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Using Forecasting to improve production planning at Wouter Witzel

Bachelor Thesis

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Management summary

Introduction

Wouter Witzel is a company that is an internationally leading producer and supplier of butterfly valves for industrial applications. A butterfly valve is a rotating disk that can be installed in a pipe to regulate the flow of fluids. Wouter Witzel produces and supplies both standard issue valves and valves tailored to the demands of the customer. Wouter Witzel, based in Losser, the Netherlands, has been part of the AVK group since 2005. Wouter Witzel mainly uses suppliers based in Europe and Asia.

Wouter Witzels planning department currently has insufficient insight into the demand levels on the long term. Peaks in demand are identified too late which results in weeks having more demand than capacity causing backlog. In order to reduce the backlog caused by the demand exceeding the capacity, a forecast model must be implemented at the planning department of Wouter Witzel. The backlog is partially caused by peaks in demand that are identified when the thresholds of the capacity have nearly or already been exceeded. By identifying these peaks earlier, demand can be spread out over multiple weeks or less demand can be accepted for a week that could results in a peak. The forecasting model will forecast the demand for all seven departments and produce a signal for the planning department based on the results of the forecast.

Forecast model

Before the forecast model was created, the input data of the model were obtained. the data from 2018 to 2021 was collected and analysed. From the data it was concluded that the welding department needed a different approach. Croston's method is selected to forecast the demand and the interval of the demand. The other six departments experimented on two different data sets as input, a data set containing the known demand. The demand known in week t for 1 to 20 weeks ahead and a data set containing the additional demand, solely the data added in week t also for 1 to 20 weeks ahead. The data contain a slight trend so both a model using and not using trend are used. Two forecasting methods have been chosen from the literature, Holt's method and Simple Exponential Smoothing (SES) for which both data sets are used. The data have been aggregated per week per department, based on the overview of hours used by the planning department. These models will be evaluated and compared to identify the optimal model for Wouter Witzel.

The forecasting models have a horizon of 20 weeks with the time bucket being one week. The available data has been split into a training set (2018 & 2019) and a testing set (2020 & 2021) for both the known demand data set and additional demand data set.

The forecasting methods that use the known demand data set result in a forecast of the expected demand within a week t for x weeks ahead. Using this, the demand that the model expects to be added between the current week and the week it must be finished. Combining this with the demand that is currently present, the total demand that is expected is calculated and compared to the available capacity.
The forecasting methods that use the additional demand data set result in a forecast of the expected additional demand for every week from now until the moment it must be finished. Taking the expected additional demand of every week results in the additional demand that is expected from

now until the moment it must be finished. The comparison with the capacity is done similar for the other data set.

Main findings

The first step of finding the optimal forecasting model is evaluating the error of the forecasting model. The first error measurement used is Symmetric Mean Absolute Percentual Error (SMAPE). Holt's method and Simple Exponential Smoothing that use the same data set have a SMAPE that is nearly equal. The models using the known demand data set are considered accurate in the first 10 weeks ahead with a SMAPE < 10% and can be considered good for the remaining 10 weeks ahead with a SMAPE mostly staying below 30%. The models using the additional demand data set have a SMAPE that is much higher, gradually increasing from a SMAPE of 40% to a SMAPE of 80%.
The other error measurement used is the Mean Absolute Deviation (MAD). Similar to the SMAPE, the models using the same data set have a very similar MAD. The MAD of the known data decreases as the x increases, this is due to the reduction of the demand for weeks further in the future. The models using the additional demand data set have a lower MAD which also decreases as the value of x increases. However, as the additional demand data set calculates the MAD using far lower values, these values for MAD are high. Comparing them to the average value of the forecast, the MAD ranges from 2 times to 6 times the average forecast. After an unreliable SMAPE and MAD, both models using the additional demand data set are no longer considered as optimal models for Wouter Witzel. The bias of the models using the known demand data set show that the forecast has a positive bias, meaning the forecast is higher than the actual value of the demand. However, this is due to the current movement of orders and the backlog, so this should decrease as the model will the reduce the impact of these factors.

The next step is the evaluation of the signals produced by Holt's method and SES using the known demand data set. First, both models are compared to the signal analysis produced by a model using Moving Average (MA), a basic forecasting method. Both models performed better than MA and are therefore better than MA. The most weeks correctly identify there should not be a signal, around 90% of the time. The two incorrect signals in giving a signal when it is not needed and not giving a signal when needed happens equally as often, 300 to 400 signals out of 10000. The number of correct signals is less, around 100. But this should increase as the movement of demand for the lower values of x decreases as the model is implemented. Comparing the two models, Holt's method resulted in an overall better analysis of the signals for $x \leq 12$. For the other values of x, the models performed equally good with a slight edge for SES. When looking at the weeks containing peak values that are not signalled by the model, 9 instances of x weeks ahead in week t contained a peak value that went unnoticed while SES only had 1.

Conclusion & Recommendations

Both methods using the known data set performed equally good in terms of creating an accurate forecast. Looking at the signal analysis of both methods, the major difference in correctly identified signals between Holt's method and SES weighs more than the slight decrease in missed alarms of SES. Therefore, Holt's method using the known demand data set is the best forecasting method for Wouter Witzel.
The model does rely on a steady input of data and a steady capacity that need to be supplied by the planning department. Sudden changes could lead to incorrect signals and therefore missed peaks in demand. While the model is tailored to the planning department, it definitely is not limited to this department. It is encouraged to use this model within other departments and thereby improve the overall planning. Such as including this model in the order acceptance at the sales department.

Table of contents

1. Introduction

1.1 Wouter Witzel

Wouter Witzel is a company that is an internationally leading producer and supplier of butterfly valves for industrial applications. A butterfly valve is a rotating disk that can be installed in a pipe to regulate the flow of fluids. Wouter Witzel produces and supplies both standard issue valves and valves tailored to the demands of the customer. Wouter Witzel, based in Losser, the Netherlands, has been part of the AVK group since 2005. Wouter Witzel mainly uses suppliers based in Europe and Asia.

Wouter Witzel can produce butterfly valves tailored to the demands of the customer which results in a lot of different valves. However, all these valves fall into one of three categories. Wouter Witzel produces assemble to order and manufacture to order valves. The manufacture-to-order valves are split into two groups, the first group consists of valves for which the raw material is on stock, the raw materials for the second group are ordered when an order from a customer comes through.

Within the planning department, Wouter Witzel uses a schedule that shows the demand from the current week until 20 weeks into the future, orders that are more than 10 weeks into the future are considered long term. Furthermore, the sheet contains the number of hours available for every week for every department of production.

1.2 Problem Identification

Wouter Witzel utilises a planning department to ensure the planning of orders is done correctly. Wouter Witzel aims to have the planned weekly demand not exceed 80% of the weekly production capacity. As a result, 20% of the production capacity is available for production errors, machine failures or other activities that require production hours outside the planning. However, the production planning is currently showing that the weekly demand is higher than the capacity in certain weeks. The exceeding of the capacity causes backlog which is a problem for Wouter Witzel.

Within Wouter Witzel, there are three departments that play an active role within the problem. These departments, the production department, the sales department and the planning department, are the stakeholders of this problem. The sales department and planning department are responsible for the input of the production process, while the production department is responsible for the execution of the production. In figure 1, a clear overview of the problems can be found. Below, the three departments are analysed on their role within the problem stated above.

As stated above, the production department is responsible for the execution of the planning that is created. Within the production department there are seven departments, all responsible for a unique part of the production. Currently, the production department is not able to live up to the planning. First, there is not always enough weekly production capacity to deal with the demand. Secondly, Wouter Witzel deals with machine failures. These machine failures have two negative outcomes, either the products get delayed due to an inactive machine, or the products are not of satisfactory quality and get refused at quality control. These two problems are the main problems the production department deals with.

Within the framework of the problem described above, the sales department is tasked with the input of the production planning. The conditions they have negotiated with the clients such as delivery date are the basis of the production planning. The production planning created by the ERP system is then taken by the planning department to smoothen out any problems that arise.

These departments have insufficient insight into the demand that will still come in between the current week and x weeks into the future. When a large order comes in, the production capacity appears to be available due to the absence of knowledge about future demand. Thus, a large order that takes up a substantial portion of the available production capacity gets planned as the capacity appears to be available. When the planning of the other demand needs to be done, the production capacity is not available due to this large order. However, if the large order had been split up over several weeks or had been moved one week, the problem could not have existed. This is caused by the absence of a forecast model.

Therefore, problems with the production capacity will only get noticed when the occupation exceeds the threshold of 80% while this should be much sooner to deal with the problem efficiently. By forecasting the demand, several production hours required to fulfil the expected demand can be determined. This will assist the planning of the large order, with potential solutions such as moving the large order one week forward or back or spread out the production of the large order. A forecasting model could assist the planning department with this insight and help plan the large orders. As this research is conducted from the planning department, the absence of a forecasting model is the core problem. This has been marked red in the problem cluster in figure 1.

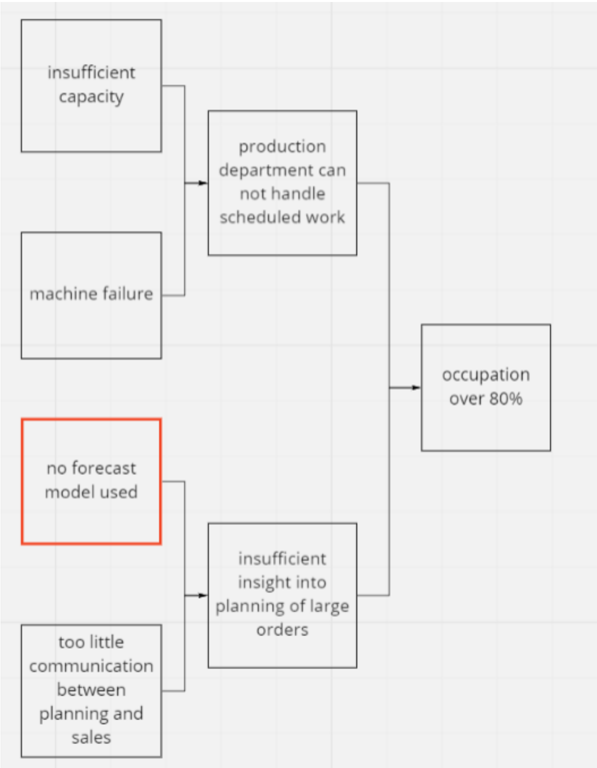


Figure 1: Problem cluster

1.3 Problem analysis

From the problem described above, 'no forecast model used' is selected as the core problem of this research. This choice has been made through the method described by Heerkens (2017).

The reality is that there currently is no forecasting model used to assist the planning of large orders. The first aspect of the norm is to have a demand forecasting model.

Another important aspect is the occupation of the production department. The occupation of the production department will be used to measure the effectiveness of the forecasting model and is therefore important to use within the norm. This will be done by improving the order planning through demand forecasting. The norm of Wouter Witzel is to keep the occupation below 80%. However, the reality is that the occupation is often higher.

Combining these norms and realities, a complete norm and reality can be formed. So, the norm is having a forecasting model that provides insight on how to keep the occupation below 80%. The reality is that there is no forecast model used for the demand in hours and the occupation is above the limit of 80%. The purpose of this research is to create a demand forecasting model that assists in the planning of large orders. This model should lower the occupation of the production department to 80% or lower.

1.4 Problem solving approach

This research will be executed in five different steps. These steps function as a structural path towards answering the main research question and creating a forecasting model.

1.4.1 Phase 1: The current situation

The first phase of the research will be analysing the current situation at Wouter Witzel. This will consist of an analysis of the current planning process, the current use of forecasting and an analysis of the data available at Wouter Witzel The most important data for the model will be the historic data about the demand, a list of the products sold and the production time of these products. The data will be operationalised for the forecasting model.

1.4.2 Phase 2: selecting a forecasting model

The second phase within the research will consist of selecting the proper forecasting method. This research is not the first research looking into the benefits of a forecasting model within a business. Therefore, the available models within the literature will be researched and the advantages and disadvantages will be analysed. Together with the available data from the first phase, a model will be selected for phase 3.

1.4.3 Phase 3: creation of the forecasting model

These results from the first and second phase will be combined and will function as the basis of the model. The forecasting model will be created in excel using VBA in the third phase. The forecasting model will notify the planners when a certain week has an elevated risk of having an occupation of over 80% given the current occupation and the estimated demand until that week.

1.4.4 Phase 4: validating the forecasting model

The fourth phase is focussed on validating the forecasting model. Research will be done in the possible methods of validating a forecasting model and selecting the relevant method. The selected model will then be used to validate the model.

1.4.5 Phase 5: implementation of the forecasting model

The final phase focuses on the implementation of the forecasting model at Wouter Witzel. The model should be easy to use and should connect to the existing schedule. This can be done through an easy-to-use interface and correct input criteria. In this section, impact on the planning process will also be discussed.

1.5 Deliverables

At the end of this research, a demand forecasting model will be provided to Wouter Witzel. The forecasting model will assist the planning department with the planning of large orders by forecasting the demand. The forecasting model will be delivered within Excel with an easy-to-use interface and will connect to the current schedule used at Wouter Witzel.

1.6 conclusion

Wouter Witzel is faced with peaks in demand that cause under-capacity while other weeks have capacity left over. The problem can be traced back to too little insight into the planning of large orders and the lack of a forecasting model. A forecasting model can signal these peaks earlier and assist in smoothing these peaks. Within this research, a forecasting model will be created that will assist the planning department at Wouter Witzel with the signalling of peaks in demand to prevent under-capacity.

2. Current situation

2.1 Current planning process

Wouter Witzel has implemented an ERP system as it is core structure of the company. The ERP requires the date of delivery and products demanded to create the production planning. The ERP is set to have an infinite horizon/capacity. This causes discrepancies within the planning. The planning department is focussed on smoothing the planning created by the ERP and solving problems that arise. These problems can have multiple causes. First, there are constantly malfunctioning machines or troubles with suppliers which causes an inability to stick to the production planning. Furthermore, having more demand than production capacity also must be manually handled. This is done using priority.

2.1.1 Contact with sales

However, as stated in the introduction, the planning does not take future demand into account and can therefore give an incorrect view of the situation. The sales department acts upon the current overview of hours. This can lead to unrealistic conditions towards the customers and an overflow of the production planning. While a regular meeting between the sales department and the planning department takes place, there lacks a definitive method to give the current plus expected demand. Due to this, a tug-of-war situation arises between sales and capacity. The forecasted model created in this research will give both departments a more realistic view of the situation and will thus improve the agreements between sales and planning.

2.1.2 Overview of hours

Next to the ERP system, the planning department at Wouter Witzel also uses an Excel sheet as an overview of the current demand and capacity. The sheet consists of the data from the current week to 20 weeks into the future. For these weeks, several aspects are considered to create a clear and complete overview. The sheet consists of the weekly capacity per department. Within production, there are seven different departments that focus on a step of the production process. In addition, for each of these departments, the weekly demand for the next 20 weeks is noted in the sheet. It should be noted that the demand in the sheet is the demand that is currently known, the expected demand is not considered. To provide a clear overview, the sheet shows the difference in capacity and demand through the hours and percentages. These percentages are colour coded. Wouter Witzel applies a norm within this sheet using three possible situations in a week. If there is an occupation of 50% or less, the department is marked as green for that week, indicating there are still a lot of hours available. The next step is between 50% and 80%. This is labelled as orange. However, it will still be underneath the limit set by Wouter Witzel. The last range is reached when the department has an occupation of more than 80%. As stated in the introduction, Wouter Witzel does not want the demand to be over 80% of the capacity. An example of the overview of hours can be found in figure 2.

