:50:00
227840	2022-10-12 13:20:00
229280	2022-10-17 11:50:00
230720	2022-10-20 10:20:00
232160	2022-10-25 08:50:00
233600	2022-10-27 15:50:00
235040	2022-11-01 14:20:00
236480	2022-11-04 12:50:00
237920	2022-11-09 11:20:00
239360	2022-11-14 09:50:00