Improving Inventory Management through Demand Forecasting at Bronkhorst High-Tech

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Preface

This report is the final result of my research conducted at Bronkhorst High-Tech, which is written to fulfil the graduation requirements of the Industrial Engineering and Management Bachelor program at the University of Twente.

Firstly, I would like to thank all the people at the company for their contribution to this research. A special thanks to Jurgen Veldkamp and Roel Lankveld for providing me with all the support and resources I needed throughout the research. Furthermore, I would like to thank Theo Kok for facilitating the research project at Bronkhorst High-Tech.

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I hope you enjoy reading my Bachelor thesis.

Emre Akgul

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Executive summary

Introduction

Bronkhorst High-Tech, based in Ruurlo in The Netherlands, develops and produces smart, sustainable and customer-specific low-flow fluidics handling solutions. Bronkhorst is a global organisation with international sales and support offices, and an extensive network of distributors across Europe, Asia Pacific, the Americas, Africa and the Middle East. A substantial part of the produced instruments is integrated into manufacturing machines or equipment of OEM-customers (Original Equipment Manufacturers). Currently, the supply chain department of Bronkhorst is taking up the challenge to improve their supply chain to better handle their uncertain demand and increase their delivery reliability. Since products are highly customizable, Bronkhorst High-Tech has predominantly adopted an assemble-to-order (ATO) manufacturing process. An ATO manufacturing process usually requires a well-organized supply chain which has the material and components in stock, to begin manufacturing without delay. This research focusses on solving the absence of a demand forecast, to achieve lower inventory levels of products components at Bronkhorst High-Tech.

Due to insufficient data on component-level demand and the high variety in product offerings, the forecast objective is to forecast monthly demand for final products in the ELSE, OEMP and CLRP capacity groups. Using a predetermined distribution of standard components of each capacity group, the material planners can derive the material requirements from the capacity forecast. This distribution of standard components is computed using the average consumption of each standard component within a specific capacity group. To cover the component demand during their 4 to 8 week supplier lead times, the time series forecasting method needs to predict at least three months into the future. At any given month t, the team wants to separately forecast the demand of month $t + 1$, $t + 2$ and $t + 3$.

Research methodology

Based on the theory of Forecasting: Principles and Practice by Rob J Hyndman and George Athanasopoulos (2018), we collect and analyse available data, assess available alternatives and evaluate selected forecasting methods. Appropriate forecasting methods are evaluated by implementing the ex-post forecasting method, which splits the available data to fit and test forecasting models. Fitting the forecasting model includes determining the demand patterns and optimizing model specific-constants. This way, the need for new data is eliminated and we prevent the models from overfitting.

Main findings

To gain a better understanding of the underlying demand patterns of the ELSE, OEMP and CLRP capacity groups, the time series decomposition method is applied to analyse the presence of trend and seasonality for three years of demand data (years 2016, 2017 and 2018). We find that the ELSE and CLRP group contains trend and seasonality. The OEMP group contains only seasonality. Based on the characteristics of the data and the forecasting objectives we select the Moving Average and Exponential smoothing method for implementation. Exponential Smoothing is split up in three variants, namely, the Simple Exponential Smoothing Method, Holt's Model and Winter's Model. For each capacity group, the models are fitted to the data using 36 periods of demand data and are tested using 12 periods of demand data (of the year 2019). Using measures of Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE) and Tracking Signal (TS), the forecast accuracy is evaluated for the selected forecasting methods.

From the tests, we find that Winter's Model has the highest forecasting accuracy for the ELSE capacity group, where the 1-, 2-, and 3-period forecasts result in a MAPE of 10.4%, 10.7%, 10.6%, respectively with tracking signals within the ±6 range. Since the identified demand pattern of the ELSE continues to occur in 2019, which includes a notable decrease in demand towards the end of each year, Winter's Model results in the lowest error. For the OEMP group we find that none of the selected forecasting models is able to capture the demand of the year 2019. This is caused by a, currently unexplained, decrease of product demand in 2019 within the OEMP group. This shift in demand confirms that the determined trend and seasonal factors of previous years do not repeat in 2019. For the CLRP capacity group, Holt's Model generates the most accurate forecast. The fact that Holt's Model performs best, indicates that seasonal factors determined using historical data of 2016, 2017 and 2018, do not accurately capture the underlying demand pattern of the CLRP group in 2019. Although Holt's Model performs best, the values of error are still high, where the 1-, 2-, and 3-period forecasts result in a MAPE of 35%, 39.7%, 46.6%, respectively. The master and material planners at Bronkhorst High-Tech speculate that the decrease in demand of the CLRP group may be negatively affected changes in the semiconductor industry.

Conclusions and recommendations

Based on the level of accuracy, it is recommended that Winter's Model is used to forecast monthly demand for the ELSE capacity group. For the OEMP capacity group, we find that all models results in inaccurate forecasts and are therefore not recommended for implementation. Lastly, for the CLRP capacity group, Holt's Model generates the most accurate forecast. However, the values of error are still high, caused by a shift in customer demand. Therefore, Holt's Model is assumed to be insufficient for material planning purposes, due to the associated cost of overstocking materials. Using Winter's Model for the ELSE capacity group, a prototype forecasting tool is developed for the material planners at Bronkhorst High-Tech. Additionally, Hyndman and Athanasopoulos' (2018) approach to forecasting is extended by incorporating operational activities that are required in the planning process, to ensure effective implementation of Winter's Model.

The main limitations of the research include the insufficient component-level demand data and the use of less recent data due to the COVID-19 pandemic. It is recommended that Bronkhorst High-Tech utilizes the Bill of Materials (BOM) of final products to improve the availability of component demand data. Additionally, Bronkhorst High-Tech needs to consider customer or product-specific demand forecasts to mitigate the poor forecasting accuracy of the OEMP and CLRP capacity groups. Recommendations for further research include, but are not limited to, the analysis of product- and customer specific forecasts, the optimization of forecasting horizon through supplier lead time analysis and the exploration of causal forecasting methods.

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ANN	Artificial Neural Network models
ARIMA	Autoregressive integrated moving average
ATO	Assemble-to-order
BOM	Bill of Materials
CPRF	Collaborative Planning Forecasting and Replenishment
CRP	Continuous Replenishment Programs
ERP	Enterprise resource planning
ES	Exponential Smoothing
MA	Moving Average
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
OEM	Original Equipment Manufacturers
PDCA	Plan-Do-Check-Act
POS	Point-of-sale
SBA	Syntetos-Boylan Approximation
SES	Simple Exponential Smoothing
TS	Tracking Signal
VMI	Vendor managed inventory

1 Introduction

This chapter presents an introduction to Bronkhorst Hight-Tech and the goal of the research. Section 1.1 gives an introduction to the products and services offered by Bronkhorst High Tech. In Section 1.2, the difficulties and problems of the supply chain department of Bronkhorst High-Tech are discussed. Next, the core problem is selected and the research aim is determined in Section 1.3. In Section 1.4 research approach is defined, which is built on the theory of *Forecasting: Principles and Practice* by Hyndman and Athanasopoulos (2018). Furthermore, the limitations of the research are discussed in Section 1.5 and the intended deliverables are covered in Section 1.6. Lastly, the validity and reliability of the research are discussed in Section 1.7.

1.1 Company introduction

Bronkhorst High-Tech, based in Ruurlo in The Netherlands, develops and produces smart, sustainable and customer-specific low flow fluidics handling solutions. Their mass flow meters and regulators for liquids and gases, which are applied in a wide variety of industries, are best known for their accuracy and reliability. A substantial part of the produced instruments is integrated in manufacturing machines or equipment of OEM-customers (Original Equipment Manufacturers). The calibration centre in Ruurlo is certified by the Dutch Accreditation Council (RvA), which guarantees the accuracy of every flow and pressure calibration performed by their calibration laboratory. Bronkhorst is a global organisation with international sales and support offices, and an extensive network of distributors across Europe, Asia Pacific, the Americas, Africa and the Middle East. Bronkhorst High-Tech does not focus solely on the low-flow technology, but also on continuity and sharing their valuable expertise. By working closely together with their partners and customers, Bronkhorst High-Tech aims to offer better solutions for more complex issues. In addition to its maintenance and support service, Bronkhorst High-Tech provides product-specific training at their training facilities. Next to their own Research & Development departments, the company has also entered into alliances with universities and research laboratories around the world. Bronkhorst High-Tech has various concepts of the Lean methodology within its business processes, including theories of Poka-yoke and Kanban.

1.2 Problem identification

The customer-specific products and a wide variety of different products offered by Bronkhorst do come with a view drawbacks. Since every order is unique, and in most cases assembled based on customer requirements, it is unlikely that the same order occurs among different customers. Therefore, the main disadvantage of offering customer-specific products is having irregular and uncertain sales demands. To meet the irregular customer demand, whilst minimizing waste and reducing the risk of insufficient supply, Bronkhorst has predominantly adopted an assemble-to-order (ATO) manufacturing process. ATO pertains to the process of assembling and fulfilling orders when they are requested by the customer. This ensures that customers are able to make variations and customizations based on their needs, because the final products are not produced yet. An ATO manufacturing process usually requires a well-organized supply chain which has the material and components in stock, to begin manufacturing without delay. Unfortunately, mistakes in stock levels can occur, which could cause a substantial number of orders to be held back. Moreover, ATO processes generally yield longer waiting times for customers, since products are not ready-made, which is also the case for Bronkhorst High-Tech. The current delivery reliability of final products is estimated at 84%, which is 11% below their targeted 95% delivery reliability. Visit Appendix 1 for the change delivery reliability over time.

Currently, the supply chain department of Bronkhorst High-Tech is taking up the challenge to improve their supply chain to better handle their uncertain demand. Since there is generally more than one thing going less than well, different perspectives and existing data on the supply chain performance of Bronkhorst High-Tech is collected to create an inventory of problems. The problem cluster in Figure 1 provides an overview of identified problems expressed as variables along with their interrelations.

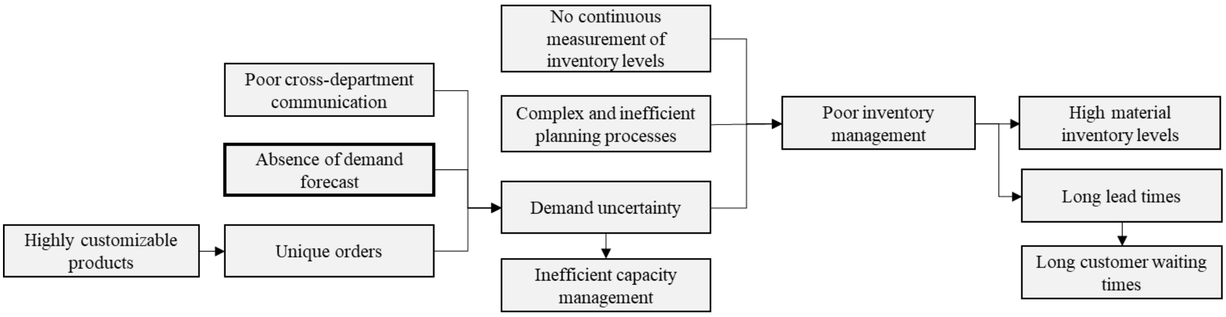

Figure 1 Problem cluster of the supply chain department

Throughout meetings with the management team, it became clear that the identified problems concerned multiple areas of the supply chain at Bronkhorst High-Tech. Namely the purchasing, inventory management and demand planning areas of the supply chain. Frequently mentioned problems by the management team included the high material inventory levels and the long customer waiting times, which, to some extent, can be caused by the ATO manufacturing process. By conducting follow-up meetings with material planners and the supply chain manager, these problems were further analysed on an operational level to determine causal relationships between variables.

First of all, the material planning process seemed complex and somewhat vague. Simple tasks are processed in multiple Excel sheets with different structures that require close guidance to be interpreted correctly. The determination of material requirements, also processed in Excel, is done manually without quantitative support (e.g. optimal order policies, statistical analysis). Material planners also indicate that there is minimal input given by the sales department. Since the production follows an ATO system, production only starts when orders are confirmed by the sales department. When orders are confirmed by the sales department, the request is communicated to the material planners. Depending on the inventory levels of product components, the orders are scheduled, assembles and shipped to the customer. However, no (or very little) information is communicated about the expected future demand of customers. This negatively affects the response time of the supply chain at Bronkhorst High-Tech. Based on employee experiences, this process generally results in an overestimation of future demand, negatively the cost-effectiveness of the inventory system. However, it is not clear how much over estimation of material occurs at Bronkhorst because the inventory performance is not continuously measured. Therefore, it is unknown how much excess inventory Bronkhorst stores or how much delay is caused by the shortage of materials.

Another aspect of the business which is affected by the demand uncertainty, is the capacity management. Due to the large number of offered products, Bronkhorst High-Tech allocates its production over different capacity groups. Each capacity group focusses on a specific segment of the customer demand, based on the technical characteristics of the products. According to the supply chain manager, the uncertain demand results in inefficient scheduling of personnel and utilization of available capacity (i.e. the utilization and layout of production locations). To meet the capacity requirements of the demand, Bronkhorst High-Tech frequently changes its allocation of personnel and the design of the product warehouse. However, these changes are often implemented as orders are placed, due to the uncertain future demand, which negatively affects the supply chain responsiveness.

One commonly accepted method in supply chain management, which deals with demand uncertainties, is demand forecasting. Demand forecasting methods use historical sales data to develop an estimation of expected customer demand. Among many benefits, demand forecasting can help optimize inventory levels and improve capacity management. Material planners indicate that customers do provide a prediction of future purchases at Bronkhorst High-Tech, but due to the low reliability of the estimations, these predictions are not considered in planning processes. This leaves room for error, mostly in the form of demand overestimation, but in some cases in the underestimation of demand. The latter occurs with materials that are not being used frequently or require high purchasing costs. Demand forecasting methods that are built on historical data of customer demand are currently not implemented at Bronkhorst High-Tech.

1.3 Research aim

Due to time limitations, one core problem is selected to form the main objective of the thesis. The core problem is the most important problem in the problem cluster. To select the core problem, we follow the chain of problems in Figure 1 back to the problems which has no direct cause themselves. Next, the identified problems are evaluated based on the power of influence. If a problem cannot be influenced, then it cannot be the core problem (Heerkens & Van Winden, 2017). For this reason, the problems of "high product variety" and "inconsistent order frequency" are excluded, given that Bronkhorst does not plan on altering the product and service offerings. Since more than one problem remains, the most important problem is determined based on an effort-benefit analysis. The effort-benefit analysis allows one to find the most important problem based on whose solution would have the greatest impact effect at the lowest effort. It is important to note that the decision in this analysis is based on an educated guess since the solution to the problems is unknown. The findings from this analysis can are summarized in the benefit-effort matrix, see Appendix 2. When we compare the four remaining problems of the problem cluster using a cost benefit analysis, it is evident that the solution to the absence of a demand forecast would result in the highest benefit for Bronkhorst High-Tech. Primarily because the answer to this problem will significantly improve the current inventory management system. Assuming the solution to this problem will be some quantitative prediction about future demand, the solution could help manage material requirements and lower the inventory levels. This would improve supply chain responsiveness, decrease material planning errors and order lead times. Additionally, the solution could have overarching benefits to other departments of the company.