Urenoverzicht MP1			5 2021 39	5 2021 40	5 2021 41	5 2021 42	5 2021 43
Laatste update	Thu 30-09	Achterstand ↓	27-sep 1-okt	4-okt 8-okt	11-okt 15-okt	18-okt 22-okt	25-okt 29-okt
350	← Nom. Capaciteit		97	327	322	348	322
1SPUIT 1	spuiten U-1	18	3	32	10	3	6
MP1			0	0	0	0	0
1SPUIT 2	spuiten U-2	203	132	197	245	222	252
MP1			0	2	0	35	172
1SPUIT G		32	0	2	0	0	5
MP1			0	0	0	0	0
Spuiten Totaal		**253**	**135**	**230**	**255**	**225**	**263**
Over/onderbezetting			-292	97	67	123	59
Over/onderbezetting Cum			-292	-195	-128	-5	54
Bez Proc			402%	70%	79%	65%	82%

Figure 2: Example of overview of hours

Above the full orange row of cells, the rows state the year and week that corresponding to the data. The orange row is the capacity of the department that can be found left of the orange row. This is the data for the 'spraying' department. The next important row is the row with the number in bold, this is the total known demand for the week. The bottom row shows the ratio between the demand and the capacity, where the colour tags are added.

2.2 Data

The other aspect of the current situation is the data available. Wouter Witzel has provided historic data on the demand and capacity from 2017 to 2022. This influences the type of forecasting solution that will be proposed. In the following paragraphs, the available data will be analysed for key aspects such a level of aggregation and bottlenecks. The overview of hours shows the current demand for the production department. For the current week of the sheet, work that has been done is excluded while demand that has been rescheduled or backlogged is included. The situation depends on what moment in the week it was last updated. To provide an as good as possible view of the situation, the graphs in this paragraph have been created using the data of the next week. While small portions of demand might not be captured within this week, it provides a better view of the current situation by excluding aspects such as backlog.

2.2.1Level of aggregation

Before looking at these aspects individually, the framework of the forecasting model must be clarified. The data that will be used is the overview of hours previously mentioned. The data consist of the weekly production hours available and the weekly demand in hours. So, the forecasting model is based on this data. Furthermore, Zotteri, Kalchschmidt and Caniato (2005) propose that an essential part of forecasting is often overlooked, the level of aggregation. While there is not "one best way" to determine the level of aggression, their practical example has shown that a higher level of aggregation improves the ability to manage variability.
A visualisation of this is depicted in figure 3.
Hence, when selecting the proper level of aggregation this must be considered.

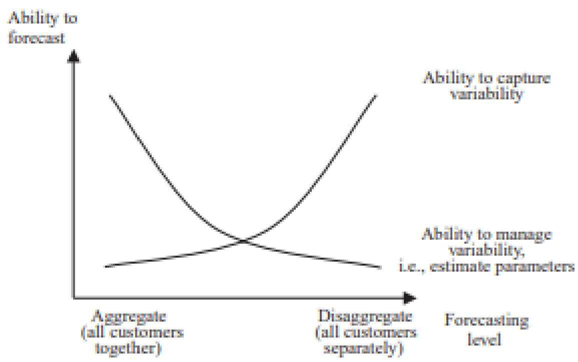
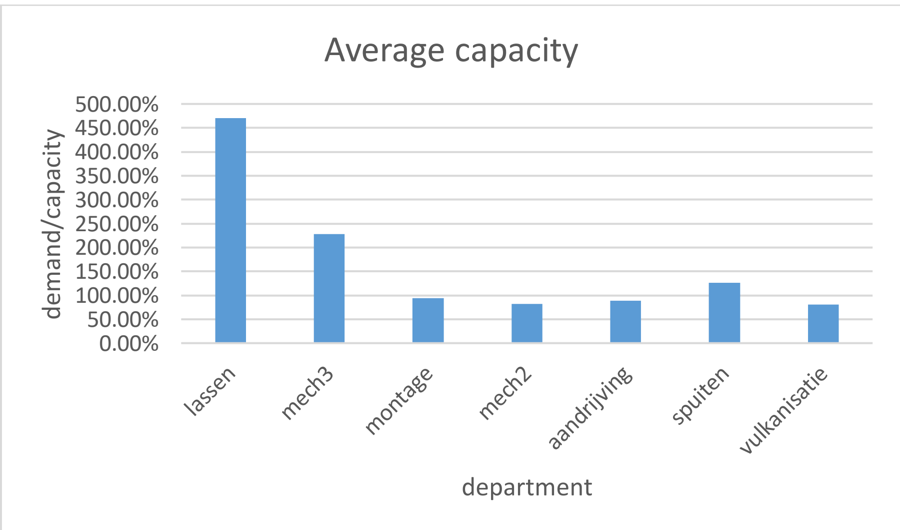


Figure 3: ability to forecast vs forecasting level

The requirement of the forecast model is to create a 20-week forecast of the hours demanded per week and per department. This does not require the model to forecast every product individually but create an aggregated forecast of all products. However, Wouter Witzel requires a distinction between the production departments. So, the forecast will give an estimation of the overall weekly demand per production department in production hours.

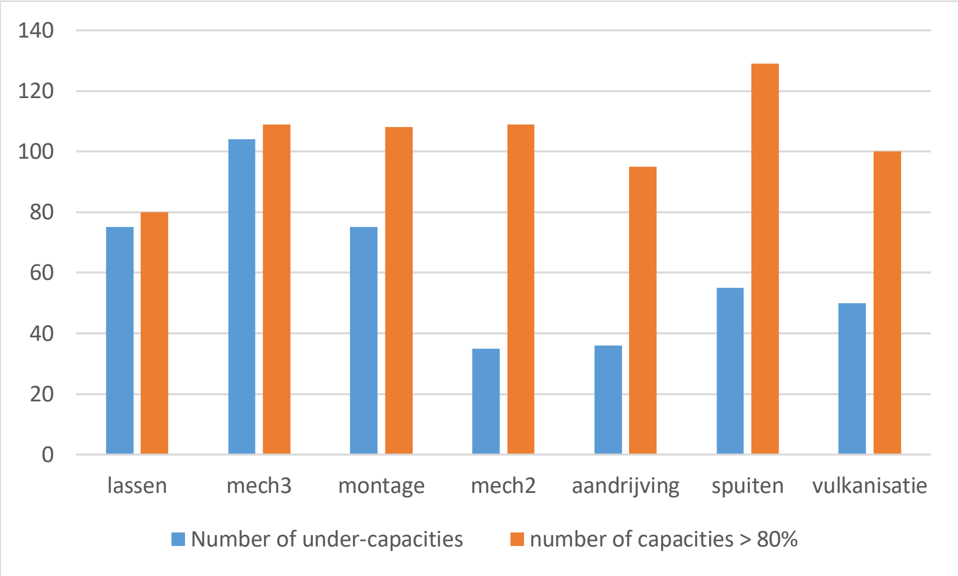
2.2.2 Bottlenecks

The problem described by Wouter Witzel is very broad. There is no distinction between the different production departments with regards to their under-capacity. However, the problem could be centred around one or a few production departments that are not able to handle demand while others are functioning properly. According to Chopra & Meindl (2016), a bottleneck is the most constraining area in a manufacturing facility. In figure 4 and figure 5 a schematic overview of the situation at Wouter Witzel can be found. Figure 4 shows the average capacity over a period of 220 weeks. There are four departments that have a capacity between 80% and 100%. This means on average these department are busier than Wouter Witzel wants the departments to be as they are over 80%. But they are manageable. The other three departments have an average score of more than 100%. It should be noted that this does not mean that there has been more demand than hours available because percentages rise quicker when they are above 100% for the same increase in demand. Furthermore, the department that stands out is 'welding' with an average occupation of 470%. While this is troublesome, it does not yield the biggest bottleneck for Wouter Witzel. The department of 'welding' negligible compared to the other department. Thus, one additional hour in demand yields a huge increase in capacity while this 1 hour extra has less impact in other departments. 'mech3' is a big department however, so the biggest focus will be put on 'mech3'. This can also be seen in figure 5, which shows the number of weeks a department has over 80% and over 100% capacity. From this we see that all the departments have around 100 weeks where the capacity is above 80% with 'welding' being lower and 'spraying' being higher. So 'mech3' is the department that requires the most forecasting aid, but all department also have a lot of cases where the capacity terms of Wouter Witzel are not met.



Legend	Translation
lassen	welding
mech3	mech3
Montage	Assembly
Mech2	Mech2
Aandrijving	Drive
Spuiten	Spraying
Vulkanisatie	Vulcanizattion

Figure 4: Demand as a percentage of capacity



Legend	Translation
lassen	welding
mech3	mech3
Montage	Assembly
Mech2	Mech2
Aandrijving	Drive
Spuiten	Spraying
Vulkanisatie	Vulcanizattion

Figure 5: Number of weeks out of 220 weeks per department where capacity was above 80% and/or above 100%

Now that a clear view of the situation has been gotten, the correct model for Wouter Witzel can be selected. To summarize, Wouter Witzel requires a model that can provide a forecast for seven different departments over a time span of 20 weeks. This model will give insight into the weeks where under-capacity could be an issue before the threshold of 80% or 100% has been hit. Before being able to select a model, a careful analysis of the available models in the literature must be made.

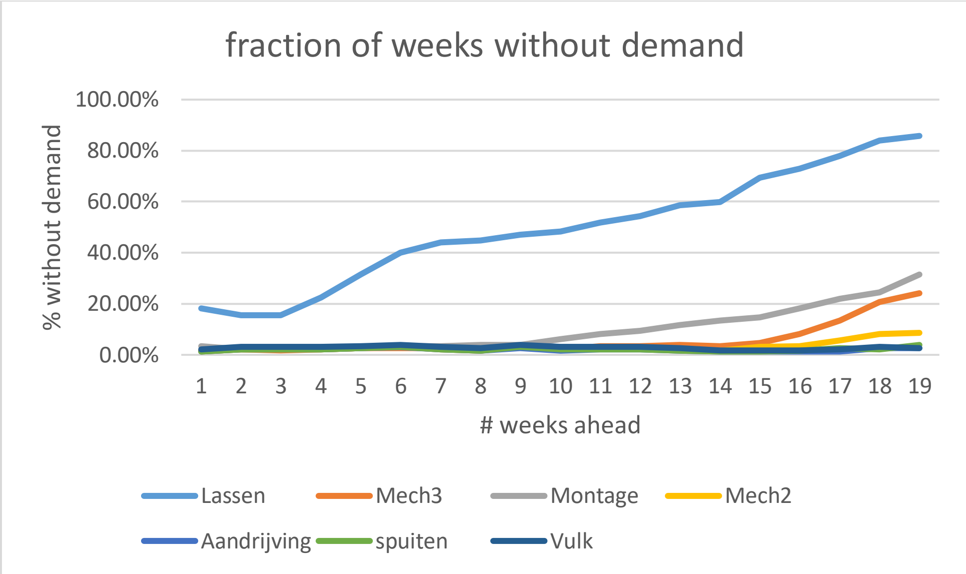
2.3 Intermittent demand

The data available is a weekly snapshot of the following 20 weeks of every department. Each week shows the demand that is currently known for each of the 20 weeks ahead for every department. While there is demand present for most weeks, there are weeks where no demand is present. This is not very significant if this happens on an infrequent basis. However, if it happens frequently, the model should take this into account. Silver, Pyke and Thomas (2017) state this is intermittent and erratic demand. They propose this can be solved by separating the 0 values from the rest using

$$y_t = \begin{cases} 1 \; if \; there \; is \; demand \\ 0 \end{cases}$$

$$F_t = y_t * F_t$$

Within figure 6 below, the fraction of weeks that contain no demand per week ahead per department is shown. The r two departments that have a higher fraction than others except 'welding' are 'mech3' and 'assembly'. Both departments have a higher fraction than the other departments. The number of weeks without demand start rising after week ten for 'assembly' and after week 14 for 'mech3'. As the fraction of weeks without demand start rising after week 10, these departments will not be considered as intermittent. Only 'welding' is considered of having intermittent demand with the percentage of weeks without demand being significantly higher than every other department. The 'welding' department will therefore be modelled using a different type of model. The model will be elaborated on in the next chapter.



Legend	Translation
lassen	welding
mech3	mech3
Montage	Assembly
Mech2	Mech2
Aandrijving	Drive
Spuiten	Spraying
Vulkanisatie	Vulcanizattion

Figure 6: fraction of weeks without demand

2.4 Trend and seasonality

An important aspect of a forecast is the trend and seasonality of the data. Trend is the continuous increase or decrease in demand. Seasonality is a reoccurring trend in the data based on a set period. The Covid crisis influenced the trend of Wouter Witzel, for a small while there was a negative trend during 2020. However, this evolved into a positive trend again from the start of 2021. This is illustrated by figure 7. This shows the total demand over all department per week per year. As a lot of backlog is present during week one in the sheets, this does not properly portae the situation. Therefore, the data from week two is taken. This shows that the demand of 2019 is almost consistently higher than 2018. In addition, the demand of 2021 is higher than the demand of 2020. Due to the Covid crisis and the corresponding drop in demand make it difficult to see whether a trend is present. The weekly demand of the different departments can be found in Appendix A. These graphs do not show a clear trend. Due to the influence of the Covid crisis and the upset it caused in demand, both options of trend and no trend will be explored. For this the demand pattern does not show a seasonal factor. However, Wouter Witzel does close in week 52 so therefore there is a huge dip in demand every year. This can be seen in the graphs in appendix A.

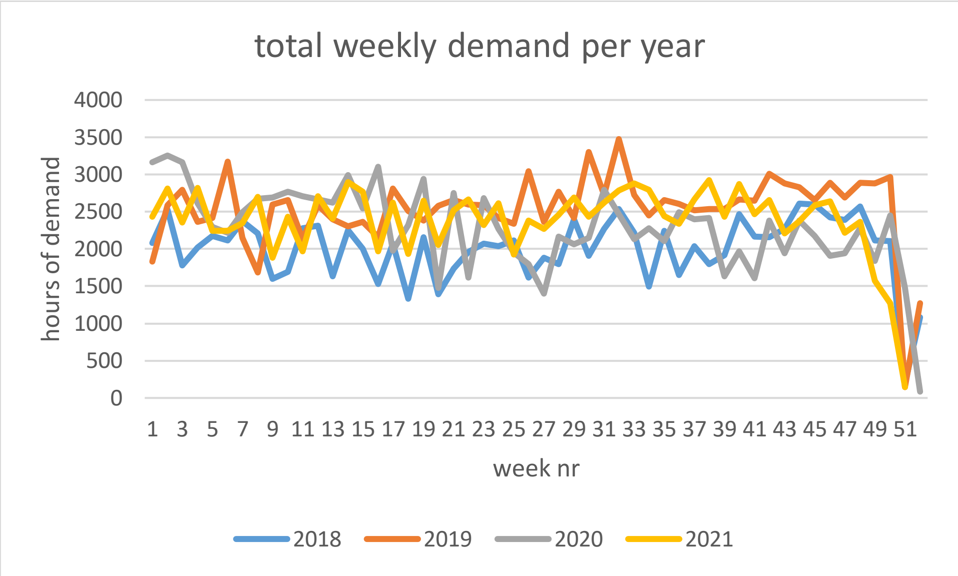


Figure 7: Demand in hours from 2017 to 2021 cumulative of all departments

2.5 Conclusion

Wouter Witzel already has a solid basis for the planning department. The overview of hours gives a clear view of the situation and serves as input for the forecasting model. Wouter Witzel requires a model so the total demand for every week from the current week to the week 20 weeks into the future is forecasted. This requires the model to forecast the additional demand from the current week until the corresponding week x weeks into the future. This expected total demand will be tested against the capacity to identify peaks in demand. The model will be based on the number of production hours demanded per week per department. The models that will be identified from the literature in chapter 3 will be modified based on the level of aggregation, the intermittent demand and the possible presence of trend and create a forecasting model for Wouter Witzel.

3. Literature review

Now that the problem has been identified and the current situation is clear, it is time to look at the available solutions in the literature. The models available in the literature will be evaluated on their advantages and disadvantages. Afterwards, the models will be tested against each other to select the fitting model for Wouter Witzel.

3.1 literature review

First, the forecast method will be a time series model. This type of forecasting model is the most fitting for the situation at Wouter Witzel as it is based on historic demand. In addition, time series work best when the demand patterns do not vary greatly each year. Within the time series approach, a distinction is made between static and adaptive forecasting (Chopra & Meindl, 2016). The static method is the more basic of the two as the assumption is made that the level, trend and seasonality do not change. The same set of data is used for every future forecast. Adaptive forecasting is done through updating the level, trend and seasonality after every new observation (Chopra & Meindl, 2016). At Wouter Witzel the assumption that level, trend and seasonality will remain constant over the future. Hence, a static method would result in incorrect forecasting values. In the paragraphs below, multiple adaptive forecasting models will be evaluated.

3.1.1 Simple exponential smoothing

The simple exponential smoothing model bases the forecast on a weighted average of the historic values and the historic forecasted values. The basis of the method is formulated in the formula below.

$$F_{t+1} = \alpha D_t + (1 - \alpha) F_t \qquad [1]$$

In the formula, C_t represents the actual demand, F_t represents the forecasted demand for time t and represents the smoothing constant. The smoothing factor influences the responsiveness of forecast to actual demand (Ravinder, 2013).

The simple exponential smoothing method is like the moving average method; thus, the advantages are similar. However, the simple exponential smoothing model has one extra advantage, the more recent values have a larger impact on the forecast than the older values (Ostertagova & Ostertag, 2011).

The model also comes with additional disadvantages to the moving average model. The simple exponential smoothing model is not equipped to handle trend or seasonality just like the simple smoothing.

3.1.2 Holt's model

As stated above, the simple exponential smoothing model is not able to incorporate trend into the model. The trend-corrected exponential smoothing model, otherwise known as Holt's model, is an adaptation of the simple exponential smoothing model that incorporates the trend into the model. It should be noted that the seasonality is still assumed to be zero within this model. Due to the absence of seasonality, the trend has a linear relationship with demand (Chopra & Meindl. 2016). Holt's formula the following

$$F_{t+1} = L_t + T_t \quad [2]$$

$$L_t = \alpha D_t + (1-\alpha)(L_{t-1} + T_{t-1}) \quad [3]$$

$$T_t = \beta(L_{t-1} - L_t) + (1-\beta)T_{t-1}$$

[4]

Both the level and trend are calculated using the level and trend calculated for time t and the observed level and trend. A smoothing factor is used in the calculation to balance the estimate at t-1 and the observed value at t.

The basis of Holt's model is the same for the simple exponential smoothing method and has the same advantages. However, the biggest difference is the ability to handle trend within the model. Furthermore, the smoothing factor adds the option of giving more weight to either the old estimate or the observed value. The biggest disadvantage of Holt's model is the inability to include seasonality.

3.1.3 Holt-Winters model

The Holt-Winters model is also known as the trend-and-seasonality-corrected exponential smoothing model. This model is an extension from Holt's model by adding seasonality to the forecast. Seasonality is defined as the data exhibiting behaviours that repeat every L periods (Kalekar, 2004). Before going into the model in more detail, a distinction should be made between two types of seasonal models, the additive and multiplicative.

3.1.3.1 Mixed

The mixed method must be applied when the seasonal value is proportional to the deseasonalized mean level and trend (Chatfield, 1978). The formula is formulated as follows:

$$F_{t+1} = (L_t + T_t) * S_t \quad [5]$$

3.1.3.2 Additive

The additive method must be applied when seasonal value is constant for every deseasonalized mean level (Chatfield, 1978). The formula of the additive method is the following:

$$F_{t+1} = L_t + T_t + S_t \quad [6]$$

For both the multiplicative and the additive method, the smoothing factor of the level and trend are computed similarly to Holt's method, however the seasonality is added. In addition, the seasonality factor is also computed using a smoothing factor.

The advantage of Holt's Winter model in comparison to Holt's model is the added seasonality. The model is now able to handle the most general form of demand data, level, trend and seasonality (Chopra & Meindl, 2016). What should be noted is that the added trend and seasonality also increase the difficulty of the model. Furthermore, there are no additional disadvantages in respect to Holt's model.

3.1.4 (S)ARIMA

The Autoregressive Integrated Moving Average or ARIMA is a forecasting model created from the time series analysis method introduced by Box and Jenkins. The standard version of the ARIMA is not able to handle seasonality. However, the (S)ARIMA does have the formulas to take seasonality into account. Furthermore, the model assumes linearity among the variables (Ghiassi, Saiane & Zimbra, 2005). The (S)ARIMA model is built with three phases. In the first phase, the data is analysed to select the type of model that best fits the data. (Vahfikyla, Hakonen & Leman, 1980). The next phase is the estimation of the parameters. The parameters are estimated by seeking the values that minimise the error variance. Lastly, the model is created and validated. The advantages of the (S)ARIMA are the ability to handle trend and seasonality. Furthermore, the (S)ARIMA can handle complex forecasting systems with a low error variance. The disadvantage of this model is that the math is complex, and it takes more time than the models above to develop.

3.1.5 Neural networks

All the forecasting models above, assume that the data used shows a linear pattern. If this is not the case, a neural network could be used for the forecast. Neural networks use a multilayer network with one or more hidden layers (Ghiassi, Saiane & Zimbra, 2005). The parameters of the model such as number of nodes and number of hidden layers are obtained using trial and error. The first steps of the neural network are to obtain a basis of the network through trial and error where the parameters with the best outcome are then further developed. Once an acceptable network has been created, the network is trained to minimise the error of the forecast. Neural networks can create a forecast from data that does not display linearity. This is a big advantage together with the constant improvement of the model. However, to create a neural network, a deep understanding of algorithms is required.

3.1.6 Croston Method

The Croston Method is used for forecasting when a product or in this case group of products has intermittent demand (SAP, 2022). Next to forecasting the level of demand, the Croston Method also forecasts the time interval on which the demand occurs. The forecast has 2 possibilities, a week with demand and a week without demand. A week with demand uses the following formulas

$$F(t) = F(t-1) + \alpha(D(t) - F(t-1)) \quad [7]$$

$$X(t) = X(t-1) + \alpha\big(q - X(t-1)\big) \quad [8]$$

In the first formula, F(t) is the forecasted demand for week t, α is the smoothing factor and D(t) is the actual demand of week t. Both formulas are subject to the constraint F(t) > 0 and D(t) >0. This formula calculates the expected demand when a week has D(t) > 0. The second formula calculates the expected interval of the demand. Where X(t) is the number of weeks between demand, q is the actual interval since the last demand. When a week has D(t) = 0, the following formula is used.

$$q = q + 1 \quad [9]$$

These two options lead to a forecasting model that measures both the expected demand and the expected interval of demand.

3.2 Model criteria

Now that the models from the literature have been identified, the most suitable model must be chosen. Hence, a list of criteria is created below. The models from the literature will be judged based on these criteria and the most suitable will be used in the next phase.
The criteria for the model are divided into two categories. The first category is about the requirements from the developer and Wouter Witzel and the second category is about the data requirements of the model.

This report is written for a bachelor thesis, this results in the developer of the forecasting model not staying at Wouter Witzel to maintain the model. Therefore, the first requirement is that the model should be easy to understand and use. This way future data can still be implemented, and the model can be permanently used at Wouter Witzel. In addition, the model should have a maximum development of 1 week. Additionally, the model should be able to deliver an accurate forecast over the span of 20 weeks.

The two most common elements mentioned in the literature review were trend and seasonality. It should be clear whether a model is able to handle these factors. Furthermore, the data present goes back to 2017. The model must both be able to handle these 4 years of data and no more should be needed to provide an accurate forecast. All the criteria can be found in figure 8.

Criteria	SES	Holt's model	Holt-Winters Model	(S)ARIMA	Neural Networks
Easily understandable and usable	🟢	🟢	🟢	🔴	🔴
Development time < 1 week	🟢	🟢	🟢	🔴	🔴
Accurate forecast up to 20 weeks	🟢	🟢	🟢	🟢	🟢
Able to handle trend	🔴	🟢	🟢	🟢	🟢
Able to handle seasonality	🔴	🔴	🟢	🟢	🟢
Able to use 4 years of historic data	🟢	🟢	🟢	🟢	🟢

Figure 8: criteria tested on the models from the literature

3.3 Model selection

To select a model, the requirements from chapter two are compared with the models found in the literature. First, (S)ARIMA and neural networks are invalid options as the models are too complicated and advances for the forecasting problem at Wouter Witzel. These will not be considered any further. Chapter two resulted in the conclusion that there is no seasonality present at Wouter Witzel. Furthermore, one of the models selected should be able to handle trend.

That leaves Holt's model and Holt-Winters model for the model that can handle trend. Both models suffice to the criteria, however the ability to handle seasonality is not needed. As stated above, the only difference is the ability to handle seasonality and since this is not required, Holt's model is the suitable choice to create a forecast with trend for Wouter Witzel. For the model that does not contain trend, SES will be used as it does meet the requirements for this type of model.

3.4 Error measurement

A good forecast does not end when the appropriate model has been identified and been elaborated. The model must be validated by evaluating the forecast using the difference in the forecasted demand and actual demand, also called the error. There are multiple methods of measuring error in the literature, the most relevant methods will be covered below.

Two of the most common methods used are the Mean Squared Error (MSE) and the Mean Absolute Deviation (MAD). The formulas of MSE and MAD can be found below.

$$MSE_n = \frac{1}{n}\sum_{t=1}^{n} E_t^2 \qquad MAD_n = \frac{1}{n}\sum_{t=1}^{n} A_t \qquad [10]\text{-}[11]$$

Where

$$E_t = F_t - D_t \qquad A_t = |E_t|$$

The methods are quite similar as they use a positive value of the error to find the average. However, the MSE punishes the large error far more than the MAD as the MSE takes the square of the error instead of the absolute value. Nevertheless, both methods are not ideal for the forecast at Wouter Witzel. Due to the difference in size of the departments, an absolute value does not give an appropriate view of the situation. An average error of 20 is massive at ‘welding’ while small at ‘mech3’.

Mean Absolute Percentage Error (MAPE) measures the error as a percentage of the demand. Therefore, MAPE gives a better view of all the seven departments and ensures an even evaluation of the error. However, due to the fluctuations in demand, MAPE might lead to large percentages while this does not properly portray the situation. To handle the error correctly, Symmetric Mean Absolute Percentage Error (SMAPE) will be used. SMAPE incorporates both the forecasted demand and actual demand to return a percentage between 0 and 100 percent. With SMAPE, 0 percent is equal to a MAD of 0 and 100 percent is equal to a MAD that approaches infinity.

$$SMAPE = \frac{100\%}{n}\sum_{t=1}^{n} \frac{|F_t - A_t|}{|A_t| + |F_t|} \qquad [12]$$

However, only using squared or absolute values of the error does not allow the signalling of constant over or under forecasting due to a shift in the demand pattern. For instance, the market could have dropped due to the outbreak of Covid. Therefore, it is important to know the bias of the forecast. The ideal situation is a bias around 0, so the errors are distributed evenly and not biased. To track the bias, a tracking signal can be calculated using the following formula.

$$bias_n = \sum_{t=1}^{n} E_t \qquad [13]$$

If the tracking signal (TS) exceeds +-6, the model is under- or over forecasting. The last method that will be used is the standard deviation. The standard deviation will be used together with the forecast to determine the value when the user of the model will be notified of a peak.

$$TS_t = \frac{bias_t}{MAD_t} \qquad [14]$$

3.5 Conclusion

After evaluating the models found in the literature, the most suitable option for Wouter Witzel has been identified. Holt’s model checks the boxes for all the criteria needed and does not contain any irrelevant aspects for Wouter Witzel. SES is a simpler model but suffices for the model that does not contain trend. These models will be created in the next chapter. The welding department has intermittent demand and will therefore not use SES or Holt’s model but the method of Croston. The models will be evaluated based on the error measurements from the literature, where the SMAPE will be the method used to evaluate the model between the departments for Holt’s model.

4 Model creation

In this chapter, the models are created using the methods found in the literature and the current situation at Wouter Witzel. From the data present at Wouter Witzel, two methods are used to implement the data into the model. Section 4.1 contains an overview of the variables used and in section 4.2 a list of assumptions can be found. Section 4.3 covers the creation of the model, elaborating on the models and methods used. The output from these models is transformed in the expected total demand in section 4.4. As the welding department differs greatly from the others, a separate method is proposed in section 4.5.

4.1 Overview of variables

Within this chapter new formulas and variables are introduced. This table only serves as an overview of the variables used. The variables will be elaborated on in within this chapter.

Variables	
t	Current week
x	# of weeks ahead
$D_t(x)$	Known demand of week t + x ahead in week t
$A_t(x)$	Known additional demand of week t + x gained in week t
$F_t(x)$	Forecasted demand of x weeks ahead in week t
$P_t(x)$	Forecasted additional demand for week t + x week in week t
$L_t(x)$	Level of x weeks ahead in week t
$T_t(x)$	Expected increase in demand between week t and t + 1 for x weeks ahead
$Y_t(x)$	Expected total demand for week t + x in week t, calculation depends on method used, see formula 23, 24 and 27
$X_t(x)$	Expected time interval on which demand occurs x weeks ahead in week t, so next week where demand is expected is t + ($X_t(x)$ - # of weeks since last demand)
C_t	Capacity of production hours of week t

Table 1: overview of variables

4.2 Assumptions

For both methods, certain assumptions are made that lead to limitations of the model. These assumptions are made to limit the complexity of the model. The model treats each week ahead as a separate week that is not influenced by the demand in other weeks, both for different values of x in the same week t and for weeks with the same t + x but a different t. This is done to limit the complexity of the forecasting model. So, a large order placed 9 weeks ahead does not influence the orders that will be placed in the next week 9 weeks ahead or the orders in the same week but for $x \neq 9$. Furthermore, the demand for each department is assumed to be independent. A large order for 'mech3' does not influence the demand for 'assembly' in the model. As there are weeks in which the demand exceeds the capacity, there are orders that will get backlogged. These backlogged hours are moved to other weeks and therefore serve as input multiple times. These hours are not denoted separately within the data sets and cause the total demand over all weeks to be higher than the actual situation. However, for the simplicity of the model the data is treated as if all input are new orders. These assumptions ensure the forecasting model does not exceed the expected level for this thesis.