Similar to the forecasting problem, the effort of solving the complex and inefficient planning processes is proportional to the gained benefit. Although an improved planning process would decrease the overall processing time of material requirements, the expected decrease in planning errors (overestimation) is small compared to a forecasting solution. Closely linked to the planning process is poor cross-department communication. The solution to the communication problem would improve the overall response time of the supply chain since more insights in the future market or customer behaviour could help the supply chain to "prepare" for future demand. After discussing possible solutions to this problem with the material planners, it became clear that material requirements usually cannot be based on the qualitative predictions of future market behaviour.. These predictions are generally not sufficiently accurate for decision making processes because of the high demand uncertainty. Therefore, the benefit gained from the solution is low, relative to the communication problem. Furthermore, the effort required to improve the inventory measurements is relatively high, due to the high product and material variety at Bronkhorst. The solution to this problem will most likely require some manual or automated control system development. In return, the company acquires more information about their inventory performance. However, the solution to this problem will not guarantee a solution to the high inventory levels, producing relatively low benefit compared to the other problems.

Based on the effort-benefit analysis and the expertise of the management team, the research will focus on solving the absence of a demand forecast to improve the inventory management at Bronkhorst High-Tech. Therefore the action problem is defined as follows: "*material (component) requirements, which are currently being determined intuitively, need to be determined using a time series demand forecast"*. To narrow down this action problem, it is important to first determine the forecasting objectives and the desired output of the forecast, based on the available data and resources. Defining the forecasting objectives requires an understanding of how and by whom the forecast will be used.

1.3.1 Forecasting objectives

As mentioned in the selection of the core problem, the overall purpose of the forecast development is to improve inventory management of products components at Bronkhorst High-Tech. Together with the management team, we decide that the main purpose of the forecast will be to lower the inventory levels. According to master- and material planners at Bronkhorst, the majority of the access inventory is caused by the standard components of final products. Similarly, the long lead times are primarily caused by special and customer-specific product components, because the majority of special components are not held in stock. This research will therefore prioritize the forecasts of standard components rather than the special components.

In ATO environments, all assembly processes are initiated by specific customer orders. Processes upstream from the decoupling point, especially purchasing of components, have to be based on the forecasts either directly on forecasts for components or indirectly on forecasts of final products (Stadtler & Kilger, 2008). The decoupling point refers to the point in the value chain of mass customization at which a customer triggers the production activities. The following three approaches could be used to estimate the future material requirements of final products: (1) by forecasting components directly from historical data, (2) by forecasting each final product offered using sales data, (3) by forecasting customer-specific demand or (4) by forecasting aggregated sales based on similar technical characteristics. Due to the insufficient amount of historical data on the usages of product components, directly forecasting product components is currently not feasible. More specifically, the current ERP system does not register the Bill of Materials (BOM) with each processed sales order, since the material requirements are determined and ordered manually. This means that the historical material requirements of specific components are not collected in the database. The next best option would be to forecast either the final products or the customer-specific demand, from which the material requirements can be estimated using the BOM. The main drawback from these approaches is the fact that the number of customers and unique products at Bronkhorst is high, often with lumpy demand patterns, which would require a large number of forecasts and more maintenance.

Lastly, forecasting the aggregated product demand based on technical characteristics of products can be achieved by using the predetermined capacity groups. Bronkhorst High-Tech currently offers products that can be categorized in 11 product types (see Figure 2). Based on the technical structure of the products, the products are further categorized in one or more capacity groups. All products in each of the capacity groups have the same set of standard components. Although the BOM of each product in the same capacity group is not identical, there exists a standard set of materials for each capacity group. By using estimates of the standard product distribution, the material requirements can be estimated using the forecasted demand of final products in each capacity group. Table 1 gives an example of the standard component distribution for the ELSE capacity group. The monthly requirements of standard components can be computed by multiplying the forecasted capacity group values with the determined percentage of each component. It is important to note that the distribution of the standard components within each capacity group are derived from the average consumption of each component, computed by the material planners of Bronkhorst High-Tech.

Although product and customer-specific forecast give more accurate information about the required standard and special components, the management of Bronkhorst High-Tech insists on developing capacity level forecasts. This is because the capacity level forecast can also be used for future capacity planning purposes, also mentioned in the problem identification phase in Section 1.2.

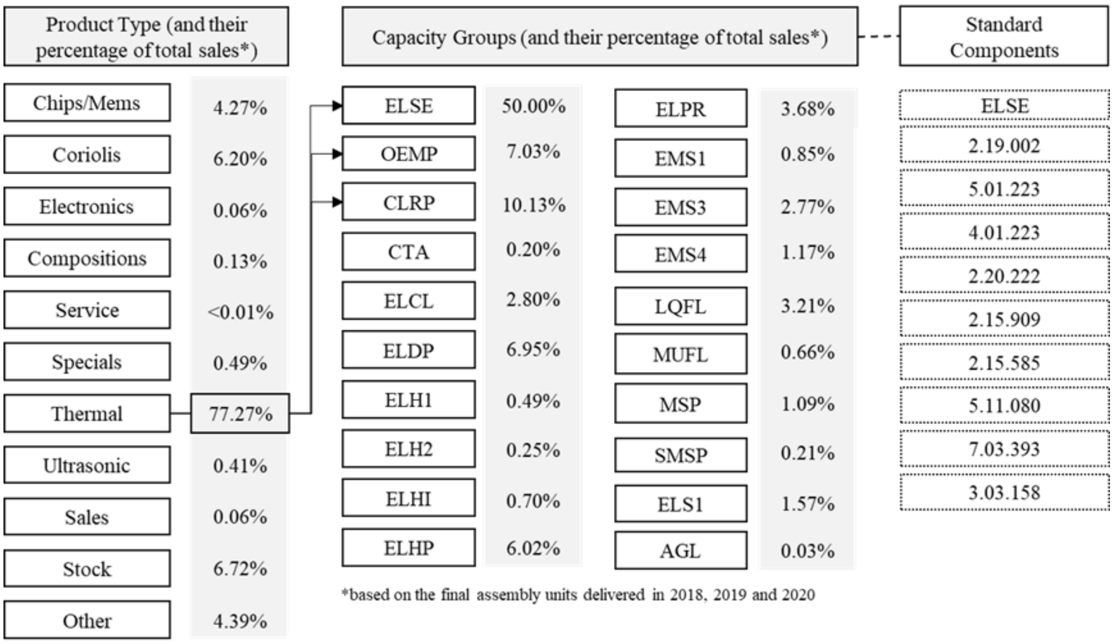

Figure 2 Product classifications and standard components

Next, we narrow down the exact objectives to be forecasted. For the scope of this research, the team wants to focus on the thermal products, because the thermal products account for the largest percentage of the total sales quantity based on the annual data from 2018, 2019 and 2020. As Figure 2 indicates, the thermal products provide 77,27% (on average) of the total products sold. The selection of the capacity group to be forecasted is determined by the percentage of total units sold per capacity group. Based on this parameter, the ELSE- and OEMP- and CLRP-group are selected to forecast a segment of the total final product demand. The ELSE, OEMP- and CLRP-group are responsible for 38.63%, 5.44% and 7.83% of the total final (and fully assembled) product demand respectively. Collectively, the three forecasts cover 51.9% of the product demand at Bronkhorst High-Tech.

Standard component	Average occurrence(%)
2.19.002 body F-201CV/F-201DV/F-201EV	65
5.01.223 sensor 2 winding C-type SW2 V	72
4.01.456 pcb Euro MBC3	86
2.20.222 spindle LFE low rad II	64
2.15.909 cover LFE low radial	65
2.15.585 sleeve topmount n.c.	92
5.11.080 plungerholder assy TM lab n.c.	98
7.03.393 coil assy topmount lab 95mm	87
3.03.158 lower part case Euro MFC	86

Table 1 Distribution of standard components in the ELSE capacity group

To determine the forecast horizon, which indicates the future period for which the forecast is generated, we analyse the material planning process and lead times of Bronkhorst High-Tech. To prevent shortages in product components, the forecast horizon should be equal to or larger than the lead time of final products. Since the production lead time of customer orders are relatively short, ranging from 1 to 3 days for the final products in the ELSE, OEMP and CLRP capacity groups, the forecast horizon is largely dependent on the lead times of suppliers. Component requirements of final products are determined on a monthly and weekly basis, depending on component type and its associated the delivery time. The material planners of Bronkhorst High-Tech schedule two types of deliveries from their suppliers: new order deliveries and partial order deliveries. New orders require longer supplier lead times, which is the time between the order placement and delivery. Partial deliveries occur when large orders of components are not delivered in one batch, but are split into several smaller delivery batches, which come with shorter supplier lead times. The supplier lead times of standard components are range from 4 to 8 weeks for new orders, and 1 to 2 weeks for partial deliveries. The exact lead times depend on size of the order. Appendix 3 shows the supplier lead times of the individual standard components. Another variable that impacts the lead time of orders is the delivery time of final products. However, due to the lack of data and the high variability of delivery times caused by international orders, the delivery times cannot be estimated effectively. Therefore the delivery times will be neglected for the determination of the forecast horizon. Currently, the team wants to focus on estimating monthly requirements for standard components with long supplier lead times (4+ weeks). To cover the component requirements during the 4 to 8 week lead times, the time series forecasting method needs to predict at least two months into the future. This ensures that material requirements are met during supplier lead times. In this case, the forecast could be generated on a weekly basis or monthly basis. Since new orders are placed roughly once a month, the forecast horizon will be met by forecasting in time buckets of one month. More specifically, at any given month t the team want to separately forecast the demand of month $t+1$, $t+2$ and $t+3$. Additional requirements and criteria of the forecast will be elaborated in Section 2.4.

From the formulated action problem and forecasting objectives derives the main research question: *"Which times series forecasting methods is most appropriate to (separately) forecast monthly demand of final products in the ELSE, OEMP and CLRP capacity groups of Bronkhorst High-Tech?* Before defining the research approach, previous forecast-related research at Bronkhorst is reviewed.

1.3.2 Previous research

Bronkhorst High-Tech currently does not utilize any forecasting methods that support the decision making processes of the supply chain department. However, previous research has been conducted by the product marketing analysts of Bronkhorst High-Tech for the development of a turnover forecast. The developed model forecasts the total sales revenue of Bronkhorst High-Tech, without the categorization of product type of regional variables. Although the output of the forecast does not contain relevant information for the supply chain operations, the research limitations and practical implications of the developed forecast are considered for the design of the research approach.

The developed model forecasts the total sales revenue of Bronkhorst High-Tech, without the categorization of product type of regional variables (see Appendix 4). Using ARIMA, different models and distributions are tested using Minitab to find the best fitting ARIMA-model for the total monthly turnover of Bronkhorst High-Tech. The forecast also comes with prediction intervals for future turnover values. However, these predictions intervals show no increase in prediction width as the forecast horizon increases, which is considered uncommon (Hyndman & Athanasopoulos, 2018). Additionally, turnover forecasts were developed for different sales offices using ARIMA (0,1,1), which is the most basic form of ARIMA-forecasting. None of the developed forecasts was tested on data accuracy using new data, mainly because the data was not split sufficiently to train and test the time series method. The absence of structured evaluations makes it impossible to assess the accuracy of the developed ARIMA models. The product marketing analyst at Bronkhorst High-Tech, responsible for the development of the forecast, experienced the overall process of designing the forecast very time consuming and too complex to be used by the employees of the sales department.

Based on the previous research, several factors need to be taken into account for the development of the research approach. The forecast to be developed needs to be fitted and tested using historical data. To do so, the available data needs to split effectively to conduct accuracy measurements. Moreover, the forecast to be developed needs to be easy to understand for material planners and supply chain employees. Complex forecast will create resistance during the implementation of forecasting methods at Bronkhorst High-Tech.

1.4 Research approach

Hyndman and Athanasopoulos (2018) define the process of developing a forecast using five steps, these steps are summarized in Figure 3. The first step toward finding a demand forecasting method is to analyse the current situation and determine the forecasting objectives of the management team, which is executed in Section 1.3. Using the objectives and scope of the research are clear, the demand data needs to be collected and analysed in Step 2 and 3, to define the main characteristics of the data. In Step 4, the alternative forecasting methods are formulated and assessed. Lastly, in Step 5, suitable forecasting methods are implemented and evaluated. In the following subsections, detailed research activities and their corresponding research questions of each step are discussed. It is important to note that all research activities within these 5 steps are performed separately for each capacity group.

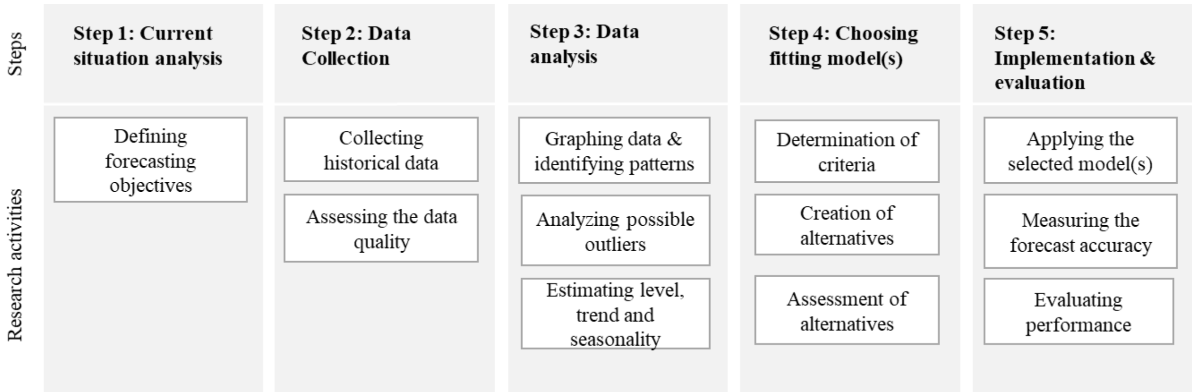

Figure 3 Research Approach

1.4.1 Data collection

Since demand forecasts are primarily driven by historical data, it is crucial to analyse the available data stored by the company to determine the forecasting possibilities. Based on the findings of Step 1, the required data to needs to be collected from the ERP-system. During this step, it is important to collect only what is necessary and leave out what is irrelevant, to improve the processing time of the data. In order to do so, data might need additional filters to extract the desired variables. Occasionally, old data will be less useful due to structural changes in the system being forecast (Hyndman et al, 2008). After the collection of the data, the quality of the data needs to be evaluated to determine if the data sufficiently represents the subject to be forecast. The evaluation will be based on four dimensions of data quality, namely the data accuracy, consistency, validity and completeness. The data needs to be collected, preferably by using software that is most compatible with existing software used by Bronkhorst High-Tech. These research activities will be completed by answering the following research questions:

- How many years of monthly demand data is available to forecast future demand?
- Does the set of data sufficiently represent the subject to be forecast?
- Are periodic quantities valid and/or are there any outliers in the sales data of Bronkhorst High-Tech that need to be explained by those with expert knowledge?