4.3 The model

First of all, within the next chapters the distinction is made between the welding department and the other departments. The welding department will be forecasted using the Croston method described in chapter 4.4. The other departments are described in chapter 4.2 and 4.3. The optimal model for Wouter Witzel is found by testing two forecasting methods with two data sets, resulting in four different forecasting models. The two forecasting methods are the methods selected in Chapter 3, Holt's method and SES. So, in the case of referring to two methods or four models, Croston is excluded. Furthermore, with method a forecasting method such as Holt's or SES is meant and with model, a model created using a forecasting method and a particular data set is meant.
The two data sets that are used as input are the 'known demand data set' and the 'additional demand data set'. The known demand data set contains the demand currently known to Wouter Witzel for every week from the current week until 20 weeks ahead. This data is noted as $D_t(x)$where t is the current week and x the number of weeks ahead from the current week until 20 weeks ahead. So $D_5(8)$ will contain the number of hours demanded in week 5 for week 13. The other formulas also use this notation of t and x unless specified otherwise. The additional demand data set contains the weekly increase in demand for each of the 20 weeks ahead. The unit used when speaking about demand is hours. This is noted as $A_t(x)= D_t(x) – D_{t-1}(x+1)$. Using t= 5 and x = 8 again, $A_5(8)$ contains the increase in demand in week 5 for week 13.
Both data sets contain the historic data from 2018 to 2021, where 2018 and 2019 is used to determine the initial values of the forecasts and 2020 and 2021 is used to test the forecasting model. The four models that are described below will all be applied to every department except 'welding'.

4.3.1 Holt's method

The first model is based on Holt's method for forecasting. Holt's method will create a forecast that incorporates a trend using the known demand data set and additional demand data set. The outcome of Holt's method for the known demand data set will yield an expected demand for each week ahead x in week t, where $(1 \le x \le 20)$. The expected demand in week t for week t + x is noted as $F_t(x)$. To clarify, the different weeks x are not linked but are separate forecasts. So, the forecast of $F_t(x)$has no influence on $F_{t+1}(x-1)$. This term will be used for the data set on total demand, the expected additional demand is denoted as $P_t(x)$ and will be used for the data set on the additional demand.

Both methods require an initial level and trend that serve as the base values for the forecast. These values are based on the historic data of the corresponding data set. The trend that will be calculated below is the trend from the start of week t till the end of week t. So, the trend used in calculations for week 18 is the trend that happened in week 17. For both data sets, there is no clear pattern visible within the data when put into a scatter plot. Hence, a linear regression was performed on the data using the method from Chopra and Meindl (2005). The initial values for both methods can be found in Appendix B.

First of all, the data set containing the known demand. Holt's method uses the level and trend to calculate the expected demand for x weeks ahead in week t. Using the initial values, the level and trend are calculated using the following formulas. The α and β are the smoothing factors of the Level and the Trend.

$$L_{t+1}(x) = \alpha * D_{t+1}(x) + (1-a) * (L_t(x) + T_t(x)) \quad [15]$$

$$T_{t+1}(x) = \beta * (L_{t+1}(x) - L_t(x)) + (1-\beta) * T_t(x) \quad [16]$$

Where $L_t(x)$corresponds the level and $T_t(x)$ corresponds the trend x weeks ahead in week t. These values are then used to calculate the expected demand using the following formula. Thus, a forecast for the week t will results in an expected demand for each of the x weeks ahead where $1 \leq x \leq 20$.

$$F_{t+1}(x) = L_t(x) + T_t(x) \quad [17]$$

The second forecasting model based on Holt's method uses the additional demand data as input for the model. The goal of the model is to determine the expected additional demand $P_t(x)$for each x weeks ahead in week t. With expected additional demand is meant, the additional demand that is expected to occur for x weeks ahead in week t. The initial values of the level and trend are also calculated using the historic data of 2018 and 2019. The level, the trend and $P_t(x)$ calculated using the following formula. While both methods use level and trend, the formulas used are different. So, formula 17 must be calculate using formula 15 and 16 while formula 20 must use the level and trend calculated in formula 18 and 19.

$$L_{t+1}(x) = \alpha * A_{t+1}(x) + (1-a) * (L_t(x) + T_t(x)) \quad [18]$$

$$T_{t+1}(x) = \beta * (L_{t+1}(x) - L_t(x)) + (1-\beta) * T_t(x) \quad [19]$$

$$P_{t+1}(x) = L_t(x) + T_t(x) \quad [20]$$

As stated in the literature review, the model selected uses smoothing to control the sensitivity of the model. A higher smoothing factor means $D_t(x)$ has more influence on the next forecast value and the model will react to changes in demand patterns faster. However, by focusing more on historical data, the model smooths out the random noise (Silver, Pyke & Thomas, 2017). To find the correct smoothing constant for the model, experiments have been set up by running the model with a smoothing constant between 0.05 and 0.4 with a step of 0.05 for both α and β. Silver, Pyke and Thomas (2017) state that selecting a smoothing constant larger than 0.3 should not happen as it raises questions about the validity of the model. The experiments were judged on the average SMAPE from $F_t(x)$ and $P_t(x)$for all t and all x. The departments are judged separately and will each receive an own α and β. For the first method, the experiments showed that for all departments, a β of optimal while the optimal α different. In table 2 and table 3 below, the SMAPE of all departments for the optimal α and β is shown. The full results of the experiment can be found in Appendix C.

Known demand data set	α	β
Mech3	0,3	0,05
Assembly	0,3	0,05
Mech2	0,25	0,05
Drive	0,2	0,05
Spraying	0,25	0,05
Vulcanization	0,25	0,05

Additional demand data set	α	β
Mech3	0,15	0,05
Assembly	0,1	0,05
Mech2	0,15	0,05
Drive	0,15	0,05
Spraying	0,2	0,05
Vulcanization	0,2	0,05

Table 2 & 3: optimal smoothing factors of both data sets

In both cases, the optimal smoothing factors do not exceed 0.3 and therefore the threshold as stated by Silver, Pyke and Thomas (2017). In Table 2, 3 departments do show an optimal value of $\alpha = 0.3$. While this is relatively high, the tests show an increase in the SMAPE when α gets a value higher than 0.3 so this is not an issue. However, the smoothing factor should be decreased as more data is added as the forecast will most likely become more reliable. The 'drive' and 'vulcanization' department have a shared optimal smoothing factor for α. The lowest optimal value has been selected. As previously mentioned, the forecast will most likely become more reliable as more data is added and thus a lower smoothing factor is better.

4.3.2 Simple Exponential Smoothing

The second method that is tested is Simple Exponential smoothing (SES). Similarly to Holt's method, SES will be applied to the known demand data set and the additional demand data set. Using the known demand data set, the model will yield a value for $F_t(x)$. The value will be calculated using the following formula. The γ is the smoothing factor used for this method.

$$F_{t+1}(x) = \gamma * D_t(x) + (1 - \gamma) * F_t(x) \qquad [21]$$

The data set containing the additional demand uses the same formula to calculate the expected additional demand for x weeks ahead in week t.

$$P_{t+1}(x) = \gamma * A_t(x) + (1 - \gamma) * P_t(x) \qquad [22]$$

The initial values of the known demand data set are calculated by taking the average of the known demand per week x ahead. Resulting in a starting value for each value of x. The initial values of the additional demand data set were calculated in a comparable way, by taking the average of the additional demand for every x. The initial values can be found in Appendix B.

Lastly, the optimal smoothing factor γ is determined by a set of experiments where the SMAPE of the forecast was measured for a γ that ranged from 0.05 to 0.4 with a step of 0.05. The values of the SMAPE can be found in table 4 and table 5 We can see that the smoothing factor from the data set contains the known demand results in an optimal γ that does not exceed 0.3 and is therefore valid. However, the optimal smoothing factors in table 5 all result in an $\gamma = 0.4$. Moreover, values higher than 0.4 are not explored so the optimal smoothing factor is most likely higher than 0.4. The full data of the results can be found in appendix D. While this forecast will be tested, the model could be considered invalid due to the required smoothing factor combined with the large SMAPE. However, this is determined in the results.

Known demand data set	γ
Mech3	0,25
Assembly	0,1
Mech2	0,2
Drive	0,2
Spraying	0,15
Vulcanization	0,1

Additional demand data set	γ
Mech3	0,4
Assembly	0,4
Mech2	0,4
Drive	0,4
Spraying	0,4
Vulcanization	0,4

table 4 & 5: optimal smoothing factor of both data sets for SES

4.4 Expected total demand

The goal of the model is to create a forecast that estimates whether a certain week x ahead will result in a peak value by crossing the threshold of 100% of the capacity. Thus, both the estimated demand for x weeks ahead in week t and the additional demand obtained for x weeks ahead in week t must lead to an estimate of the expected total demand of week t + x. The expected total demand of week t + x in week t is noted as $Y_t(x)$. The total demand is calculated by adding the expected demand between the current week and week t + x to the known demand in week t.

The expected total demand for the method using the known demand data set is calculated using the following formula. The expected demand is calculated by taking the difference in the expected value of demand x weeks ahead, $F_f(x)$, and the expected value of demand 0 weeks ahead, the week in which the demand is due, denoted as $F_t(0)$.

$$Y_t(x) = D_t(x) + (F_t(0) - F_t(x)) + x * T_t(x) \qquad [23]$$

The methods that use the additional demand data set use the following formula to calculate the expected total demand of week t + x in week t. Similar to formula 23, the total expected demand is calculated by adding the expected demand between week t and week t + x to the known demand in week t x weeks ahead, at the start of week t. The expected demand is calculated by taking the weekly additional demand from x weeks ahead until 0 weeks ahead.

$$Y_t(x) = D_t(x) + \sum_{z=0}^{x} P_t(x - z) \qquad [24]$$

4.5 Croston Method

For the 'welding' department the Croston Method for intermittent demand is used. The model analyses the current week $D_t(x)$ for all x to see whether t + x has D(x) > 0. If week t + x does have demand in week t, the model calculates the new expected demand and the new expected interval. This is done through the following formulas obtained from SAP (2022). $X_t(x)$ denotes the expected average interval on which demand occurs

$$F_t(x) = F_{t-1}(x) + \alpha * (D_t(x) - F_{t-1}(x)) \qquad [25]$$

$$X_t(x) = X_{t-1}(x) + \beta * (q - X_{t-1}(x)) \qquad [26]$$

As demand is not always present, $F_t(x) = F_{t-1}(x)$ and $X_t(x)= X_{t-1}(x)$ if $D_t(x)=0$. The other formula used for weeks where $D_t(x) = 0$ is q = q +1. q denotes the number of weeks since the last $D_t(x) > 0$. The initial values of the model are based on the method from SAP(2022) where if $D_1(x)) = 0$, then $F_0(x) = 1$ and $X_0(x)= 2$. If $D_0(x) > 0$, then $F_0(x) =$D $F_1(x)$and $X_0(x)= 0$.

The smoothing factors has been determined using the same experiment as for the four models above, showing an optimal smoothing factor of α = 0,35 and β = 0,5. The full experiment can be found in appendix E.

The $Y_t(x)$ of the Croston Method is calculated using formula 27. The formula takes the demand that is currently known and adds the difference in demand between the forecast of the week ahead minus the demand that is forecasted in week t for week t + x. The difference between these values leads the total expected increase in demand.

$$Y_t(x) = D_t(x) + (F_t(0) - F_t(x)) \qquad [27]$$

4.6 Conclusion

This chapter has created the basis of the four forecasting models that will be executed in the next chapter. The models are based on Holt's forecasting method and Simple Exponential smoothing using a data set that either contains the total known demand for x weeks ahead in week t or the additional demand that has been obtained for x weeks ahead in week t. Having calculated the initial values and obtaining the optimal smoothing factor using experiments, the models have got all the necessary components to be executed. Furthermore, the method of comparing the forecast to the capacity has been determined. Lastly, Croston's method for the welding department has been turned into a usable model for Wouter Witzel. The next chapter will test the models created and measure their performance.

5. Results

In this chapter, the results created by the five models will be analysed to determine the optimal forecasting method for Wouter Witzel. The methods will be judged on the error comparing the forecasted demand to the actual demand. Moreover, the $Y_t(x)$ will be compared to the capacity to generate signals whether the model correctly predicts demand exceeding the capacity. This will generate the necessary data to select an optimal forecasting model for Wouter Witzel.

5.1 SMAPE

The first error measurement method used is SMAPE. The SMAPE will be measured of the Ft(x) and the $P_t(x)$ for the known demand data set and the additional demand data set. $Y_t(x)$ will be studied later this chapter. As stated in chapter 3, SMAPE is a variation of MAPE that limits the possibility of huge peaks, as the SMAPE is not able exceed 100%. The forecast is evaluated for every week x ahead separately, so a SMAPE is measured for x weeks ahead over every week t per department. However, to judge the entire forecast, the average of the different departments is taken. Holt's method is judged using the scale of Lewis (1982, cited in Klimberg et al., 2010). The scale is shown in table 6.

SMAPE	Forecast accuracy
0-10%	Very accurate forecast
11-20%	Accurate forecast
21-50%	Medium forecast
51-100%	Inaccurate forecast

Table 6: judgement of SMAPE

Figure 9 shows the average SMAPE for every week x ahead of the four models. It immediately stands out that both methods that use the additional demand data set have a SMAPE almost permanently is above 50% and thus an inaccurate forecast. This is because every data points error is measured based on a single week, leading higher values as the hours cannot be smoothed over multiple weeks. Furthermore, the values are smaller hence a deviation of one hours has a much larger impact on the error. Only week 1 of Holt's method and week 20 of both can be considered medium forecasts. Due to this, these two methods cannot be considered as being an optimal forecast for Wouter Witzel based on the SMAPE. The two methods based on the known demand data set show a better SMAPE. The first 6 weeks can be considered accurate and up till week 14 the forecast is good. So based on the SMAPE, these two methods can be considered as the forecasting method for Wouter Witzel. In addition, the graphs show the type of data matters far more than the forecast method used, as both methods yield a similar SMAPE for each data set. Hence, the choice of forecasting method cannot be based on the SMAPE.

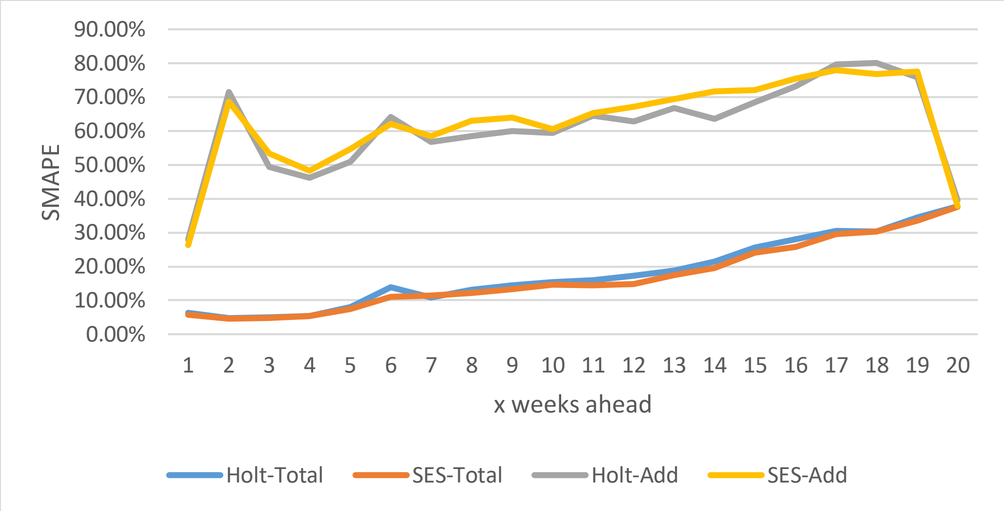


Figure 9: SMAPE per x weeks ahead

5.2 MAD

MAD is the other error measurement method used. Within this method, the distinction between the two data sets is made. As the known demand data set forecasts the cumulative demand for week t + x that is known in week t, while the additional demand data sets forecast the additional demand for week t + x in week t and the MAD is only for x weeks ahead in week t. As a result, the MAD is interpreted differently.

Figure 10 shows the MAD of the 4 models. First of all, similarly to the SMAPE, the deviation of both data sets for the different methods are very similar. The average difference in MAD is 3,4 hours for the known demand data set and 1,1 hours for the additional demand data set. So, Holt's method and SES do not vary much in terms of SMAPE and MAD. The known demand data set decreases in MAD as x rises. This is due to the size of the known demand, weeks further in the future have a lower known demand and therefore a lower MAD. In addition, all four models have a similar MAD for x = 20. As there is no demand known for x > 20, the total known demand for x = 20 can also be regarded as the additional demand gained for x = 20. Hence, the forecasts and MAD are similar.

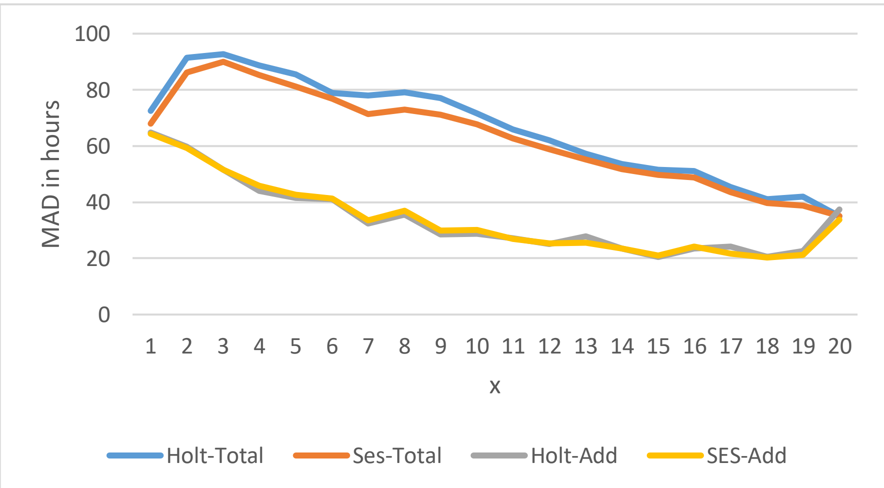


Figure 10: MAD of the four models in hours for x week ahead

However, seeing as the MAD of the known demand data set is cumulative and the additional data set, the values of the MAD are much higher in respect to the $F_t(x)$ or $P_t(x)$. This is visualised in figure 11. In this figure it can be seen that both forecasts using the additional demand data set have a MAD that is not lower than at least 1 time the average value of the forecast. Holt's model has a MAD that is around 2 times the average of the forecast, which is a large error. SES produces an even larger error using the additional demand data set having 2 times the average value of the forecast for most values of x and reaching 11 times the average value of the forecast for x = 17, x = 18 and x =19. The large ratio must be put in perspective as the value of $P_t(x)$ is relatively small so a small MAD can already cause a large ratio. However, an average ratio of 10 is unacceptable as it leads to very inaccurate results. In addition, the ratios are similar for x = 20 for the similar reason as in figure 10. The graph shows that the ratio of the forecasting methods using the known demand data set are very similar and have a ratio starting at 22% at x = 1 and consistently increasing to 65% for x = 20. The increase in ratio is caused by the fact that a forecast for a larger x is more uncertain and has a larger error compared to the average of the forecast. As the forecasts using the known demand data set use data that is cumulative, the average of the forecast is lower as x increases. So, the ratio increases while the MAD decreases.
The forecasts using the additional demand data set have yielded a SMAPE that is considered inaccurate and a MAD that is at least 2 times the forecasted value. Hence, the forecasts using the additional demand data set will no longer be considered as an optimal solution in this thesis and will therefore not be researched any further.

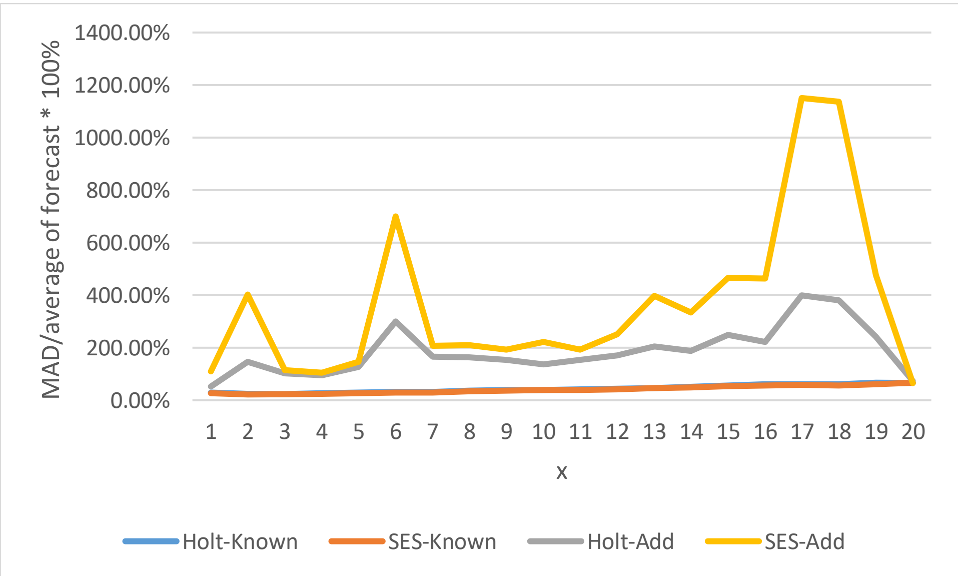


Figure 11: MAD compared to the average value of the forecast of all models for x week ahead

5.3 Bias

Prior to the identifying the week where the threshold of 100% is exceeded, the bias of both models is measured. The bias of the error provides insight whether the model has the tendency to over- or underestimate the forecasted values. The bias is measured through the method described in chapter 3 and the results can be found in figure 12. The importance of the bias for the model is to obtain more insight into the influence of an over- or underforecast on the signalling of peaks in demand. A positive bias leads to a larger expected total demand and thus a broad range of values which are forecasted to be higher than the capacity. Logically, a negative bias led to a smaller range. As the signals in the next section will be based per t, figure 12 shows the bias compared to the capacity per week for each x. All departments for both methods have an average bias that is positive. Most values lie around 1-2%, meaning a positive bias that should be noted but which will not have a considerable influence on the analysis of the signals. A cause of the positive bias could be Covid, due to the dip in demand which was not incorporated in the training set as Covid was not present yet. So, a higher forecast was generated, not incorporating the situation. As Holt's model has a lower smoothing factor, the model responds slower to this change which can be seen in the higher bias. In general, the bias of SES lies much lower than Holt's method. For the assembly department, the bias is much larger for both models. As mentioned in the assumptions, the backlog is not taken into account in the model. As the assembly is the final step for most butterfly valves, a delay in another department also causes a delay and therefore backlog in the assembly department. Due to backlog the hours are counted double within the model which leads to a higher forecast than the actual situation. This causes the bias to be much higher for the assembly department than the other departments.

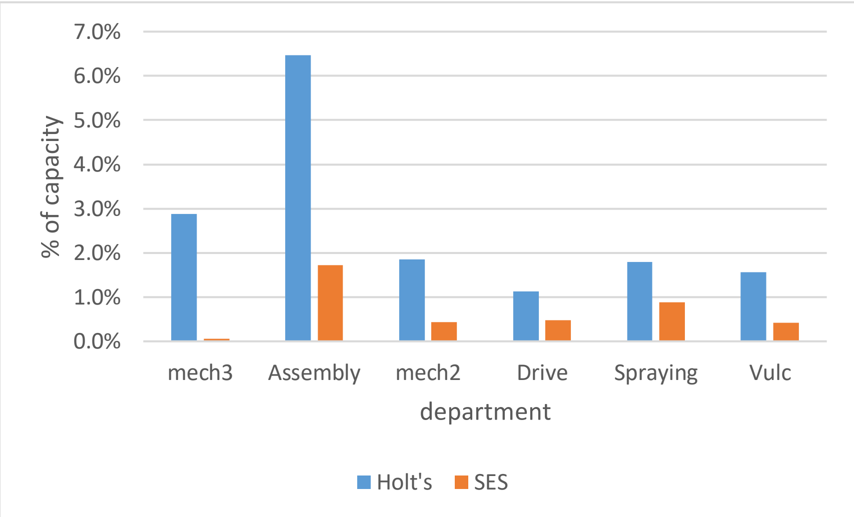


Figure 12: weekly bias as a percentage of the capacity per department for both methods

5.4 identification of alarms

The final step of both models is to estimate whether the demand will surpass the 100% capacity threshold for each x weeks ahead in week t. Each $Y_t(x)$ will be evaluated based on two different criteria. The first criterion is whether the forecast surpasses the capacity and the second criteria is whether the actual demand of week t + x surpasses the capacity. The capacity is denoted as $C_{t+x.}$ The judgement of the alarms can be found in table 7.

	$D_t(x) > C_{t+x}$	$D_t(x)) < C_{t+x}$
$Y_t(x) > C_{t+x}$	Correct Alarm (CA)	False Alarm (FA)
$Y_t(x) < C_{t+x}$	Missed Alarm (MA)	No Alarm (NA)

Table 7: Type of alarms

The signals will be analysed using 2 different methods. A threshold based on the standard deviation will be used in this section and in section 5.5 the Empirical Distribution Function (EDF) will be used. The method that results in the best results will be used in the final model. The measure of uncertainty is calculated using the MAD of the forecast, derived from the formula of the standard deviation. To find the optimal threshold, an experiment was conducted where the threshold was determined by i*MAD where $0 \leq i \leq 1.25$ with a step 0f 0.05. To be able to select the optimal i and therefore threshold, a trade off must be made. By increasing i, the number of MA's and CA's will increase while there will be less FA's and NA's. Wouter Witzel has stated that their preference lies with more FA's and less MA's as the FA's allows them to judge an FA with their own expertise while an MA flies under the radar.

The alarms are grouped into two groups, there is the combination of CA and MA and the combination of FA and NA, grouped on the fact whether the actual demand is higher or lower than the capacity. The sum of CA and MA yields the similar outcome for each I, similar for the sum of FA and NA. The adaptation of factor i yields in a trade-off between these to groups. Decreasing i creates a lower threshold and therefore causes CA to increase and MA decrease against the increase of FA and decrease of MA. Looking at the absolute number of NA's and CA's, the optimal i = 1.25 and likely higher. However, the sum of FA's and NA's is 10024 while CA's and MA's are merely 464. While the distinction between CA's and MA's is valued more. Hence the optimal i is determined by taking the percentage of own group of CA and MA and compare these values. This yields an optimal i = 0, so the model produces the optimal number of alarms without a measure of uncertainty. Decreasing the value of i leads to more CA's, less MA's but also more FA's. As more correct alarms and especially less MA's are very important, taking a low i is logical. The experiments can be found in appendix F.

Prior to the comparison of Holt's method and SES, both will be evaluated by being compared to the signal analysis of the moving average method. The MA was performed over years 2020 and 2021 of the know demand data set using the average of 10 weeks prior. This method is the most basic method used when forecasting and is used as benchmark. Within the data set used, there are 464 cases of x weeks ahead in week t where $D_t(x) > C_{t+x}$, so under-capacity. While there are 10024 cases where there is no under-capacity. So, by comparing them on an absolute level the cases of x weeks ahead in week t where undercapacity is present will have little influence on the comparison while these are the most important cases of the model. So, the models are compared by the percentage of cases the model signalled correctly with respect to their type of week. So, the percentage of cases of x weeks ahead in week t where a CA is signalled in the case of under capacity and the percentage of cases when no alarms was signalled in the case of no undercapacity. In figure 13, the percentages of the weeks that have signalled the correct type of alarm are shown. These are based on the weekly analysis of the forecast for every value of x for each of the 6 departments. So, for x = 13, 61,48% of the weeks in 2020 and 2021 resulted in a correct alarm or no alarm for the 6 departments. The figure shows that MA initially outperforms Holt's method and SES. This shows that the additional factors that SES and Holt's model provide do not matter for low values of x. These weeks where demand fluctuates less benefits from a smaller sample on which the forecast is based. However, around x = 7 both models catch up to MA and start outperforming MA. At this point demand fluctuates more and therefore a larger basis of historical data and smoothing increases the performance of the forecast model. After x = 7, both Holt's method and SES perform consistently better than MA. Taking the fact that the first few weeks are less important for Wouter Witzel, it can be concluded that both models perform better than the benchmark set by the MA method.