1.4.2 Data analysis

In this third step, the goal is to achieve a better understanding of the underlying demand patterns in the collected data. The data needs to be decomposed to estimate the level, trend and seasonality because the mechanisms of forecasting models are designed based on these characteristics. These features found in the data must then be incorporated into the selected forecasting method (Hyndman et al, 2008). Before estimating these values, however, the data will be plotted to evaluate outliers or possibly unusual demand behaviour. The following research questions need to be answered to gain a better understanding of the demand data:

- Is there a trend in the sales data of Bronkhorst High-Tech?
- Does seasonality occur in the sales data of Bronkhorst High-Tech?

1.4.3 Choosing fitting models

Next, the alternative methods that are appropriate for the research objectives need to be formulated and assessed. Usually, there is more than one model that can be appropriate to forecasts a specified variable. Using a literature review, alternative forecasting methods will be formulated. The assessment of the alternatives will be performed using the requirements of the management team and the key characteristics found in Step 3. To find the forecasting methods that are appropriate for Bronkhorst High-Tech the following research questions will be answered:

- Which time series forecasting methods can be used to predict product demand?
- What criteria does the demand forecast need to meet?
  Using the findings of stage one, and the determined forecasting purposes, a set of criteria needs to be developed to assess the alternatives. Criteria will be developed using employee interviews and literature review.
- Which forecasting methods are most suitable for demand forecasting at Bronkhorst High-Tech with respect to the developed set of criteria?
  The most suitable methods will be selected using the determined criteria. Again, the assessment will involve supply chain employees, including managers and material planners. When the results of the assessments are known, they can be evaluated and appropriate alternatives can be selected for testing.
- What methods can be used to help assess the accuracy of the selected forecasting methods?
  Once suitable forecasting methods are selected, relevant measures of error need to considered parameters to effectively determine the performance during Step 5. The forecast error is a common parameter to determine the accuracy of the forecasting model.

1.4.4 Implementation and evaluation

Once the alternatives are selected using the criteria, the selected methods are implemented and evaluated. Generally, the performance of the model is evaluated after the data for the forecast period has become available. Due to time limitations, the ex-post forecasting method will be applied to split the available data into a fitting and testing part. The *ex-post forecasting* method involves running a forecast in past periods for which the actual demand history is available (see Appendix 5) (Nicolaisen & Driscoll, 2014). The first data group contains older values used for the initialization (fitting), where the key characteristics of the data are determined. The second group is used to carry out the ex-post forecast (testing). As a rule of thumb, 75% of the available data is used for the initialization and 25% is used for the ex-post forecast, as visualized in Figure 4. Since the forecasting objective requires three different forecasting horizons (i.e. h=1, h=2, h=3), the testing data set with n periods of month demand will be utilized in the following manner. For a forecast horizon of one month, all periods n will be forecasted and evaluated using the actual demand. For the forecast horizon of h=2 and h=3, n-1 and n-2 periods of demand are used (respectively) to evaluate the forecasting accuracy.

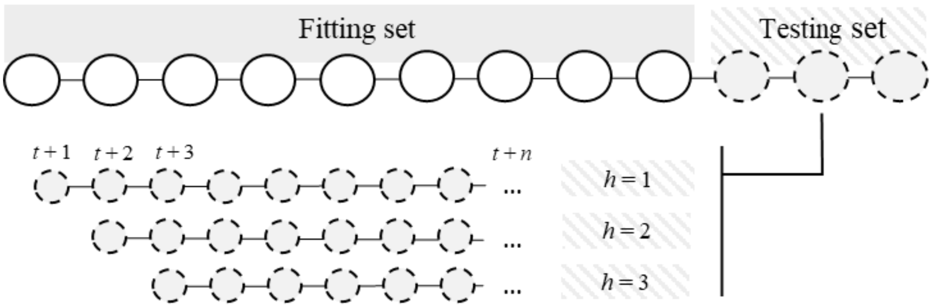

Figure 4 Training and testing data

This approach eliminates the waiting time for the collection of new data for the evaluation of forecast accuracy. This way, the need for new data is eliminated and the performance of the forecast can be evaluated effectively. The main research question of this section is formulated as follows:

- Which of selected time series forecasting methods are most suitable for Bronkhorst High-Tech based on measures of accuracy?

  After implementing the selected forecasting methods, performance measurement needs to be made. From on the findings of the measurements, we will determine whether or not the forecasting methods are recommended for implementation at Bronkhorst High-Tech.

1.4.5 Implementation

Next, the implementation of the demand forecasts are considered. The forecasting model needs to be presented in a understandable manner for non-technical employees of Bronkhorst High-Tech. Therefore, a prototype forecasting dashboard needs to be developed. This prototype should include the main outputs of the forecasting model, which are relevant for the material planners. Since forecasting is new for Bronkhorst Hight-Tech, it is also important to develop a strategy for the company to effectively implement and further develop appropriate forecasting methods. This results in the following, and final, research questions:

- How can Bronkhorst High-Tech effectively implement demand forecasting in their current supply chain processes to support the current planning process?

  Effectively implementing forecasting methods is a business challenge, especially during the implementation phase. For this reason, an appropriate implementation strategy needs to be developed for Bronkhorst High-Tech. This strategy needs to give the material planners a general overview of the practical implementation process of a suitable forecasting method.

1.4.6 Conclusion and recommendations

The findings of the research will be evaluated and summarized in a final conclusion. With the conclusion, additional considerations and recommendations will be discussed. The latter includes research activities that need to be considered for future research.

1.5 Limitations

Like any research, it is essential to take into account time and resource limitations. Since the research needs to be executed in ten weeks, some restrictions need to be set. First of all, this research will focus only on solving the absence of a demand forecast and does not include an analysis effects on inventory levels or delivery reliability. Additionally, the research will not directly forecast component demand to predict future component requirements. Since there is no historical data on component-level demand, final products will be forecasted using aggregated values (from capacity groups) of monthly demand, from which requirement of standard components can be derived (see Section 1.3).

Ideally, the determination of the forecast horizon should take into account the entire supply chain process, from the moment the order is confirmed until the product is delivered at the customer. However, due to time limitations, the determination of the forecast horizon will only be based on the supplier lead time and production lead time at Bronkhorst High-Tech. Moreover, for the determination of material requirements of products with a lead time of 8 weeks, the two-period forecast horizon should ideally predict the two-period *cumulative* demand. By aggregating monthly demand, the cumulative forecast generally yields lower forecast error. However, to conform to the request of the management team, the two-period forecast will predict the two months separately.

Time series methods generally capture characteristics of trend and seasonality but ignore external variables that might influence the demand. Causal forecasting methods can help explain changes in demand patterns by analysing these external factors. In this research, the causal factors will be considered but not studied in-depth, due to time and resource limitations.

1.6 Deliverables

The purpose of this research is to present an approach to demand forecasting at Bronkhorst High-Tech. This research will include a description of the available methods and a instructions on the selection and the implementation of fitting models. The choice in forecasting method will depend on what data is available, the predictability of the event to be forecast and the amount of time and resources. For the final deliverable, the most appropriate forecasting method will be selected for the ELSE, OEMP and ELSE capacity groups. In addition to the implementation and evaluation of the selected forecasting methods, a general strategy will be developed to serve as an implementation plan for the material planners at Bronkhorst High-Tech. This plan should provide Bronkhorst High-Tech with a strategy to effectively incorporate forecasting methods in their current supply chain processes. Along with an implementation strategy, a prototype forecasting tool in Excel will be provided for each of the three capacity groups.

1.7 Reliability and validity

According to Cooper and Schindler (2014), there are three major characteristics of a measurement tool, these characteristics are reliability, validity, and practicality. Reliability is the extent to which a research instrument consistently has the same results if it is used in the same situation on repeated occasions. The second measure of quality in a quantitative study is research validity, which is the extent to which a concept is accurately measured in a study

During the problem identification phase in Section 1.2, interviews are conducted to obtain different perspectives on company performance. If the same interviews were to be repeated weeks or months apart, the findings are most likely going to be unchanged because of the minimal change in operational and organizational structures. Different employees, including mangers material planners, are involved in the collection of information. However, not all employees from the departments are involved in this research. The limited number of research subjects could negatively influence the interrater consistency and validity of the research. If different people were interviewed, the findings of the research might have turned out differently, influencing conclusions found during the research (e.g. during current situation analysis). To ensure that there are enough participants that are also representative of the population, the research subjects are carefully selected by Bronkhorst based on employee position and experience, which improves the inter-rater consistency and research validity. Additionally, strategic choices and research goals are continuously communicated to employees from different hierarchical levels to prevent misinterpretations or misassumptions.

To ensure that research methods and measurements are targeted to measure precisely what is required, the research approach is based on a respectable theoretical framework. The fixed techniques applied during the exploratory stage are supported by literature to ensure consistent application of the methods. Future deviations in collected data measurements are not possible, because the primary data used in the exploratory stage consists only of fixed and historical values.

The practicality of the research design is ensured in multiple ways. First of all, the research mostly consists of quantitative research, which requires little input from research subjects. From an economic perspective, this lowers to the cost of the research because the research is less time consuming for the employees of Bronkhorst Hight-Tech. Moreover, the cost-benefit analysis of the core problem suggested a positive return on investment, assuming the designed forecast will improve the cost-effectiveness of the inventory system. Another factor that influences the practicality of the planned research is the interpretability of results. The interpretability of the research is achieved by accurately describing computations, assumptions and trad-offs made through the development process. This allows the company to perform any of the measurements and analysis conducted in the research.

2 Preliminary Analysis

In this chapter, Steps 2 to 4 of the research approach are carried out. In Section 2.1, the required data is collected and assessed on data quality. Using the decomposition method, the data is further analysed in Section 2.2. In Section 2.3 a literature review is conducted to formulate forecasting alternatives and relevant measures of error. Based on the data characteristics and a set of criteria, the alternatives are assessed in Section 2.4 to select appropriate forecasting methods for Bronkhorst High-Tech.

2.1 Data collection

Demand forecasts are primarily driven by historical data, therefore it is important to analyse the available sales data stored by Bronkhorst High-Tech. Data needs to be collected and filtered according to the predetermined forecasting objectives. Due to confidentiality reasons, the collection of the demand data is executed by one of the material planners at Bronkhorst High-Tech. The initial set of data contained cover 107 order specific attributes, with over five hundred thousand registered orders since the year 2014. These attributes administer different characteristics of customer orders. For the development of a demand forecast for the three capacity groups the desired data set needs to contain (1) monthly sales data of the ELSE, OEMP and CLRP group, (2) only final, and therefore completely assembled, products and (3) no data from the years 2014, 2015, 2020 and 2021. The years 2014 and 2015 need to be left out because of the low number of data points registered in these years. Due to the outbreak of the pandemic, the three capacity groups experienced a decreasing in customer demand during the beginning of 2020. Such events are impossible to predict and have a large impact on market behaviour. Consequently, using these values during the testing of forecasting methods will most likely results in high values of forecasting error. For this reason, demand data of the year 2020 will be left out of the fitting and testing of forecasting methods. The excluded data of the year 2021 contains information about scheduled, but not yet fulfilled orders.

Figure 5 shows the demand of final products of the ELSE capacity groups between the year 2016 and 2019. The demand of final products is based on the desired delivery data requested by the customers. We use the desired delivery date, instead of the order date or delivery date, to ensure that the monthly values represent the moments when the customer demands to receive the final products. Figure 5 also shows the data split into two data types, namely, fitting and testing data. Periods 1 to 36, equivalent to January 2016 to December 2018, are used to fit the forecasting models. Period 37 to 48, equivalent to January 2018 to December 2019, are used to test and validate the applied forecasting models. Visit Appendix 5 and 6, for an overview of the data for the OEMP- and CLRP-group, which included information on the number of data points and applied filters.

//Confidential//

Figure 5 Monthly orders of final products in ELSE group

From the monthly data of the ELSE capacity group, we can observe that there is a repeated decrease in demand towards the end of each year (i.e. period 12, 24 36 and 48). We can also see a slight decrease in customer demand in 2019. This is caused by a relocation of products within the ELSE capacity group, where several products of the ELSE group were temporarily produced in an external facility in Almelo. Due to this change in production location, the final products of the ELSE group were transferred to the EMS1 and EMS4 capacity groups. More specifically, from Period 41 to 48, an average of 140 units was transferred from the ELSE to EMS1. From Period 40 to 48, an average of 97 units was transferred from ELSE to EMS3. These changes will be taken into account when computing forecasted values by subtracting 97 units of the forecasted value for Period 40 and a total of 237 units, for all forecasted values of Periods 41 to 48. From the demand patterns it is also evident that the customer demand is smooth with moderate monthly variation ($CV^2 < 0.49$) where all periods contain non-zero customer demand (Syntetos, Boylan & Croston, 2005).

The data of the OEMP and CLRP capacity groups (Appendix 6), also show a moderate decrease in customer demand, especially towards the end of 2019. With a demand of 40 units in December, which is more than 80% below the monthly average, the OEMP group reaches its lowest demand in four years. Master- and material planners at Bronkhorst High-Tech argue that the decrease in demand within the OEMP and CLRP capacity groups are related to an annual decrease in the month of December. Moreover, the decrease in product demand within the CLRP demand could be related to market changes in the semiconductor industry. In Section 2.3, we will analyse the seasonal factors to test whether or not this claim can be supported by the annual demand data.

2.2 Data quality

Next, the data quality needs to be assessed to ensure validity of test results. *Data quality* is about whether data meets implicit or explicit expectations of people who will use the data. This implies that the degree of quality is dependent on what the data consumer expects from the data. These expectations can be complex since they do not only depend on what the data is supposed to represent, but also on why and how the data consumer uses the data. For this reason, it is assumed that the quality of data is dependent on two factors: how well it meets the expectations of the data consumer and how well it represents information it is created to represent (Sebastian-Coleman, 2013). In this section, we briefly evaluate the data quality of the dataset collected at Bronkhorst High-Tech. Although different scientific papers suggest different sets of data quality dimensions, most of them include some type of accuracy, validity, completeness and consistency.