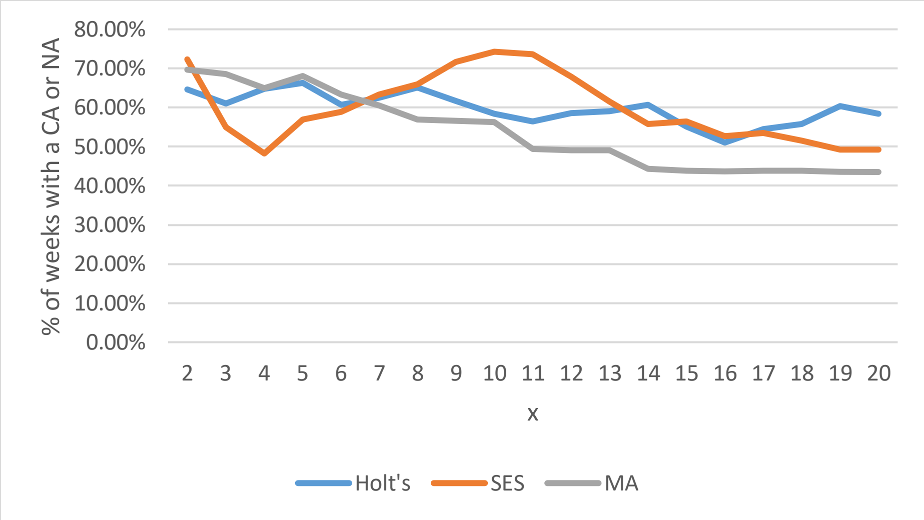


Figure 13: Percentage of weeks with a correct type of alarms for each x

Comparing Holt's method to SES, the total number weeks a week t + x was given the correct signal against the weeks where the signal was wrong is presented. This is visualised in figure 14. First of all, as there are 6 departments for which signals are created, there are 6 * 104 weeks for which signals are created. From this figure it can be seen that initially, Holt's method outperforms SES by a lot. This is mainly caused by the large number of FA's that are produced by the SES method. For the first few values of x, SES forecasts high values that results in these false alarms. These values are not visible within the SMAPE and MAD because they are cancelled out by the average. The forecast for the first few values of x does not contain extreme results, however it is almost constantly above the capacity. However, around 12 to 13 weeks ahead, SES outperforms Holt's method, however only marginally.

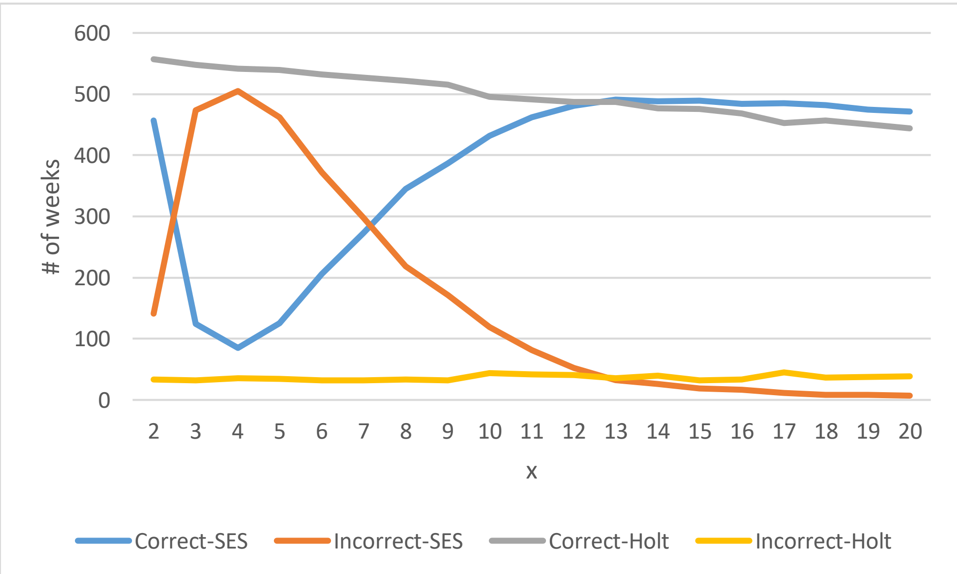


Figure 14: Total correct and incorrect alarms for both methods

As stated before, a MA's is regarded as the worst type of alarm as it can not be noticed. However, the analyses of the alarms do not take the possibility into account that a missed alarm can be noticed in a later week. The same week denotes the same value of t + x. What we can see that for both models, almost all MA's are observed in a later week, where out of 104 weeks and 6 departments, 9 weeks were missed by Holt's method and 1 week by SES.

As stated in the previous section, the forecast of both models contain a positive bias. For assembly the bias was considerably higher compared to the capacity than the other departments. The effect of the bias for the assembly department for Holt's method can be seen in figure 15. The figure shows the amount of FA's per department over all values of x. The graph shows a similar pattern to figure 12, that the high bias leads to more false alarms due to the over estimation of demand in the forecast. Hence, the bias should be factored in in the delivered model to deliver more insight into the alarms created by the forecast.

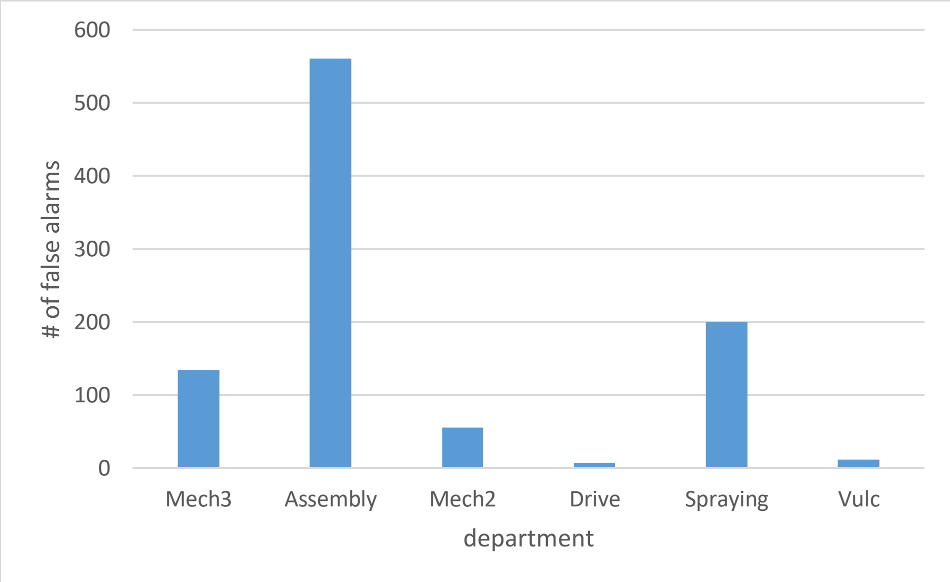


Figure 15: amount of FA's per department for Holt's method

5.5 Signal analysis based on empirical distribution

In chapter 5.4 the signaling is done based on a threshold to determine whether a value is a peak value or not. However, the signals can also be identified using an Empirical Distribution Function (EDF). The cumulative distribution is calculated using 1 year of historic data prior to week t and contains the expected additional demand for both Holt's method and SES. Within week t, if the known demand has not surpassed the capacity, a number of hours, $C_t(x) – D_t(x)$, is left. Using the formula below based on the formula stated by Singer and Andrade (2010), the probability whether the remaining capacity will be exceeded by the additional demand between week t and week t + x for the known demand data set. So, the probability equals the fraction of weeks from the past 52 weeks in which the additional demand exceeds the current remaining capacity.

$$R_t(x) = \frac{1}{52} * \sum_{z=t-53}^{t-1} I(C_t(x) - D_t(x) \leq \; F_{z+x}(0) - F_z(x)) \qquad [28]$$

Where i is an indicator function assuming the value 1 if $C_t(x) – D_t(x) \leq F_{z+x}(0) – F_z(x)$ and the value 0 otherwise. The fraction 1/52 equal the number of summations which equals 1 year. Based on the probability whether a week will exceed the capacity given the known demand for that week, an experiment is run to determine the threshold for what probability a signal will be given. Probabilities ranging from 0.5 to 0.95 were tested for both Holt's method and SES resulting in a threshold of 0.5 for Holt's method and 0.85 for SES. The signals created by the model are visualized similar to MA in section 5.4. The results are visualized in figure 16. First, looking at the absolute and empirical threshold of Holt's method. The empirical threshold performs better for x =15 and x=16. However, the absolute threshold yields better values for every other value of x. In addition, Holt's method using the EDF results in a very low number of correct signals for x =2. Within the data, there were many weeks for which there was no capacity left. While these were not analyzed for a signal, they are incorporated the calculations for weeks where there is capacity left. So, weeks with high demand for x = 2 contribute to the probability. So, a high probability to exceed the capacity while this does not happen as often leads to many wrong signals. This effect reduces as x increases but is clearly visible for x = 2. It can be concluded from this that the signal analysis using the absolute threshold produces better results for Holt's method. In the case of SES, the values are much closer and the absolute threshold yields better values in only 13 weeks. However, the absolute thresholds are easier to interpret for the planning department than the values produced by the EDF. Combining the slightly better results with the easier implementation at Wouter Witzel, the absolute threshold will also be used for SES.

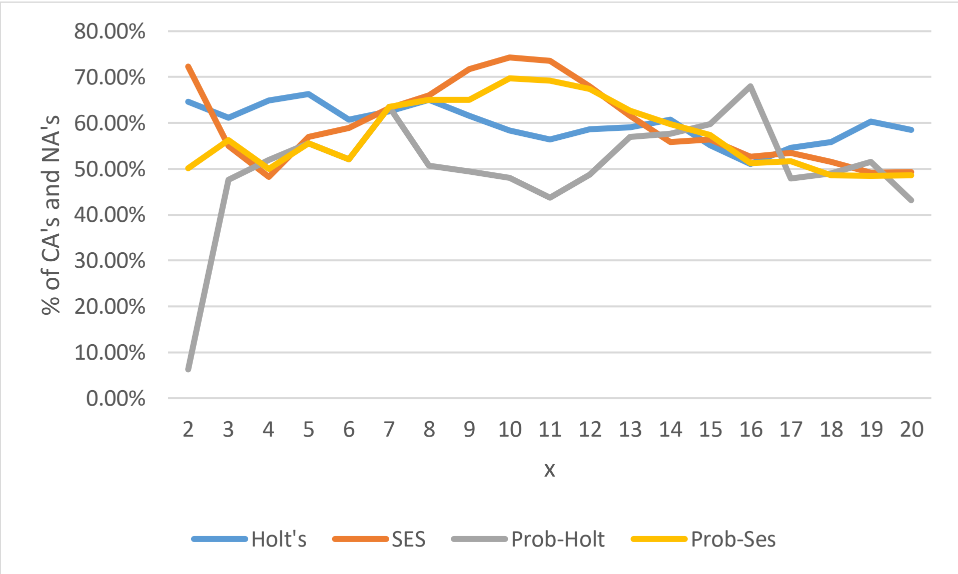


Figure 16: percentage of CA's and NA's for both methods based on the type of threshold

5.6 Croston method

The welding department uses Croston's method to create a forecast. Differently from Holt's method and SES, Croston's method will be judged based on the average forecasted demand x weeks ahead for week t and the average forecasted interval on which demand occurs.

The first and more important aspect is whether Wouter Witzel is able to handle the demand of x weeks ahead in week t. Formula 27 is used to calculate the values of the total expected demand $Y_t(x)$.

$Y_t(x)$ is than compared to the capacity of week t + x to see whether the capacity has been surpassed. Furthermore, the demand is intermittent with an average interval of $X_t(x)$. Hence, the current value of q is compared to $X_t(x)$ and if $q > X_t(x)$, this will be highlighted. The combination of the total expected demand and the comparison of the current interval and the expected interval is communicated to Wouter Witzel in the model. This will enable the planning department to gain insight into the welding department. As the welding department is small and handled differently than other departments, no signal will be given, merely data that provides insight.

However, the results will be given in signals, using the same format as before. In figure 17 it can be seen that a lot of alarms have been correctly identified. So, the Croston method delivers a forecast that is able to correctly forecast the situation. However as stated above, the welding department is very small and not very relevant within this research. So, no further error measurements will be done.

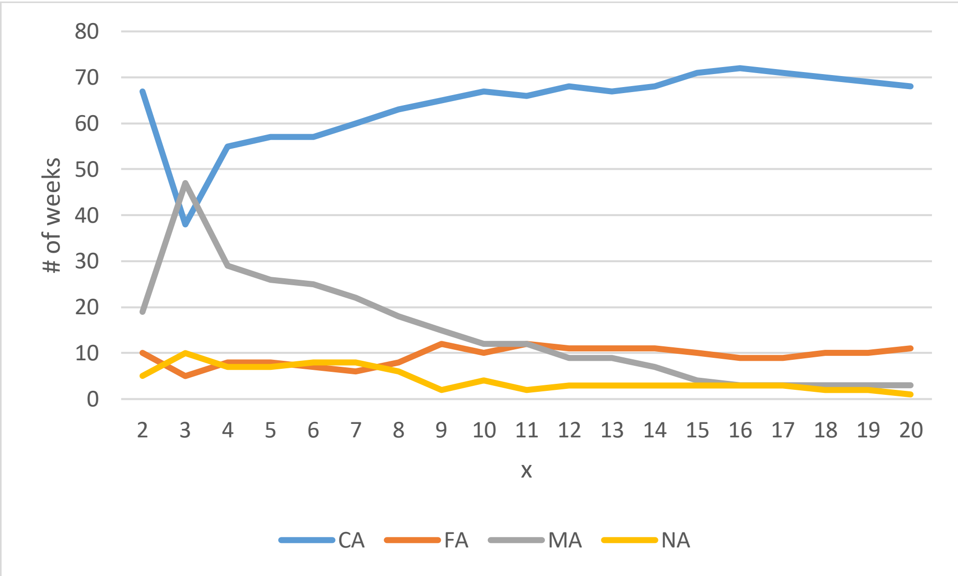


Figure 17: Number of weeks with a type of alarms for the welding department

5.7 Conclusion

To conclude, looking at the error of SMAPE and MAD, the forecasting models using the additional demand data set produced insufficient results and are not optimal for Wouter Witzel. Both SES and Holt's method yield accurate forecasting models when using the known demand data set. The SMAPE and MAD of these models show the models are usable and able to generate accurate signals. In addition, both these models outperformed a model based on the Moving Average with the regard of the correct signals. This chapter has also shown that an absolute threshold creates a better signal analysis than a threshold based on an EDF. In the next chapter, the optimal model for Wouter Witzel will be selected based on the results, advantages and disadvantages of Holt's method and SES.

6. Conclusion & Implementation

This chapter contains the conclusions on which model created in chapter 4 is the optimal forecasting model for Wouter Witzel using the results of chapter 5. Furthermore, the implementation of the model within the existing structure of the planning department of Wouter Witzel is described.

6.1 Conclusions

The goal of this thesis is to create a forecasting model that will assist the planning department of Wouter Witzel in identifying peaks in demand. The forecast is made with a horizon of 20 weeks and with time buckets of 1 week. The current situation concluded that the welding department has an intermittent demand pattern and should therefore be forecasted using a different method than the other departments. This research led to the following conclusions.