Data accuracy refers to whether data values in the dataset are the correct value. For data to be accurate, values must be represented with consistency and in an unambiguous form. Unless a dataset can be compared to other data which has 100% confidence level of correctness, it is not possible to determine what the correct and accurate data is. For our dataset, the data is retrieved directly from the ERP system.

Since the dataset cannot be compared to other primary data, the accuracy of the data cannot be fully tested. However, the consistency and validity of the data can indicate the data accuracy.

Data consistency means that there is consistency in the measurement of variables throughout the datasets. Discrepancies in data meanings between data sources can create inaccurate, unreliable datasets. Consistency can be understood in relation to a standard rule, other values within the same database or to data in external systems. For our dataset, all ranges of values are formatted according to its attributes with respect to range and cell structure, ensuring consistency in formatting. Nevertheless, one aspect that might need improvement is the use of languages. Attributes are titles in English and Dutch, which in some cases creates confusion. In order to make values and attributes easy to trace back, the variables from the dataset will remain unchanged throughout the report.

Data validity is the extent to which the scores from a measure represent the variable they are intended to (Prince, Jhangiani & Chiang, 2015). It is the extent to which data conform to a set of business rules. The measurement of validity is built on comparisons to a standard or rule that is set to define a domain of values. Although the data is collected using an automated and structure approach, not all values are in-line with the default value(s). More specifically, the range of values shows large (unexplained) deviations. The main problem in the dataset is that the order quantities include negative values. According to material planners these values provide some sort of compensation for material components. Since the applied filters (Appendix 5) fully eliminate the negative values, the invalid values are not further investigated .

Completeness of data denotes the degree to all required data are available in the dataset. For data to be complete it must meet the following three requirements: (1) the dataset must be fully defined so that it includes all desired attributes (2) the dataset must contain the desired amount of data (3) the data attributes must be entered to the desired extent (Sebastian-Coleman, 2013). As mentioned before, our datasets contain over 107 different attributes including customer-, delivery- and product-related information. Although these attributes do not include components requirements of each order, the final dataset sufficiently represent the desired output of the data and is in-line with research purposes. The amount of data is also in line with the research purposes, since the data quantity exceeds the requirements of the most basic time series forecasting methods (i.e. exponential smoothing and moving average models). However, not all attributes are entered correctly. 4.39% of the orders are categorized under an unknow capacity group, with most products types that are labelled as “other” and have no registered delivery date. Although these values are all excluded using our filters, these characteristics might indicate an inefficient data management system.

2.3 Data analysis

The goal of any time series forecasting method is to predict the systematic component of demand and estimate the random component (Chopra & Meindl, 2016). The systematic component of demand data can contain a level (L), a trend (T), and a seasonal factor (S). Depending on the nature of the demand, the equation for calculating the systematic component can take an additive, multiplicative or mixed form. To gain a better understanding of the underlying demand patterns of the ELSE, OEMP and CLRP capacity groups, the time series decomposition method is applied to analyse the presence of trend and seasonality for three years of demand data (36 periods of monthly demand).

First, the demand is deseasonalized and linear regression is applied to estimate level and trend. The *deseasonalized demand* represents the observed data in the absence of seasonal fluctuations. We obtain the deseasonalized demand, $\overline{D}_t$, for Period t, using

$$\overline{D}_t, = \frac{\left[D_{t-\left(\frac{p}{2}\right)} + D_{t+\left(\frac{p}{2}\right)} + \sum_{i=t+1-\left(\frac{p}{2}\right)}^{t-1+\left(\frac{p}{2}\right)} 2D_i\right]}{2p} \tag{2.1}$$

Here, periodicity p equals 12, representing the number of periods after which the seasonal cycle repeats. Values of L and T of the deseasonalized demand can be estimated using linear regression with deseasonalized demand as the dependent variable and tim e as the independent variable. The deseasonalized demand of any Period t (where $0 < t \leq 36$) for each capacity group is represented by the linear equations found in Table 2.

Capacity group	**Deseasonalized demand $\bar{D}_t$**
ELSE	1810.82 + 17.77t
OEMP	331.76 + 3.55t
CLRP	240.10 + 6.80t

Table 2 Estimates of level and trend for the ELSE, OEMP and CLRP capacity groups

From Table 2 we observe that all three capacity groups contain a positive trend value . This positive trend indicates a growth in monthly orders of final products in the ELSE, OEMP and CLRP groups. For the OEMP group, however, we observe a relatively low value of T. To test the statistical significance of the trend, we run an additional linear regression using the actual demand as the dependant variable, visualized in Figure 6. Using the t-test we find that that there is no statistically significant change in the mean product demand within the OEMP capacity group over time (t=0.26, r^2=0.002, P=0.79). Similarly, using the regression analysis for the ELSE and CLRP groups, we find P-values smaller than 0.05, indicating the occurrence of change in monthly demand over time (see Appendix 7 for detailed test values).

//Confidential//

Figure 6 Linear regression OEMP capacity group

Next, using Equation 2.2 the seasonal factors $\bar{S}_t$ for Periods t are computed for all three groups using the actual demand D_t and the deseasonalized demand $\bar{D}_t$. Given periodicity p, we obtain the seasonal factor for a given period by averaging seasonal factors of the years 2016, 2017 and 2018 that correspond to similar periods using Equation 2.3.

$$\bar{S}_t = \frac{D_t}{\bar{D}_t} \tag{2.2}$$

$$S_i = \frac{\sum_{j=0}^{r-1} \bar{S}_{jp+i}}{r} \tag{2.3}$$

Given periodicity p=12, we obtain the seasonal factor for a given period by averaging seasonal factors that correspond to similar periods. Figure 6 shows the seasonal factors for each month per capacity group. Seasonal parameters have an average value of 1.0, a seasonal factor of 1.2 (or 120%) would indicate that the season had 20% more than the seasonal average. Consequently, strong seasonality in demand is characterized by large deviations in seasonal factors. From Figure 7 we can see that, according to the decomposition method, the customer demand does show some seasonal pattern in each capacity group.

However, we can also observe that most seasonal factors of the ELSE capacity group are relatively close to 1.0, which creates uncertainty in the presence of seasonality.

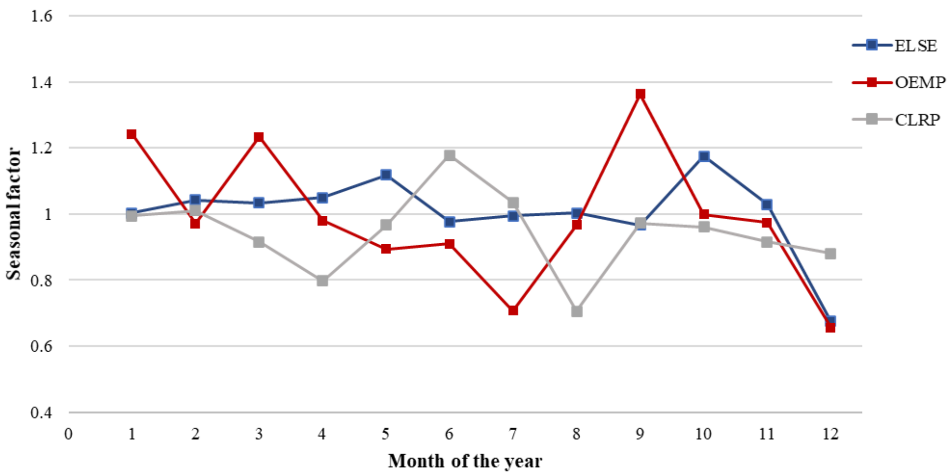

Figure 7 Seasonal factors for each capacity group

According to the material and master planners at Bronkhorst High-Tech, there are no evident changes in demand of ELSE group caused by seasonal factors. To test this claim we test the statistical significance of the seasonal factors in of the ELSE group, a Chi-Squared test is conducted. Contrary to the observations of the employees, we find that there is a statistically significant variation in annual monthly demand (χ^2= 171.38, df=11, p=2.23x10^-9).

Recall that we observed a decreasing demand of the OEMP and CLRP groups towards the end of 2019 in the previous section of this chapter. The OEMP seasonal factors do indeed show a decrease in demand towards the end of the year, with a seasonal factor of 0.66 in December. Looking closer at the seasonal factors of the years 2016, 2017 and 2018, the demand for 2017 does not show a notable decrease in the month of December with a seasonal factor of 0.87. We will have to test to what extent the seasonal factors are able to account for the decreasing demand towards the end of 2019. Contradictory to the hypothesis for the CLRP group of the master and material-planners, there is no evident decrease in demand towards the end of each year, which a seasonal factor of December being relatively close 1.0. The CLRP group does show a repeating increase in demand in the month of June.

Based on these findings, the forecasts to be developed for the ELSE and CLRP group needs to handle trend and seasonality. The forecast of the OEMP group needs to handle seasonality, but the ability to handle trend is not a prerequisite.

3 Selecting Fitting Models

Now that the most important characteristics of the data are known, forecasting alternatives need to be formulated. These forecasting alternatives need to be appropriate with regards the forecasting objectives discussed in Section 1.3, as well as the characteristics of the data analysed in Section 2.2. Therefore a literature review is conducted in Section 3.1 to formulate these alternatives. In Section 3.2, model criteria are developed and alternatives are assessed. Additionally, relevant measures of error are reviewed to further analyse the selected forecasting methods.

3.1 Literature review

The most basic time series forecasting methods are based on historical data of the variable to be forecast. Contrary to causal models, which help explain the causes of variations in demand, the core concept of time series forecasting is to predict what will happen as accurately as possible. Therefore time series forecasting does not attempt to discovering the factors that affect the variable behaviour (Hyndman et al, 2008). Time series models can comprise trends and seasonality but ignore external influences, such as market behaviour, change in regulation, et cetera. In this section we introduce the most common static and adaptive time series methods used in demand forecasting.

3.1.1 Static forecasting methods

Classical decomposition forecasting, a static forecasting method, forms the starting point for most other time series forecasting methods (Hyndman & Athanasopoulos, 2018). The decomposition method, which originated in the 1920s, assumes that the level, trend and seasonal factors of the data remain unchanged as new observations are made. Chopra and Meindl (2016) distinguish the following three forms of forecasting: the additive, multiplicative and mixed form. In this static forecasting method, the forecast is generated in Period t for the demand in Period t + l. While classical decomposition is widely known in forecasting, it is often not recommended, since it does have some drawbacks. Another static forecasting method is the trend projection method, also known as the Least Square method, which fits a trend line to mathematical equations and then projects it into the future by means of this equation. Trend projection methods are particularly useful for long-term forecasting (e.g. annual sales or revenue). The main problem with these static methods is that it assumes that past trends and seasonal changes repeat every year. Static forecasting methods are also less effective with small sets of data, where external factors might create unusual values in the data which the model cannot handle well.

3.1.2 Adaptive forecasting methods

Contrary to static forecasting, adaptive forecasting methods update the estimates of level, trend and seasonality after each demand observation. Appendix 8 presents an overview of the most common adaptive time series forecasting methods, including the Moving Average (MA), Exponential Smoothing (ES), Autoregressive integrated moving average (ARIMA), trend projection methods and Artificial Neural Network models (ANN).

The moving average method is generally used when the data has no observable trend or seasonality. Therefore the systematic component of the time series only consists of the level. The level is estimated as the average demand over the most recent N periods. The current forecast for all future periods is based on the current estimate of the level. In general, a larger number of periods N means a smoother forecasting curve. As we increase N, the forecasting becomes less responsive to more recent data.

Exponential smoothing, which was proposed in the late 1950s, has motivated some of the most successful forecasting methods (Hyndman et al, 2008). Contrary to MA methods, exponential smoothing methods produce forecasts that are based on weighted averages of past observations. As observations get older, the weights decay exponentiality. This way, more recent observations are assigned a higher weight using the smoothing constant α. The value of the smoothing constant controls the sensitivity of the forecast to recent data. The most important ES methods are the simple exponential smoothing, Holt's model and Winter's model. Simple exponential smoothing (SES) is appropriate for forecasting time series with no clear trend or seasonal pattern. Similar to the moving average method, the systematic component of the demand is equivalent to the level. Holt's Model, also known as the trend-corrected exponential smoothing method, is appropriate when demand is assumed to have a level and trend, but no seasonality in the systematic component. Winter's Model, also known as the trend- and seasonality corrected exponential smoothing method, is appropriate when the demand is assumed to have a level, trend and seasonality.

While exponential smoothing models are based on a description of the trend and seasonality in the data, ARIMA models aim to describe the autocorrelations in the data (Hyndman & Athanasopoulos 2018) . Autocorrelation is the degree of similarity between a given time series and a lagged version of itself over successive time intervals. ARIMA models are usually superior to exponential smoothing techniques when the data is reasonably long and the correlation between past observations is stable. ARIMA models are well known for their statistical properties and the incorporated Box-Jenkins methodology (Jenkins, 1970). The largest limitation of ARIMA model is the pre-assumed linear form of the model meaning no nonlinear patterns can be captured by the ARIMA model (Khandelwal, Adhikari, & Verma, 2015). More advanced forecasting methods use artificial neural networks (ANNs) which are based on mathematical models of the brain. They allow complex nonlinear relationships between the response variable and its predictors. Comparted to other models, ANN is often described as complex and hard to interpret for a non-technical audience.

3.2 Assessment of alternatives

3.2.1 Forecast requirements

The forecast to be developed needs to meet a set of criteria related to both the requirements of the research company as well as the characteristics of data. As stated in Section 1.3, the forecast to developed needs to predict monthly demand of final products in the ELSE, OEMP and CLRP capacity groups. From previous research we have learned that the forecasts need to be easy to understand and apply for material planners. Due to time limitations, the three prototype forecasting tools (one for each capacity group) need to be developed within a week. This includes the fitting and testing of suitable forecasting models. These practical requirements can be summarized in the following criteria:

[1.] The demand forecast needs to accurately predict short-term monthly demand (1-2 months)

[2.] The forecast needs to be easy to understand and apply for the material planners.

[3.] The forecast for all three capacity groups needs to be developed within one to two weeks.

In Section 2.2 the collected data is analysed and decomposed to better understand the characteristics of the data. We observed that the data of the ELSE and CLRP group contained both trend and seasonality. The OEMP group contained no significant trend, but de monthly demand does indicate seasonality. Based on the findings of Section 2.2, the forecast needs to meet the following set of criteria:

[4.] The forecast of the ELSE and CLRP group needs to be applicable for data with trend and seasonality

[5.] The forecast of the OEMP group needs to be applicable for data with seasonality.

[6.] The forecast needs to predict monthly demand using three years of monthly demand data.

3.2.2 Assessment of alternatives

Table 3 gives an overview of the assessment of these alternatives for Bronkhorst High-Tech, using the formulated criteria. Based on the short-term forecasting accuracy of each time series technique, it is clear that trend projection methods are not suitable for the forecast of the capacity groups. Although trend projection methods are easy to understand and apply, the poor short-term forecast accuracy is not sufficient for the desired application of the forecast (criterion 3). Contrary to trend projection, neural network forecasts can provide a very accurate short-term forecast. Neural Network forecasts can even handle vague and incomplete data by recognizing complex patterns in the demand data. However, the main disadvantage of this time series method is the required time for the development of the forecast. Fitting a neural network involves using a training dataset and algorithms to update weights and accurately predict outcomes. Since the development of such a forecast will require more than 1 to 2 weeks (criterion 4), this technique is not appropriate for the scope of this research.

ARIMA models can handle trend and seasonality, with good short-term forecasting accuracy, but are most optimal for stationary data with no trend and seasonality. As mentioned in Section 2.2 developing ARIMA-forecast can be very time-consuming compared to exponential smoothing methods, taking more than 2 weeks to develop. ARIMA forecasting usually requires more advanced programming skills for development, which is not ideal for Bronkhorst High-Tech. For these reasons, the ARIMA forecasting method will not be tested for the capacity groups. Contrary to ARIMA-models, exponential smoothing comes with the benefit of being easier to apply, since no advanced programming skills are required for the computation of parameters and the forecast values. Additionally, exponential smoothing methods have good short-term forecasting accuracy and can handle both trend and seasonality. Since exponential smoothing meets all requirements of the developed criteria, the most common variations of ES will be implemented and evaluated on forecasting performance (i.e. SES, Holt's Model and Winter's Model).

Moreover, From Table 3 we can see that the Moving average method (MA) also has a sufficient score on most criteria. Moving averages are good generating short-term forecast, with a very short development time. However, this two-parameter time series forecasting method is not good at handling data with trend and seasonality. Given the weakness of seasonal factors within the three capacity groups, it is worth considering the MA method. Especially for the OEMP group, where the trend is insignificant, the MA method might perform well in forecasting demand.

Technique		**Moving Average**	**Exponential Smoothing**	**ARIMA**	**Trend Projection**	**Neural Network**
Criteria				*Usability*		
1	Good short-term forecasting accuracy	🟢	🟢	🟢	🔴	🟢
2	Easy to understand and apply	🟢	🟢	🔴	🟢	🔴
3	1-2 week development period	🟢	🟢	🔴	🟢	🔴
				Data characteristics		
4	Can handle trend	🔴	🟢	🟢	🔴	🟢
5	Can handle seasonality	🔴	🟢	🟢	🟢	🟢
6	Can forecast using 47 months of historical data.	🟢	🟢	🟢	🟢	🔴
Yes: 🟢 ***No:*** 🔴						

Table 3 Assessment of alternatives

3.2.3 Measuring forecast error

To determine which forecasting method is most suitable for the ELSE, OEMP and CLRP capacity groups, the MA and ES methods will be implemented and evaluated using measures of error. The forecast error reflects the remainder component time series forecast, also known as the random component. One measure of forecast error is the *mean squared error* (MSE), which can be calculated by

$$MSE_n = \frac{1}{n}\sum_{t=1}^{n} E_t^2 \tag{3.1}$$

The MSE is an effective measure of error variance when the cost of a large error is higher than the gains from very accurate forecasts. This is caused by the fact that the errors are squared, which penalizes large errors more than the smaller errors. For the three capacity groups, this measure is less relevant because the is no consequence to larger error such as a capital loss or a direct cost that incurs with backorders. Moreover, by its nature, the customer demand has very large fluctuations, which makes large errors almost inevitable. Another measure of error is the *mean absolute deviation* (MAD), which is the average of absolute deviation over all periods and is defines as

$$MAD_n = \frac{1}{n}\sum_{t=1}^{n} A_t \tag{3.2}$$

Here the *absolute deviation* in Period t is given expressed by

$$A_t = |\, E_t| \tag{3.3}$$

MAD is appropriate when the cost of forecast error is proportional to the size of the error, which applies to the forecast of the three capacity groups at Bronkhorst High-Tech. Furthermore, *the mean absolute percentage error* (MAPE) is the average absolute error as percentage of demand, expressed by

$$MAPE_n = \frac{\sum_{t=1}^{n}\left|\frac{E_t}{D_t}\right|\cdot 100}{n} \tag{3.4}$$

The mean absolute percentage error (MAPE) is one of the most widely used forecasting accuracy measures (Armstrong & Collopy, 1992; Goodwin & Lawton, 1999; Ren & Glasure, 2009). The MAPE is a good choice of error measurement when the underlying demand pattern has significant seasonality and a high demand variation from one period to the next. The *tracking signal* (TS) is the ratio of the bias and the MAD and is given by

$$TS_t = \frac{bias_t}{MAD_n} \tag{3.5}$$

$$Bias_t = \sum_{t=1}^{n} E_t \tag{3.6}$$

The tracking signal is a ratio of the bias and the MAD. If the TS is larger than 6 or smaller than -6, it signals that the forecast is either over- or underforecasting. In that case, either the forecasting method is flawed or the underlying demand pattern has shifted (Chopra & Meindl, 2016). For the evaluation of forecasting accuracy of the values of MAD, MAPE and TS among the different methods will be compared to find the most accurate forecasting method.

4 Results

In the previous chapter, the selection of forecasting techniques is determined, namely the Exponential Smoothing and Moving Average Method. In this chapter, we focus on the final step of the problem-solving approach: the implementation and evaluation of forecasting methods. A fraction of the collected data is used to test the accuracy of the forecast, instead of waiting for new data to be collected. Accordingly, the years 2016, 2017 and 2018 are used to fit the models to the data set, which includes optimizing model-specific constants to minimize the resulting error. Using the fitted models, 12 periods of monthly demand in the year 2019 are used to test the models. Based on measurements of forecast accuracy, the forecasting methods are evaluated for each capacity group to find the most appropriate forecast method for Bronkhorst High-Tech. In Section 4.1, 4.2 and 4.3 the results of the accuracy measurement of forecasting methods are evaluated for the ELSE, OEMP and CLRP capacity group respectively. In Section 4.4, alternatives are proposed to achieve a higher forecasting accuracy. Lastly, Section 4.5 discusses the main findings of this chapter.

4.1 ELSE

First, the MA and SES models are fitted to 36 periods of data of the ELSE group, collected in Section 2.1. For the MA method, the value of N (periods) needs to be optimized. Recall that the moving average method estimates the level using the average demand over the most recent N periods. Since the value of N determines the responsiveness to the most recent data, the forecast values and errors also vary with the value of this constant. To determine the optimal value of N, we compare the values of MAD, MAPE and TS that result from alternate values of N ($2< N \leq 10$). From Figure 7 we observe that the 3-MA model results in the lowest error, where MAD_{36}=265 and $MAPE_{36}$=13.3 From measures of TS, we find that all values of N result in biased forecasts. More specifically, the MA model is consistently underforecasting the monthly demand of the ELSE capacity group.

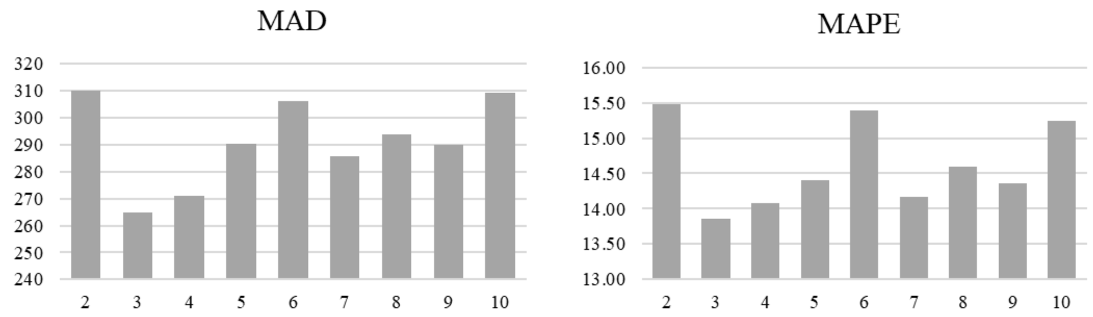

Figure 8 MAD and MAPE for values of N

Next, we consider the exponential smoothing methods. For ES models, the smoothing constants are optimized to achieve the lowest resulting error. To, do so the Excel Solver function is utilized to minimize the values of MAD. For the SES model we find the lowest error using $\alpha = 0.5$, where MAD_{36}=280 and $MAPE_{36}$=13.9. Holt's Model performed best using $\alpha = 0.54$ and $,\beta = 0.15$, which results in MAD_{36}=244 and $MAPE_{36}$=12.3. For Winter's Model the lowest resulting error comes from using $\alpha = 0.1, \beta = 0.05, \gamma = 0.05$, where MAD_{36}=175 and $MAPE_{36}$=8.4. The resulting values of TS, using these smoothing constants, are within the ±6 range. From the error measures of the models, it is clear that Winter's Model performs best for the 36 months of monthly demand. The smoothing constants of the SES method and Winter's model are somewhat high, indicating that the models do not fit the data well. Ideally, it is best to use a smoothing constant that is no larger than 0.2 (Chopra & Meindl, 2016). However, a model which fits the fitting data well will not necessarily forecast future demand well. Since the seasonal factors of Winter's models are based on the 36 periods of data, it might also be that the model is over-fitted. Therefore, the performances of the models need to be validated using the testing data.

As stated in Section 1.3, the forecasting objectives include a three-period forecast horizon. This means that at Period *t*, a forecast is generated for $t+1$, $t+2$ and $t+3$(where $t \geq 36$). To determine which forecasting models is most appropriate, the forecast error of both horizons need to be evaluated separately. Without adjusting the values of N, L_0 and T_0, we generate and optimize the smoothing constants on a monthly basis using the demand data of the year 2019. This includes increasing the smoothing constant in periods where older data becomes less relevant. Recall that we identified a significant decrease in demand during the year 2019 (see Section 2.1). To account for the reallocation of products within the ELSE group during these periods, the forecasted values are adjusted manually using registered transfers to the ELS1 and EMS4 groups. Figure 9 and 10 show the resulting errors of the forecasting models using the testing data. For each forecast horizon, separate measures of error are applied over the testing data. Hence, the MAD, MAPE and TS of forecasting one month into the future are measured using 12 periods of forecast error. Similarly, the error measures of forecasting two and three months into the future are computed using 11 and 10 periods of forecast error.

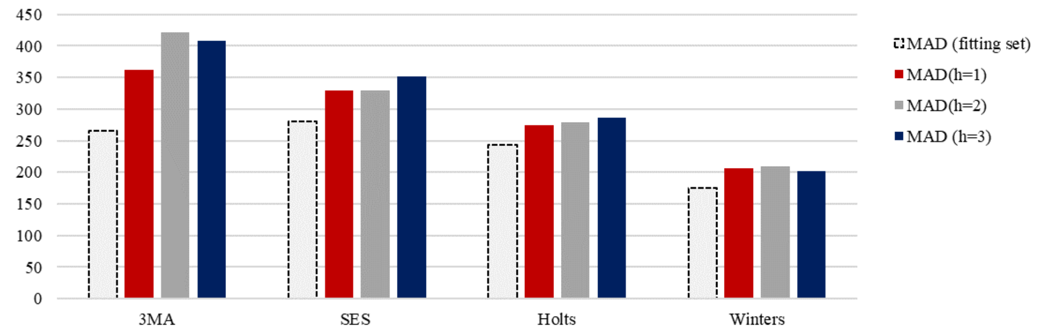

Figure 9 ELSE: MAD 48 for h=1, h=2 and h=3

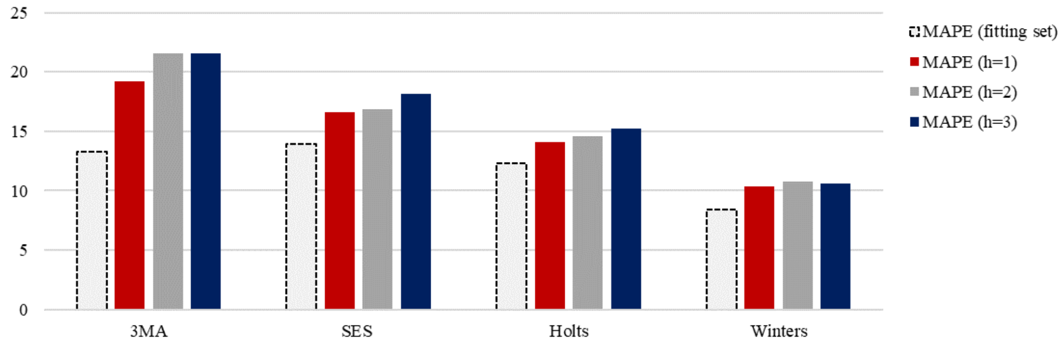

Figure 10 ELSE: MAPE 48 for h=1, h=2 and h=3

From Figure 9 and 10 we can see that Winter's Model has the lowest resulting error, when applied to the testing data. Forecasting $t+1$ periods ahead results in MAD=206 and MAPE = 10.4, where $1.0 \leq TS \leq 5.2$. Forecasting $t+2$ periods ahead results in MAD=210 and MAPE= 10.7, where $1.0 \leq TS \leq 4.6$. Lastly, Forecasting $t+3$ periods ahead results in MAD=202 and MAPE=10.6, where $0.72 \leq TS \leq 4.0$. All three forecasting horizons result in TS values within the ±6 ranges, indicating unbiased forecasts. The fact that Winter's Model performs best, confirms that seasonal fluctuations are present and reoccur in the year 2019. When we plot the forecasted values of the different models (see Appendix 9), we also find that all models seem to be overforecasting in Period 42 and 44, despite the manual correction made for the reallocation of products within the ELSE capacity group. This analysis also shows that the testing values are higher than the fitting values, as shown in Figure 9 and 10.

4.2 OEMP

Following the same approach as conducted for the ELSE group, the forecasting models are evaluated for the OEMP capacity group. Again, the models are fitted to optimize model-specific constants using 36 periods of demand data. For the MA model, the 5-Period MA results in the lowest error, where MAD_{36}=111 and $MAPE_{36}$=31.1. The TS values is for 5MA model indicate an unbiased forecast, where -2.48≤ TS≤ 3.00. For the SES model we find the lowest error using $\alpha = 0.5$, where MAD_{36}=102 and $MAPE_{36}$=27.9. Holt's Model performed best using $\alpha = 0.22$ and $\beta = 0.05$, which results in MAD_{36}=107 and $MAPE_{36}$=30.4. For Winter's Model the lowest resulting error comes from using $\alpha = 0.1$, $\beta = 0.05$, $\gamma = 0.05$, where MAD_{36}=84 and $MAPE_{36}$=22.6. All fitted ES models are unbiased and within the acceptable TS range. Next we attempt to validate the forecasting performances of the fitting models, using the testing data set. Figure 11 and 12 show the resulting measures of error for the 1-, 2,- and 3-period forecast horizon.