- The current situation at Wouter Witzel led to the use of two different data set containing the known demand and the additional demand. From the literature Simple Exponential Smoothing and Holt's model arose as suitable models. Combining the current situation with the literature, 4 forecasting models have been developed and tested.
- After the use of SMAPE and MAD as error measurement, it became evident that the forecasting models that used the additional demand data set performed badly and should no longer be considered as good options for Wouter Witzel. The known demand data set caused both forecasting methods to perform nearly equally as good for both SMAPE and MAD. The difference in both error measurements was minimal and are therefore considered equally good.
- The forecasting models used the forecast to determine whether a week will exceed the available capacity and will become a peak in demand. This was done through the use of signals, comparing the signals created by the forecasting method to the actual situation for the forecasted week. To be able to judge whether a value should be marked as a peak value, two methods were tested. The use of both an absolute threshold based on the standard deviation and an Empirical Distribution Function gave good results. However, the use of an absolute threshold resulted in more correct signals and is therefore used in the final forecasting model.
- The decision on the use of which forecasting method was based on the signal analysis. While SES performed better for $x > 11$, the difference is too minimal to compensate for the better performance of Holt's model for the other values of x. Looking at figure 14, there are too many false alarms given by SES for the smaller values of x. So, Holt's method is used for the final forecasting model. Resulting in a forecasting model that is based on Holt's method, using the known demand data set as input and using the standard deviation to determine the threshold for signals. Using this forecasting model, only 9 weeks are not identified as peak values for all six departments and a time span of 2 years. So, while in some weeks the signal is picked up. In 1 of the 20 weeks, weeks that results in under-capacity are identified and a signal is produced.
- The welding department is forecasted using Croston's method that yields an expected demand and the interval in which the demand occurs. Due to the small size of the department, merely data is given to support the planning department to stay below the capacity instead of the production of signals.

6.2 Implementation

The final deliverable of this research to Wouter Witzel is an Excel tool that neatly fits into the existing structure present at the planning department. The tool is built up of several steps to ensure the proper use of the model. Firstly, the new data of the overview of hours must be implemented in the data set. This is done by importing the data from the overview of hours into the excel tool using the corresponding button. It should be noted that before inserting the new data, the variables regarding the insertion of the data such as current week and correct rows of the data should be checked and adapted if needs be. After the data has been added, the variables of the forecast must be set to the preferred levels. Variables such as the smoothing factor or the sensitivity of the threshold regarding the capacity can be altered by the user. However, it is recommended that the two groups of variables previously mentioned should be altered separately as the impact of the changes cannot be individually interpreted when both altered simultaneously. The results generated by the forecast will be visualised using the framework of the overview of hours. Each week ahead for each department will receive an estimate whether it will pass the threshold and thus exceed the capacity. Furthermore, each week will note the expected total demand. It is important that the forecasting model is updated weekly with the data of the overview of hours to avoid missing data. The results provided by the model serve as assistance and should always be looked at critically as mistakes can happen with forecasting. The model is not intended to blindly copy the results. While the main use of the model is to assist the planning department by signalling possible peaks in demand in time, the use of this model could also improve communication between the planning department and the sales department. The planning department can use this data to back up their demands in the more even spread of demand and request the sales department to not promise large orders to customers in weeks that are already busy.

6.3 Discussion

This research has encountered certain limitations that influence the outcome of the research. These limitations are discussed below.

- The data available contained the years in which Covid was present and had an influence on the demand of Wouter Witzel. Due to this dip in demand, the testing set contained lower values than expected. As a new wave of infections might be upon us, there is no saying when the fluctuations due to Covid do not have an effect on the forecast anymore.
- The analysis of the threshold based on an empirical distribution did not perform better than an absolute threshold. The distribution was selected to be empirical based on a visual check. A more sophisticated method could be used to explore other distributions in a better fashion.
- Using SMAPE restricts the penalization of huge errors, over forecasting is penalized less than for MAPE. While this is beneficial to the model, it does allow forecasting which could be seen in the bias. So, it might have been better to use MAPE or a different variant of MAPE so under- and overforecasting are treated equally. Especially as these huge errors should not occur anymore due to the model.
- In order for the forecasting model to run smoothly, the input of the model and therefore the planning of orders should be consistent. First of all, it is essential that backlog is reduced to a minimum. As stated before, the backlog is not taken into consideration within this model and is treated as new input. As a result, the forecast produces higher estimates as demand is used as input twice. Furthermore, peaks in demand that are visible to the planners should be solved before inserting the data into the model. The increased demand will also increase the forecast unnecessarily.

6.4 Recommendations

The research also results in some recommendations that are proposed to Wouter Witzel. The following recommendations will allow the forecasting model to run efficiently.

- Similarly, to keeping the input consistent, the capacity of the departments should also remain consistent. Especially a decrease of capacity causes the judgement of the remaining capacity to change and therefore the signaling of peaks in demand. An increase will also change the judgement however this will merely allow more demand to be planned in a week.
- The forecasting model is a tool that assist the planning department signal peaks in demand before they are noticeable for the planning department. Thus, the responsibility for a correct planning is still with the planning department that can use this tool as an aid to make the correct decisions.
- Improvements on the model itself can be made. First, the model currently has to be implemented manually while there are systems available that upload the data automatically. This makes the model more efficient and eliminates the possibility of human error. Furthermore, aspects that have been left out to limit the complexity of the model should be explored and implemented. Aspects such as the correct input of backlog and the dependance of demand between the weeks. Implementing these features into the model will most likely increase the accuracy of the model.
-

6.5 Further research

Within this research, several aspects were deliberately left out of this research and new problems arose. These aspects give the opportunity for further research.

- The forecasting model has been created as a tool for the planning department. However, the planning or orders is not only influenced by the planning department. Further research could explore the impact of the model on other departments and analyze opportunities to improve the planning even more.
- The ARIMA model and Neural Networks are not selected as viable options due to the time constraint. However, these models could significantly improve the forecast even further within research with a broader time frame. Both models are able to handle more complex situations and incorporate the aspects that have been left out for simplicity such as the incorporation of backlog and the dependence between departments.

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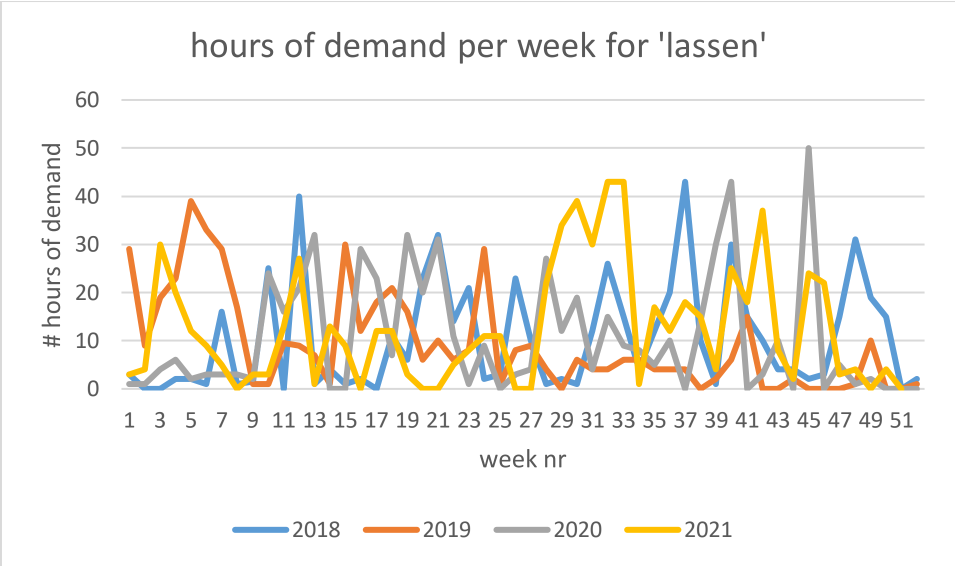
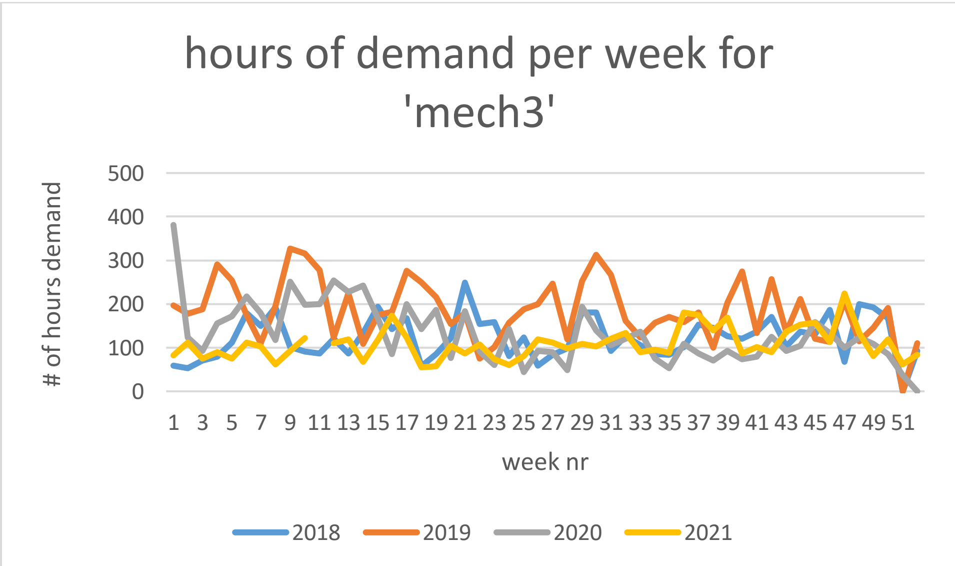
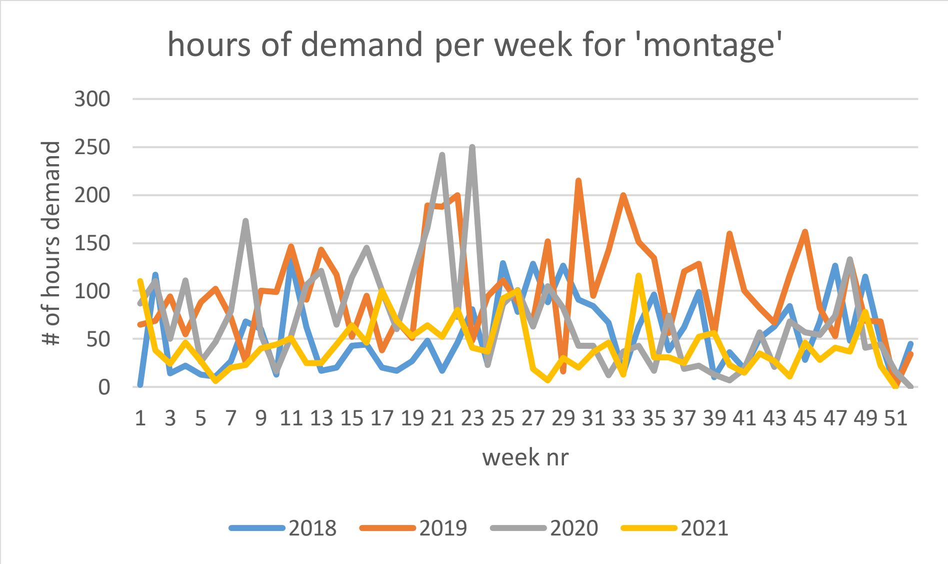
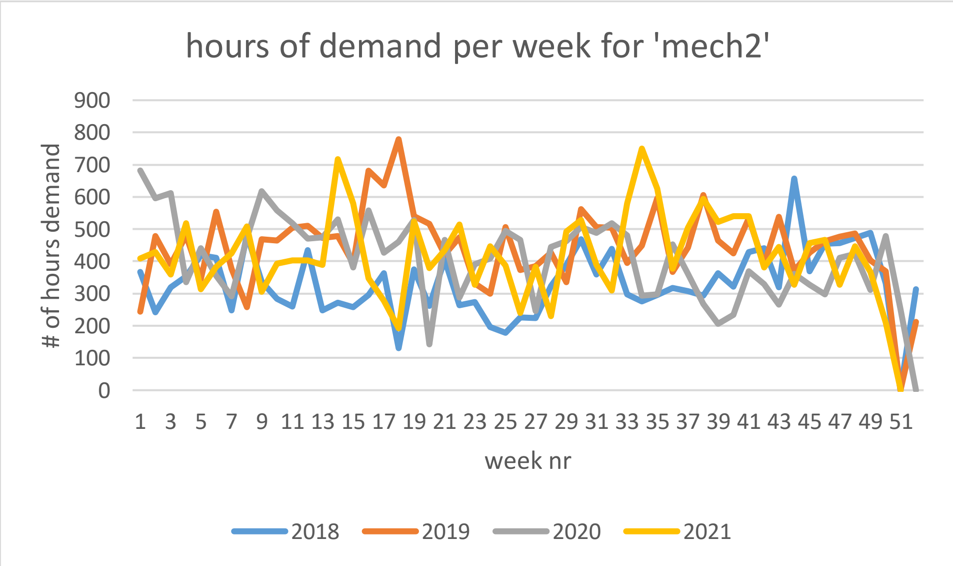
Appendix A

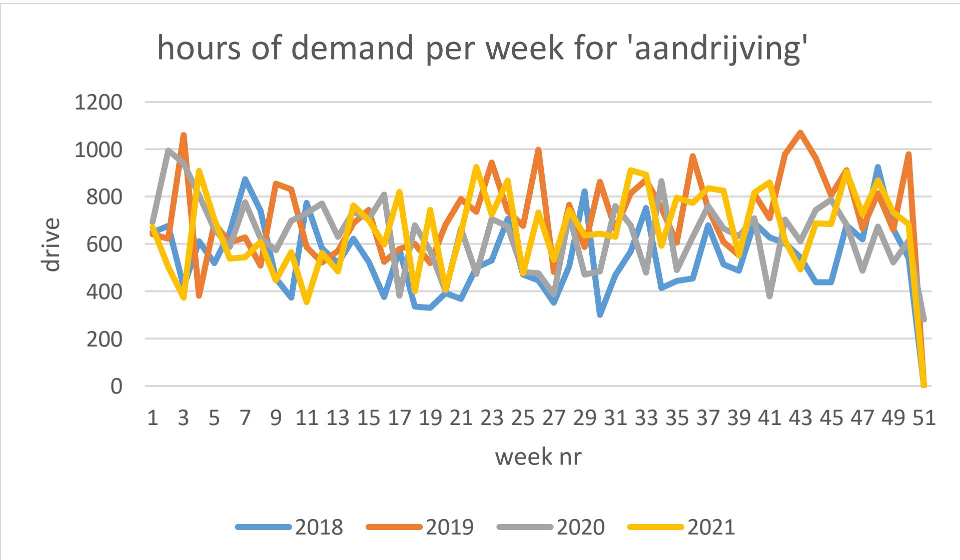
This appendix shows the weekly demand per year for each department. The department can be found in the chart title.