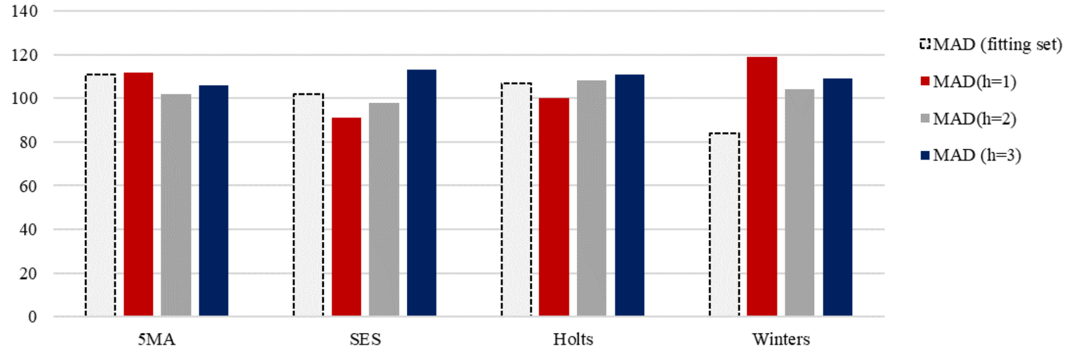

Figure 11 OEMP: MAD 48 for h=1 and h=2

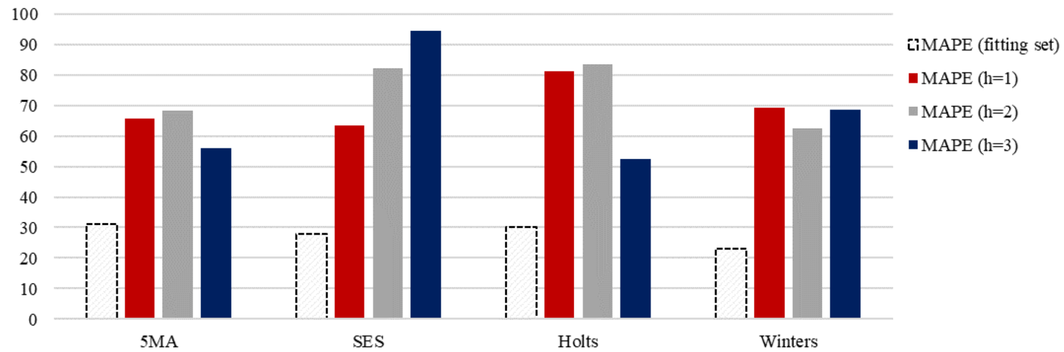

Figure 12 OEMP: MAPE 48 for h=1 and h=2

Although Winter's Model performed best whilst fitting the model, the figures indicate that the 5-Period Moving Average Method fits the demand the best. We also find that all values of TS of the four methods are within the acceptable ±6 range. Compared to an average demand of 351 units per month, the values of MAD are still very high. Moreover, the values of MAPE for the MA method of all three forecasting horizons are above 56%, which indicates very poor forecasting accuracy. The large increase in MAPE-values is mainly caused by a decrease in customer demand in the last two months of 2019, which is discussed in Chapter 2. Although the values of TS for all forecasts for the OEMP group, there is a visible increase in TS between Periods 36 to 42 and Period 46 to 48, which are directly caused by the sudden decrease in customer demand (Appendix 9 and 10). Based on the measures of error of Holt's and Winter's Model, it is clear that the trend and seasonal factors are not able to account for this decrease in demand, despite increasing the smoothing constant in periods of decreasing demand. This due to the fact that the identified patterns are not repeated in the year 2019. Consequently, the MA method, which only utilizes recent data to forecast future demand, results in the lowest error.

4.3 CLRP

Using the 36 periods of data, the four forecasting models are fitted to minimize values of error. For the CLRP group, the 2-Period MA results in the lowest error, where MAD_{36}=88 and $MAPE_{36}$=24.7. The TS values indicate that the 2-MA model is biased, due to underforecasting demand, where -10.8≤ TS≤ 7.01. For the SES model, we find the lowest error using $\alpha = 0.4$, where MAD_{36}=80 and $MAPE_{36}$=25.4. Holt's Model performed best using $\alpha = 0.43$ and $\beta = 0.05$, which results in MAD_{36}=80 and $MAPE_{36}$= 24.8. For Winter's Model the lowest resulting error results from using $\alpha = 0.1$, $\beta = 0.05$, $\gamma = 0.05$, where MAD_{36}=75 and $MAPE_{36}$=20.8. The tracking signals of the fitted ES models, which are between the ±6 range, indicate that all ES models are unbiased.

Next, the models are tested by forecasting demand of the year 2019. Figure 13 and 14 summarize the resulting MAD and MAPE values from testing the four models using 12 months of demand data. From these figures, we can see that Holt's Model has the lowest resulting error using the testing data. Using Holt's Model with a $t + 1$ forecast horizon results in MAD = 92, $MAPE$ = 28.8 and the tracking signal is between -2.8 and 2.7. For the $t + 2$ forecast horizon, MAD = 115, $MAPE$ = 39.1 and the tracking signal is between -2.0 and 3.6. For the $t + 3$ forecast horizon, MAD = 128, $MAPE$ = 48.26 and the tracking signal is between -2.0 and 5.2. Observe that all values of TS are within the ±6 ranges, indicating unbiased forecasts. However, the values of MAD and MAPE of the testing sets are high and indicate inaccurate forecasts. From Figure 14 it is evident that the forecasting accuracy of all four models decreases as the forecasting horizon increases. The main cause of this decrease in accuracy, is the decrease in demand in for 2019, which does not align with previously identified trends and seasonal factors. Especially between Period 40 and 42, we identify a significant increase in tracking signals, where the model is overforecasting the demand. Consequently, Winter's Model results in the highest error, due to the inaccurate seasonal factors of 2019. This indicates that the seasonal factors determined in Chapter 2 do not accurately capture the demand patterns of the CLRP group.

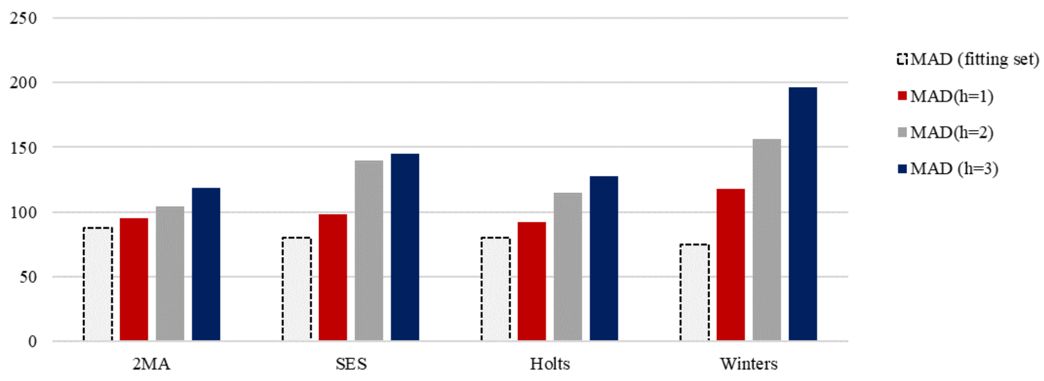

Figure 13 CLRP: MAD 48 for h=1 and h=2

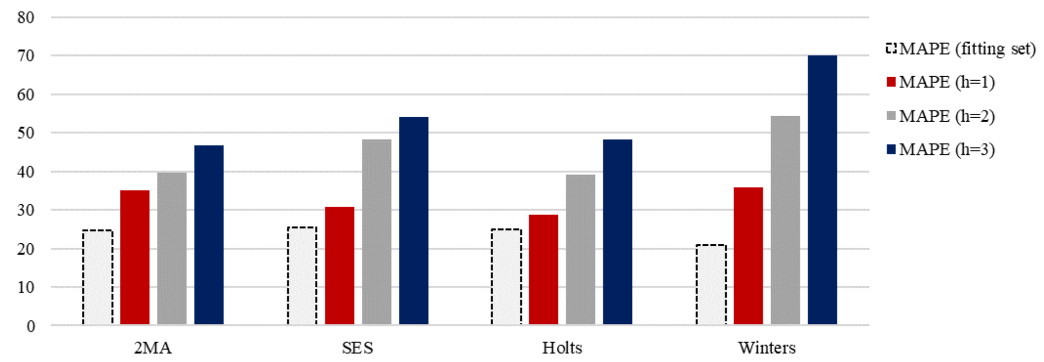

Figure 14 CLRP: MAPE 48 for h=1 and h=2

4.4 Improving forecasting accuracy

In the previous section, we found that MA and ES forecasting models were not able to accurately forecast the monthly demand of the OEMP and CLRP capacity groups. The identified inaccuracies, indicated by high values of MAD and TS, are mainly caused by a shift in customer demand within the two capacity groups. Generally, when large deviations in demand occur, it is best to adjust the smoothing constant to increase the importance of most recent data. For the OEMP and CLRP group, we find that increasing the smoothing constants does improve the forecast to some extent. Despite adjusting the smoothing constant on a monthly basis, the resulting errors remain high. According to the master- and material planners at Bronkhorst High-Tech, there is no direct cause for the decreasing demand within the OEMP and CLRP group. Unlike the ELSE group, there are no changes in production locations or transfers of final products to other capacity groups. However, as mentioned in Chapter 2, there might be a cause and effect relationship between the semiconductor industry and the product demand within the CLRP capacity group. To better understand the causal relationship between these two variables, further research needs to be conducted.

Another approach could be to forecast either customer-specific or individual product demand within the capacity groups. However, it is important to take into account that the level achievable accuracy of the objective also depends on the demand pattern. Syntetos, Boylan, and Croston (2005) classify four patterns of demand: smooth, erratic, intermitted and lumpy demand. The classification is determined using values of the Average inter-Demand interval (ADI) and the Squared Coefficient of Variation (CV^2). Based on a small sample analysis of the 10 largest customers within the OEMP capacity group, we find that 60% of these customers contain intermitted demand (ADI>1.32, CV^2<0.49), and 40% contains lumpy demand patterns (ADI>1.32, CV^2>0.49). The percentage of lumpy demand patterns increases as the percentage of total annual purchasing volume decreases. For the CLRP group over 50% consist of demand with smooth patterns, because the order frequency of CLRP products is higher with fewer periods of zero-demand. Previous research at Bronkhorst estimates that 39% of the total final product demand is intermitted and 33% contain lumpy demand patterns, where the majority of the smooth demand is categorized in the ELSE capacity group. These types of demand patterns are generally harder to forecast. However, forecasting models such as Croston's Method and the Syntetos-Boylan Approximation (SBA) methods are able to handle these types of data, further research is necessary to analyse to lowest achievable error.

4.5 Conclusion

In this chapter, the Moving Average method, Simple Exponential Smoothing method, Holt's Model and Winter's Model were applied to the collected data. 36 periods of monthly demand of each group is used to fit the forecasting models to the data. By optimizing the model-specific constants, measures of error were minimized. Next, using 12 months of demand data was used to test the fitted models. Using measures of MAD, MAPE and TS, the models were tested and evaluated on their 1-, 2- and 3-period forecasting accuracy to find the best fitting model for each capacity group.

From the test, we find that Winter's Model has the highest forecasting accuracy for the ELSE capacity groups, where the 1-, 2-, and 3-period forecasts result in a MAPE of 10.4%, 10.7%, 10.6%, respectively. Based on the level of accuracy, it is recommended that Winter's Model is used to forecast monthly demand of the ELSE capacity group. For the OEMP capacity group, we find that none of the four forecasting models are able to accurately estimate future customer demand. This is caused by a, currently unexplained, decrease of product demand in 2019 within the OEMP group. This shift in demand confirms that the determined trend and seasonal factors of Chapter 2 do not repeat in 2019. The lowest achievable forecasting error results from using the 5-Period Moving Average model. The values of MAPE for the 5-MA method of all three forecasting horizons are above 56%, which indicates very poor forecasting accuracy. Therefore, none of the models is recommended for the OEMP capacity group.

Lastly, for the CLRP capacity group, the Holt's Model generates the most accurate forecast. The fact that Holt's Model performs best, indicates that seasonal factors determined in Chapter 2, do not accurately capture the underlying demand pattern of the CLRP group. Although Holt's Model performs best, the values of error are still high, where the 1-, 2-, and 3-period forecasts result in a MAPE of 35%, 39.7%, 46.6%, respectively. Similar to the OEMP group, the increasing values of error are mainly caused by a negative shift in customer demand. Since these values of MAPE are considered to be insufficient for material planning purposes, due to the associated cost of overstocking materials. Therefore it is not recommended that Holt's Model is used for material planning purposes. The master and material planners at Bronkhorst High-Tech speculate that the decrease in demand could be related to changes in the semiconductor industry. However, the analysis of this causal relationship is beyond the scope of this research.

To achieve higher forecasting accuracy for products in the OEMP and CLRP capacity groups, it is recommended that Bronkhorst High-Tech considers forecasting customer-specific demand or individual products within these groups. Based on a small sample analysis, it is expected that these forecasts will require models that can handle intermitted and lumpy demand patterns, such as Croston's Method and the Syntetos-Boylan Approximation (SBA). However, further research is necessary to analyse the lowest achievable error using this alternative forecasting approaches.

5 Implementation

A large factor that influences the effectiveness of forecasting at Bronkhorst High-Tech is the resistance to change the current planning processes (Håkansson & Waluszewski, 2002). One way to decrease the resistance to change for the material planners is to conform to current business processes at Bronkhorst High-Tech. To do so, a prototype forecasting tool is introduced in Section 5.1, which presents the concept of forecasting in a user-friendly and understandable manner for non-technical employees. In Section 5.2, a forecasting strategy is developed for the supply chain department, which describes how forecasting can be effectively implemented and continuously improved in the planning process.

5.1 Forecasting tool

As the final deliverable of the conducted research, a prototype forecasting dashboard is designed. Since Bronkhorst High-Tech is currently in the process of developing its PowerBI platform, the prototype model can be utilized in the design of a forecasting interface. Figure 15 shows the developed Excel tool, which is based on Winter's Model for the ELSE capacity group. The forecasting tool includes the three measures of error discussed in previous chapters, estimates of future demand and the expected material requirements. The top-left graph shows the forecasted demand plotted over the actual demand. Additionally, the top right graph shows the forecasted demand of the next month and the historical demand of past years for the same month. Using the bottom left graph, the tracking signal can be monitored. Most importantly, the bottom right histogram shows the projected requirements for the standard components, based on the average consumption within the ELSE capacity group. Using values of MAD and the predictions of future demand, the material planners can determine the material requirements for standard components in the ELSE capacity group. Since this model is a prototype, the tool does not automatically update forecasting values when new observations are registered in the ERP system.

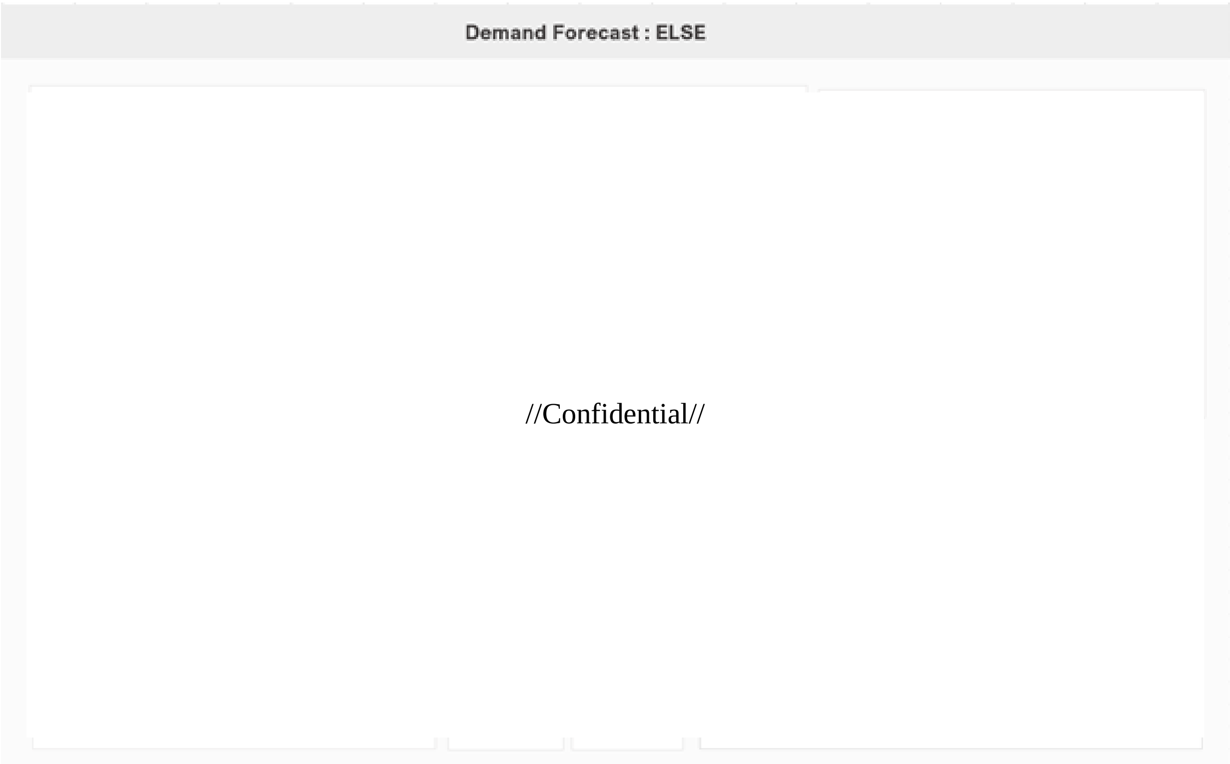

Figure 15 Prototype dashboard design

5.2 Forecasting Strategy & operationalization

Since the forecasting methods have not been tested in real-world environments, it remains to be seen if demand forecasting methods will be an effective tool in the organization. We now consider several important steps towards effective forecast implementation, to ensure that these methods are implemented and monitored correctly. In Section 1.4, Hyndman and Athanasopoulos' (2018) approach to forecasting was introduced and implemented in the following chapters. This approach is very effective in finding appropriate forecasting techniques, but it does not ensure continuity that the forecasting methods require during the implementation at Bronkhorst High-Tech. To conform to the current planning process at Bronkhorst High-Tech, the forecasting approach is extended by incorporating operational activities that are required in the planning process. This revised version of the forecast approach incorporates the iterative four-step management method, known as the PDCA (plan-do-check-act) cycle, is visualized in Figure 16.

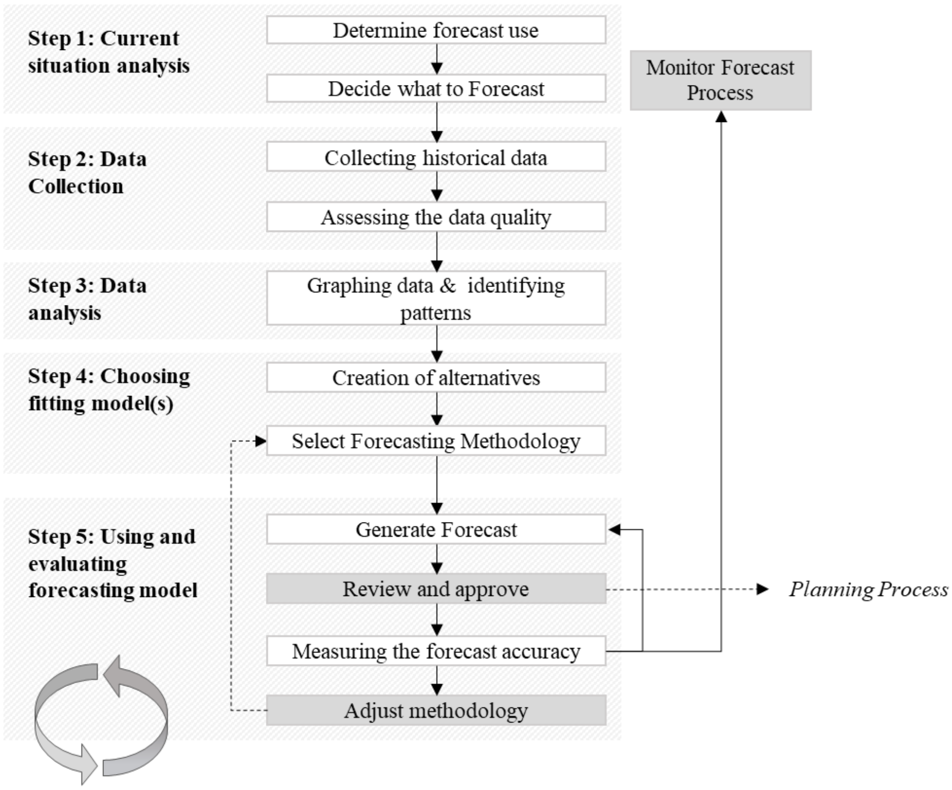

Figure 16 Forecast development process

The added steps to the existing forecasting approach are marked in grey. It is important to note that this figure is not intended to depict every strategic or operations task within the department, but rather illustrate major features of the relevant supply chain processes. To implement forecasting methods, the selected forecasting methods need to be properly maintained and improved when possible. Using the metrics introduced in Section 3.2 the forecast can be consistently measured to determine where the forecast is off, help manage demand uncertainty and optimize the forecasting process.

As proposed by Hyndman and Athanasopoulos (2018), the process is divided into five steps which can be categorized into two phases. The first phase (Steps 1 - 4) is focussed on the preliminary research to support strategic decision making (i.e. determine what and how to forecast). The second phase (Step 5) is where the selected methodology is applied and evaluated, also known as the implementation phase. In the implementation phase, new methods and existing forecasting methods are evaluated. The preliminary phase is organized as follows:

Step 1. Current Situation Analysis. This involves identifying who will use the forecast and for what purpose the forecast will be developed. More specifically, what sort of planning activities will be supported using the forecast (e.g. production, personnel). Accordingly, the forecaster needs to decide which stream of data needs to be forecasted. Here, the level of data aggregation and the forecast horizon is determined. If possible, expected levels of accuracy need to be assigned by the management.

Step 2. Data gathering. Here, the necessary data is collected and formatted. Additionally, outlier detection may be performed to improve data accuracy.

Step 3. Data analysis. The collected data is analyses and if applicable, patterns are identified using the decomposition method

Step 4. Selecting fitting model(s). Based on the previous step, available alternatives need to be formulated and a forecasting approach (method) is selected. If applicable, appropriate software systems need to considered. In the case of forecast auditing, which occurs when existing forecasting methods are revised, forecaster and managers need to discuss previous forecasting performances and redesign the forecasting methodology.

Next, arriving at the implementation phase, the selected methodology is implemented and evaluated. Since forecasting requires continuous monitoring and evaluation, the activities within the implementation phase are repeated in cycles. The frequency of these activities depends on the forecasting horizon, for example, short term forecasting may require weekly forecasting and evaluation, whereas annual forecast might require quarterly evaluation. The fifth and final step of the forecasting approach is structures as follows:

Step 5. Forecast generation. Using the collected data, the selected forecasting method is implemented. If applicable (i.e. when existing forecasts are regenerated) previous forecasting inputs (such as smoothing constants or parameters) are adjusted, based on previous accuracy evaluations. Next, the forecaster meets with required representatives from the company (e.g. sales, marketing, finance) to review anticipated demand and growth expectations. If the values are approved the forecasting values are approved by the representative(s), the outputs can be used for planning purposes. If not, managers need to be consulted to resolve inconveniences. When new data is collected, the forecasted demand is quantitatively evaluated using the values actual demand. The forecasts are evaluated on accuracy using a set of relevant metrics (as suggested in Section 3.2) depending on the characteristics of forecasting objectives. Using the measures of error, constants and parameters can be optimized for following forecast periods. The evaluation of the forecast accuracy needs to be executed on an individual level, as well as on an aggregated level using both current and historical values of the metrics. The findings of the evaluation in this step need to be summarized for manager review. Together with the management team, high-level forecasting output needs to be reviewed. Depending on the performance of the forecast, the parameters can be adjusted, the forecasting method can be modified or the forecasting process itself might need to be changed.

6 Conclusions and recommendations

This final chapter provides the conclusion, discussion and recommendations of the conducted research. Section 6.1 covers the main findings of the research and in Section 6.2 the research limitations are discussed. Based on the findings and limitations of the research, several recommendations for Bronkhorst High-Tech and future research are made in Section 6.3.

6.1 Conclusions

This research aimed to find appropriate demand forecasting methods to improve inventory management at Bronkhorst High-Tech. Based on the situation analysis, the forecasting objectives were determined together with the management team, from which the forecast requirements were derived.

Due to the uncertain future demand at Bronkhorst High-Tech, the material planners need information that can help the component-level material planning. Based on the requirements of the management team of Bronkhorst High-Tech, the research objective is to create a capacity forecast for the ELSE, OEMP and CLRP capacity groups from which the monthly material requirements can be estimated. These capacity groups account for a total of 51.9% of the total sales at Bronkhorst High-Tech. Each of the capacity groups contains products with the same set of standard components. By forecasting the demand of final products within each capacity group, the material planners can determine the monthly requirements of the standard components. The determination of material requirements can be derived from a predetermined distribution of standard components within each capacity group that is based on the average consumption of each standard component. To cover the supplier lead times, a forecasting horizon of three months is required.

After the determination of forecasting objectives, the data was collected, evaluated on its quality and the underlying demand patterns were identified. These demand patterns are defined using three components: the level, trend and seasonal factor. Only the ELSE and CLRP capacity groups contained a statistically significant trend and all three capacity groups contained seasonality. Using the findings of the data analysis and a set of criteria, appropriate forecasting techniques were formulated and assessed. The methods that sufficiently met the criteria where the Moving Average Method (MA) and the Exponential Smoothing Method (ES). Since ES has different variants, the most relevant methods were considered, namely the Simple Exponential Smoothing, Holt's Model and Winter's Model. Using the ex-post forecasting method, we found that Winter's Model was able to accurately forecast the demand of the ELSE group, where the 1-, 2-, and 3-period forecasts result in a MAPE of 10.4%, 10.7%, 10.6%, respectively. None of the selected methods was able to capture and forecast the demand of the OEMP group. The inaccurate forecasts for the OEMP groups are mainly caused by a negative shift in demand. From accuracy measurements, we observe that the determined seasonal factors do not align with the demand pattern of the OEMP group. For the CLRP capacity group, Holt's Model generates the most accurate forecast. Although Holt's Model performs best, the values of error are still high. Due to the high value of MAPE, the model is assumed to be insufficient for material planning purposes, because of the associated cost of overstocking materials. Master and material planners at Bronkhorst speculate that the changes in demand patterns within the CLRP group may be related to changes in the semiconductor industry.

Using Winter's Model on the ELSE capacity group, a prototype forecasting tool is developed for the material planners at Bronkhorst High-Tech. To ensure effective implementation of Winter's Model and future forecasting methods for planning purposes, Hyndman and Athanasopoulos' (2018) approach to forecasting is extended by incorporating operational activities that are required in the planning process. This 5-step forecasting approach incorporates the iterative management method, known as the PDCA (plan-do-check-act) cycle, which ensures continues monitoring and evaluation for long term forecast improvement.

6.2 Discussion

In this research, multiple forecasting methods have been evaluated on forecasting accuracy for the ELSE, OEMP and CLRP capacity groups using the theory of Hyndman an Athanasopoulos (2018). In this section, the most important limitations of the implemented approach and their effects on the research validity and accuracy are discussed.

A large factor that influences the validity of the research is the outbreak of the pandemic. The COVID-19 pandemic caused a significant change in customer demand of Bronkhorst High-Tech. Developing a forecast based on data with increased uncertainty in future demand negatively affects the performance measurements. For this reason, data of the year 2020 was not used for the testing of the forecasting methods. This negatively affects the reliability of the assessment of forecasting alternatives, due to the decreased relevancy of data. If the demand patterns do not recover to a state where it aligns with previous years, the validity of the selection of the best fitting model decreases.

During the problem identification phase, several forecasting approaches were proposed to the research company, including the objective to forecast product or customer-specific demand. Such forecasts would give more detailed and accurate information about the material requirements. Nevertheless, the management and the material planners were in favour of forecasting the capacity group demand instead, mainly to support additional capacity planning processes. This negatively affects the effectiveness of the solution to the predetermined research aim, namely lowering the inventory levels of standard components. Furthermore, by forecasting the capacity groups, the material requirements are estimated by translating the monthly demand using a distribution of component requirements. This distribution of components, introduced in Chapter 2, is based on the average consumption of standard component within a specific capacity group. This implies that the estimates of the standard components also have a standard deviation. Consequently, the risk of over or under forecasting is increased, due to the changing proportions of material requirements over time. Since the distribution of material requirements is researched by material planners using historical data and their own experience, the exact standard deviations of these values is currently unknown. This negatively affects the reliability of the recommended ELSE forecasting model.