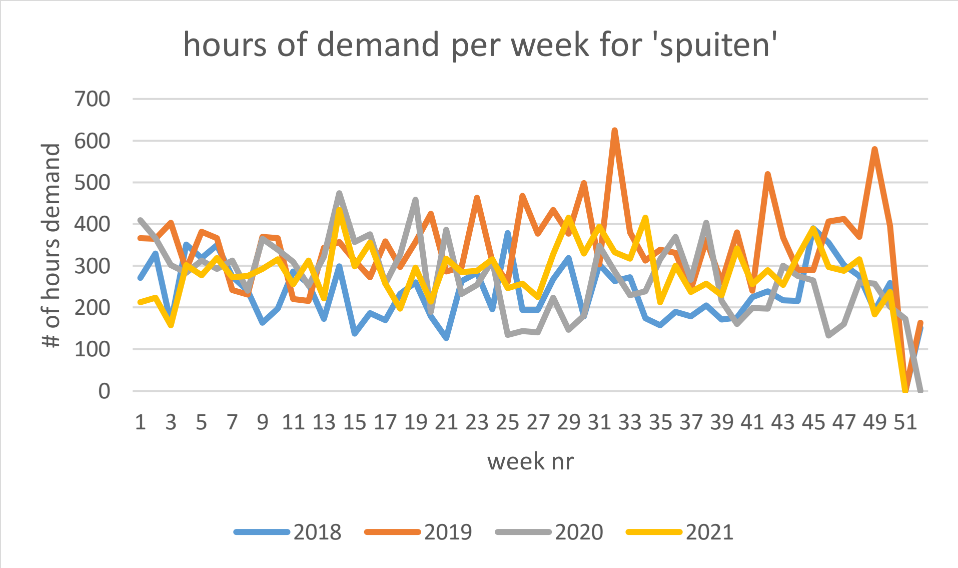


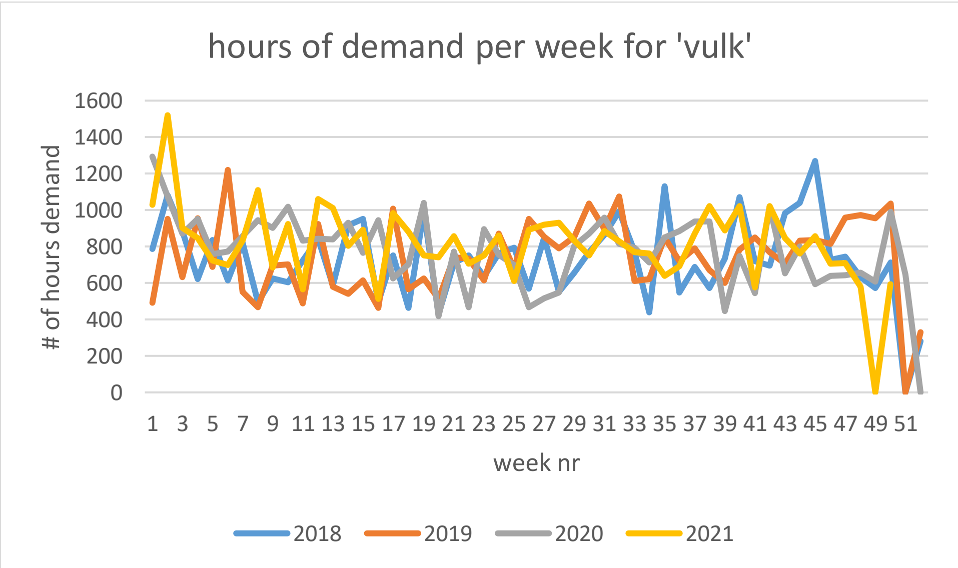



hours of demand per week for 'montage'
300
250
200
150
100
50
0
# of hours demand
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51
week nr
2018
2019
2020
2021


hours of demand per week for 'mech2'
900
800
700
600
500
400
300
200
100
0
# of hours demand
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51
week nr
2018
2019
2020
2021


hours of demand per week for 'aandrijving'
1200
1000
800
600
400
200
0
drive
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51
week nr
2018
2019
2020
2021


hours of demand per week for 'spuiten'
# of hours demand
700
600
500
400
300
200
100
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51
week nr
2018
2019
2020
2021


hours of demand per week for 'vulk'
# of hours demand
1600
1400
1200
1000
800
600
400
200
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51
week nr
2018
2019
2020
2021

Appendix B

These contain the initial values of the different forecasting methods.

Total	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
mech3																				
level	5	7	5	2	8	5	1	9	8	7	1	1	1	3	6	8	1	2	7	1
trend	3,8	4,1	4	3,8	3,6	3,6	3,7	3,7	3,7	3,7	3,7	3,6	3,5	3,4	3,3	3,2	3,2	3,1	3	2,5
montage																				
level	17	9	9	2	2	2	3	0	19	15	13	9	2	15	12	8	6	2	0	11
trend	1,6	1,7	1,7	1,7	1,7	1,7	1,7	1,7	1,6	1,6	1,6	1,6	1,6	1,5	1,5	1,5	1,5	1,5	1,5	1,4
mech2																				
level	6	11	14	5	6	9	2	11	14	3	17	15	13	8	4	6	15	4	14	0
trend	2,7	3,1	3,0	2,9	2,8	2,7	2,7	2,6	2,5	2,5	2,3	2,2	2,1	2,0	1,9	1,8	1,7	1,7	1,6	0,0
aandrijving																				
level	7	16	5	12	16	6	12	14	10	3	18	19	12	17	6	17	9	7	18	0
trend	3,2	4	4,1	3,9	3,7	3,6	3,4	3,2	3	2,9	2,7	2,5	2,4	2,3	2,2	2	1,9	1,8	1,7	0
spuiten																				
level	0	2	14	7	17	2	8	11	19	7	12	18	10	17	5	15	3	16	16	0
trend	2,5	2,7	2,6	2,5	2,3	2,3	2,2	2,1	2	2	1,9	1,8	1,8	1,7	1,7	1,6	1,6	1,5	1,5	0
vulkanisatie																				
level	13	22	20	1	4	0	4	6	0	13	1	12	4	17	9	7	11	0	15	0
trend	3,4	4,1	4	3,8	3,4	3,2	3,1	3,1	3	2,8	2,7	2,5	2,4	2,2	2,1	2	1,9	1,9	1,8	0

Figure showing the initial values of level and trend for each week x per department for Holt's method using the known demand data set

Additional	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
mech3																				
level	-67,42	27,41	15,60	34,25	2,59	2,59	10,26	-2,84	13,82	1,99	28,76	3,57	-12,43	-8,68	16,59	17,83	2,66	3,41	-7,81	1,80
trend	0,14	-0,07	0,05	-0,09	0,00	0,00	-0,07	0,00	-0,06	-0,01	-0,12	0,01	0,09	0,07	-0,06	-0,04	0,02	0,00	0,05	0,12
montage																				
level	14,05	10,88	-5,26	0,04	1,30	-2,21	3,72	-5,56	6,23	6,23	2,72	2,43	-0,18	-15,91	1,01	14,97	11,93	-2,79	-3,37	-4,13
trend	-0,13	-0,05	0,05	0,01	-0,01	0,01	-0,01	0,03	-0,01	-0,01	-0,01	0,00	0,02	0,09	0,00	-0,06	-0,04	0,02	0,03	0,12
mech2																				
level	-251,27	181,47	102,90	63,34	69,82	-26,90	-8,09	20,89	-1,44	-1,44	-21,18	-26,05	12,12	0,93	-35,20	-39,14	-20,65	-26,54	-7,70	-105,22
trend	0,78	-0,80	-0,32	-0,19	-0,26	0,17	0,10	-0,03	0,09	0,09	0,24	0,21	0,05	0,14	0,31	0,30	0,16	0,18	0,08	0,78
aandrijving																				
level	-383,80	-15,87	83,30	56,22	130,43	25,74	-3,16	143,45	79,37	79,37	-27,58	-28,64	-42,22	-12,73	1,92	-6,37	-49,36	-16,93	0,53	-132,17
trend	0,91	0,07	-0,19	-0,06	-0,43	0,05	0,28	-0,49	-0,23	-0,23	0,26	0,35	0,38	0,14	0,17	0,18	0,41	0,12	0,04	1,05
spuiten																				
level	-156,17	-8,47	43,67	23,29	29,66	16,90	-4,62	33,72	5,33	5,33	-10,98	-12,37	-25,83	-11,65	-4,31	-0,65	-9,01	5,26	-6,99	-30,35
trend	0,53	0,09	-0,07	0,06	-0,07	-0,01	0,12	-0,09	0,04	0,04	0,14	0,13	0,16	0,11	0,09	0,05	0,10	-0,02	0,07	0,31
vulkanisatie																				
level	-630,72	110,40	377,66	320,66	158,05	-72,90	-78,79	-12,72	59,39	59,39	-0,32	-101,64	-19,49	-55,15	-36,60	-41,34	-24,81	5,87	37,20	8,68
trend	1,84	-0,37	-1,23	-1,09	-0,50	0,49	0,35	0,21	-0,12	-0,12	0,17	0,62	0,24	0,40	0,34	0,32	0,20	0,01	-0,10	0,41

Figure showing the initial values of level and trend for each week x per department for Holt's method using the additional demand data set

Total	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Mech3	108	143	130	106	91	87	93	98	101	101	97	88	78	71	63	53	45	36	29	54
Montage	59	71	71	64	66	67	68	65	62	58	57	54	46	40	37	32	30	27	24	35
Mech2	288	372	355	321	299	283	276	265	246	236	208	185	162	134	110	91	79	67	56	117
Aamndrijvi	402	592	602	563	523	485	444	398	354	327	304	264	234	214	178	149	119	95	85	196
Spuiten	226	274	266	239	206	190	173	155	141	129	114	100	93	80	68	57	45	39	38	77
Vulkanisat	463	708	672	548	454	406	383	379	345	318	285	255	229	202	172	148	131	115	107	220
Additional	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Mech3	-40	14	25	16	2	-3	-4	1	0	4	6	6	5	5	10	7	7	4	3	27
Montage	-12	1	5	2	0	0	1	0	3	0	2	4	3	2	2	3	1	1	2	21
Mech2	-91	18	37	25	17	7	13	15	15	28	16	22	30	29	23	12	8	10	8	55
Aamndrijvi	-199	-2	43	43	42	35	53	44	32	26	43	36	17	37	30	34	24	8	8	83
Spuiten	-48	10	28	36	16	15	19	14	13	18	13	8	12	13	10	11	5	1	7	33
Vulkanisat	-254	36	125	97	56	26	-7	30	34	35	25	30	26	32	25	16	12	7	17	93

Initial values of the SES method

Appendix C

Each table shows the SMAPE per week per smoothing factor of a department. The two columns on the left correspond with the smoothing factor of trend and level.

β	α	Mech3	Assembly	Mech2	Drive	Spraying	Vulcanization
0,05	0,05	52,45%	52,40%	13,38%	12,50%	16,42%	15,25%
0,05	0,1	42,50%	48,97%	11,08%	10,10%	14,85%	13,33%
0,05	0,15	35,10%	42,79%	9,71%	9,07%	12,70%	12,65%
0,05	0,2	32,79%	37,60%	9,02%	8,87%	10,88%	12,40%
0,05	0,25	32,65%	36,13%	8,14%	8,87%	10,25%	12,21%
0,05	0,3	32,25%	35,54%	8,19%	8,97%	10,39%	12,21%
0,05	0,35	32,55%	36,62%	8,43%	9,22%	10,50%	12,26%

Table showing average SMAPE of the forecast for the different smoothing factors for the total demand data

β	α	Mech3	Assembly	Mech2	Drive	Spraying	Vulcanization
0,05	0,05	70,49%	82,75%	60,39%	51,62%	55,15%	59,31%
0,05	0,1	70,78%	79,80%	59,56%	50,20%	55,39%	56,47%
0,05	0,15	70,15%	82,99%	58,38%	49,80%	54,51%	55,20%
0,05	0,2	71,08%	81,96%	59,66%	50,34%	52,55%	55,10%
0,05	0,25	71,37%	81,67%	59,56%	50,83%	52,55%	55,93%
0,05	0,3	71,72%	81,47%	59,31%	51,37%	54,95%	56,57%
0,05	0,35	72,16%	81,67%	59,12%	51,81%	55,69%	56,76%

Table showing the average SMAPE of the forecast for different smoothing factors for the additional demand data

Appendix D

γ	Mech3	Assembly	Mech2	Drive	Spraying	Vulcanization
0,05	33,69%	36,07%	10,11%	8,92%	9,66%	11,42%
0,1	31,94%	34,93%	9,18%	8,92%	9,31%	11,23%
0,15	31,68%	35,24%	8,82%	8,73%	9,12%	11,32%
0,2	31,42%	35,50%	8,20%	8,68%	9,17%	11,42%
0,25	31,11%	36,07%	8,36%	8,92%	9,56%	11,67%
0,3	31,27%	35,96%	8,51%	8,97%	10,00%	11,76%
0,35	31,94%	36,53%	8,67%	9,26%	10,15%	11,91%
0,4	32,20%	37,00%	8,46%	9,26%	10,15%	11,91%

γ	Mech3	Assembly	Mech2	Drive	Spraying	Vulcanization
0,05	92,21%	95,46%	90,66%	83,53%	84,26%	85,64%
0,1	89,16%	94,17%	87,77%	78,58%	80,98%	81,13%
0,15	87,25%	92,41%	84,57%	75,25%	76,81%	76,52%
0,2	85,04%	90,30%	81,63%	72,01%	73,28%	73,09%
0,25	84,11%	88,96%	78,74%	69,02%	70,69%	70,93%
0,3	83,13%	87,46%	76,32%	66,23%	68,33%	68,82%
0,35	81,99%	87,36%	73,94%	65,20%	68,19%	68,14%
0,4	81,06%	87,00%	71,67%	64,36%	66,91%	68,04%

Tables showing the average SMAPE for the different smoothing factors for the known demand data set and the additional demand data set

Appendix E

α	MAD of F(t, x)
0,05	12,37937025
0,1	8,002528658
0,15	6,156458141
0,2	5,233398496
0,25	4,730546884
0,3	4,511960794
0,35	4,411494606
0,4	4,418899154
0,45	4,414009165
0,5	4,452451808

β	MAD of X(t, x)
0,05	4,1544378
0,1	2,6571505
0,15	1,860495
0,2	1,399361
0,25	1,1408251
0,3	0,9930334
0,35	0,9093345
0,4	0,8696957
0,45	0,8526395
0,5	0,8453152
0,55	0,9326774
0,6	1,0174023

Tables showing the average MAD for the different smoothing factors of both the α and β for Croston's Method

Appendix F

Total	CA	FA	MA	NA
0	49	133	415	9891
0,05	47	131	417	9893
0,1	47	127	417	9897
0,15	46	126	418	9898
0,2	46	125	418	9899
0,25	46	124	418	9900
0,3	45	124	419	9900
0,35	45	122	419	9902
0,4	45	120	419	9904
0,45	44	117	420	9907
0,5	40	113	424	9911
0,55	40	112	424	9912
0,6	39	112	425	9912
0,65	39	107	425	9917
0,7	39	106	425	9918
0,75	39	102	425	9922
0,8	37	101	427	9923
0,85	0	2	21	481
0,9	0	3	20	475
0,95	37	97	427	9927

Experiment of the optimal value of I for SES using the known demand data set

Total	CA	FA	MA	NA
0,5	99	417	365	9607
0,55	98	400	366	9624
0,6	96	389	368	9635
0,65	94	378	370	9646
0,7	93	367	371	9657
0,75	86	355	378	9669
0,8	86	344	378	9680
0,85	84	335	380	9689
0,9	84	326	380	9698
0,95	83	314	381	9710
1	83	303	381	9721
1,05	80	287	384	9737
1,1	80	280	384	9744
1,15	80	267	384	9757
1,2	80	261	384	9763
1,25	79	257	385	9767
1,3	77	245	387	9779
1,35	0	5	21	478
1,4	0	4	20	474
1,45	74	234	390	9790

Experiment of the optimal value of I for Holt’s model using the known demand data set