Using the characteristics of the demand data, appropriate measures of error were selected in Section 3.2. These measures included MAD, MAPE and Tracking Signal. Since the concept of forecasting is new to the supply chain department and material planners, levels of sufficiency were determined relative to the average demand of each capacity group. This leaves room for error, because the validity of recommended forecasting methods might turn out to be insufficient in practice. Only through real-world application and experience can the sufficiency of the forecasting methods be validated.

During the data analysis in Section 2.2, the data was plotted and possible outliers were evaluated to ensure the validity of monthly sales values. However, the detection of outliers was done qualitatively using the expertise of material planners, which negatively influences the reliability of this analysis. To accurately detect outliers, more advanced statistical detection methods should be applied. Moreover, some changes in OEMP and CLRP demand over 2019 are currently not explained fully. The most notable deviation in demand occurred in December 2019, where the OEMP group reached its lowest monthly demand in four years. Such unexplained deviations negatively affect the reliability of the performance measures, because the cause of inaccuracies cannot be substantiated.

6.3 Recommendations

Based on the findings and limitations of the research, several recommendations can be proposed to effectively implement and improve the forecasting at Bronkhorst High-Tech. In this section we focus on practical recommendations for Bronkhorst High-Tech and future research.

6.3.1 Practical recommendations

According to the accuracy measurements conducted in Section Chapter 4, Winter's Model is able to accurately forecast the demand of the ELSE capacity group. For this reason, it is recommended that this method is implemented at Bronkhorst High-Tech to support the decision making process of the material planners. However, the management team does need to consider the limitations of the conducted research and the associated risks in demand forecasting. If implemented, errors in forecasts can lead to misallocation of resources in inventory levels. The risk associated with forecast errors must be considered when utilizing the research findings for planning purposes. Risk caused by internal factors often comes from poor coordination and communication throughout the supply chain. Risks caused by external factors include, but are not limited to, completely unpredictable Black Swans (e.g. outbreak of a global pandemic) and expected market changes (e.g. new market opportunities) (Makridakis, Williams, Kirkham & Papadaki, 2019). A wide range of factors can cause forecast error, but some require specific mention for Bronkhorst High-Tech. The following recommendations should be considered by the management team.

- Due to insufficient component-level demand data, the forecasts are generated based on aggregated demand of final products. This approach increases risk of under- or overestimating material requirements. To improve inventory management of product components, Bronkhorst High-Tech should combine the BOM of orders with the sales data in their ERP system. This way, component demand forecasts can be generated, using component-specific forecasts. This will greatly improve the forecasting accuracy of individual components.
- The long lead times at Bronkhorst High-Tech require forecast to be made further in advance. As the forecast horizon increases, the reliability of the forecast decreases. One way to mitigate the forecast risk is to increase to supply chain responsiveness. Higher responsiveness, through improved coordination, requires smaller forecast horizons which reduces forecast error and risk. The first step towards better coordination within the supply chain is by aligning goals and incentives so that the efforts of all stages are directed at maximizing total supply chain profits. Next, managers can improve information flow by improving the visibility and accuracy of the information available in different parts of the supply chain (Chopra & Meindl, 2016). It is highly recommended that the management team considers the concepts of point-of-sale (POS) data and Collaborative Planning Forecasting and Replenishment (CPFR). By sharing POS data across the supply chain, accurate and timely data can be made available to each entity in the supply chain (Stadtler, 2009). Moreover, the purpose of CPRF is that companies can be more successful by joining forces to bring value to their customers, share risks of the marketplace and improve their performance. Especially by collaborating with material suppliers, the responsiveness of the supply chain can be improved greatly. By sharing the developed forecast with suppliers, the suppliers can anticipate the production requirements and achieve smaller lead times. Visit Appendix 11 for a detailed discussion of supply chain coordination at Bronkhorst High-Tech.
- The forecasting accuracy can be further developed by better understanding the dynamics and components of the system for which the forecasting is made. Preferably using a flowchart, the relative positions of the different elements of the distribution system, sales system and production system should be mapped. With respect to the objectives of this research, the flowchart needs to show the elements that are directly affecting the capacity group forecast (e.g. introduction of new products, transfer/removal of products, market behaviour). Parts of the system where Bronkhorst High-Tech has total control, cause-and-effect relationships should be analysed. Accordingly, the management should consider using forecasting techniques that take causal factors explicitly into account (Zsidisin & Richie, 2009). Especially for the OEMP and CLRP capacity groups, which show inconsistent demand patterns, a better understanding of the demand patterns can lead to lower forecasting errors.

- Seasonality also tends to increase forecast error, especially when there are few historical data to build on when producing a forecast. In this research, seasonal factors are determined using only three years of deseasonalized demand. To achieve better forecasting accuracy, the seasonal factors should be reviewed and optimized using expert knowledge. If possible, historical data before 2016 should be considered to revise the estimated seasonal factors of Chapter 2.
- To properly evaluate future forecasting performances of implemented forecasting methods, Bronkhorst High-Tech needs to establish fix error requirements for each forecast. After gaining experience using Winter's model, material planners and future forecasters need to revise the requirements, which will lead to better forecast evaluation.
- A large factor that influences the effectiveness of forecasting at Bronkhorst High-Tech is the resistance to change the current planning processes. According to Markus (1983), the supply chain manager of Bronkhorst High-Tech, responsible for the implementation of the demand forecast, may hold on to the three theories about why resistance occurs: (1) People-Determined (2) System-Determined and (3) Interaction Theory. Appendix 12 discusses the types of resistance that might occur at Bronkhorst High-Tech. Most importantly, the managers at Bronkhorst High-Tech need to ensure that the forecasting system is technically sound and properly conforms to the way material planners currently work. The latter can be achieved by involving the users in the design process of the forecasting system. It is recommended that automated forecasting packages are considered, which may provide an improved user experience for the material planners.

6.3.2 Further research

As mentioned in the earlier, several components of the research approach influence the reliability and validity of the conducted research. The following suggestions can be made for further research:

- It is highly recommended that Bronkhorst High-Tech considers product or customer-specific demand forecast to achieve higher forecasting accuracies. These forecasting approaches allow the material planners to obtain more information about standard and special product components. If Bronkhorst High-Tech decides to forecast individual product or customer demand, future research needs to analyse the distribution of demand patterns (i.e. smooth, erratic, intermitted, lumpy) and select the most appropriate forecasting model accordingly. There are several time series forecasting methods that perform significantly better at handling intermitted demand. Croston's method and the bootstrapping method, in particular, are widely used to forecast intermitted demand (Zhou & Viswanathan, 2011). Moreover, the Syntetos–Boylan approximation, is the only Croston improvement that has substantial empirical support (Syntetos, Zied Babai & Garner, 2015). For this reason, it is recommended that these methods are further researched, and possibly implemented using historical data.
- For the determination of the forecasting horizon, an in-depth analysis of supplier delivery times needs to be conducted. Using the standard set of components or the BOM, the components need to be quantitatively analysed on the order frequency and supplier delivery times. For components with short supplier lead times, weekly forecasting models need to be researched. Additionally, the concept of forecasting cumulative demand should be considered for forecasting horizons larger than one period. By calculating the cumulative demand over multiple periods, the resulting error can lowered.
- Appropriate causal forecasting methods should be researched to improve forecasting capabilities at Bronkhorst High-Tech. Both internal and external factors should be considered whilst determining relevant relationships that affect the demand data. In particular, the effects of market changes on customer demand. For example, the relationship between the semiconductor industry and CLRP product demand. Moreover, a literature study needs to be conducted to research available time series forecasting methods that integrate causal forecasting methods.

- Mainly due to time limitations, the ARIMA forecasting method is not considered for the demand forecast at Bronkhorst High-Tech. Although ARIMA forecasts are harder to understand and compute, the forecasting method might be considered by the company if a significant improvement in forecasting accuracy is found. ARIMA models are particularly useful when forecasts are computed with confidence intervals. This can help the material planners to better handle safety stocks, and possibly prevent overstocking. It might also be the case that variations of ARIMA models are better at capturing the demand patterns of the OEMP and CLRP group, which show insufficient forecasting accuracy using the Moving Average and Exponential Smoothing Methods.
- To improve the reliability of the forecasting output of the recommended forecasting method (Winter’s Model), advanced outlier detection methods should be conducted in future research. This prevents the use of inaccurate customer demand data.
- An explorative study on forecasting systems (forecasting packages) can be performed to simplify the forecasting process. Although the provided Excel sheets are relatively easy to understand, more comprehensive IT-systems might improve the overall forecasting experience for material planners. Some systems allow for automated identification of demand patterns and implementation of models.

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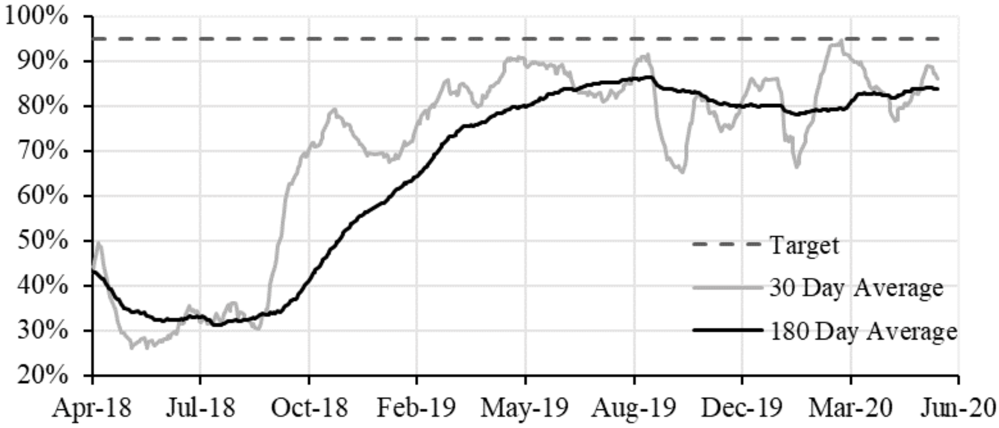
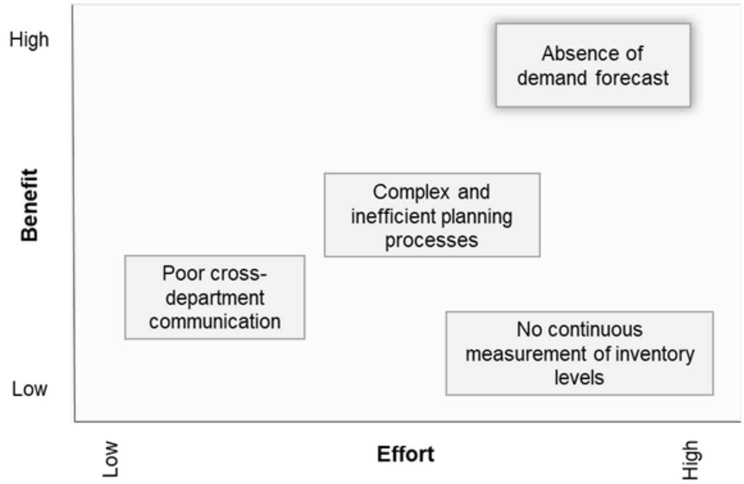
Appendix

Appendix 1 Delivery reliability of final products



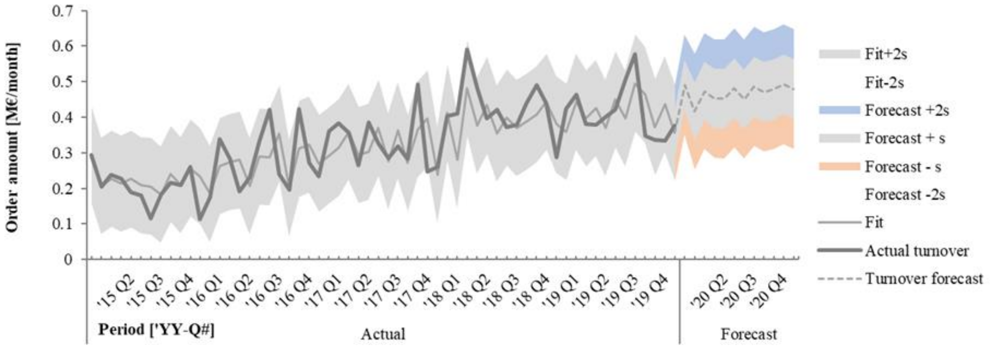
Appendix 2 Benefit-effort analysis



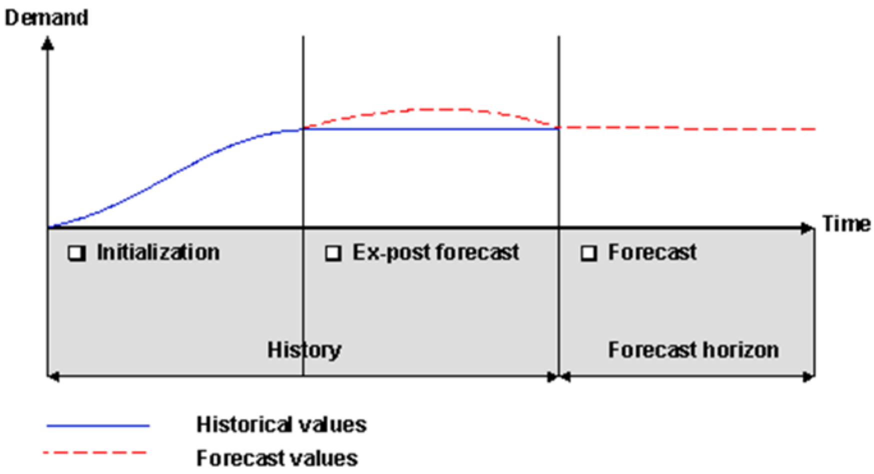
Appendix 3 Supplier lead time

Part code	Part name	New order lead time	Partial order lead time
2.19.002	Body F-201CV/F-201DV/F-201EV	6 weeks	1 week
5.01.223	Sensor 2 winding C-type SW2 V	4 weeks	2 weeks
4.01.456	Pcb Euro MBC3	4 weeks	*Not applicable*
2.20.222	Spindle LFE low rad II	4 weeks	1 week
2.15.909	Cover LFE low radial	4 weeks	1 week
2.15.585	Sleeve topmount n.c	4 weeks	1 week
5.11.080	Plungerholder assy TM lab n.c.	1 week	*Not applicable*
7.03.393	Coil assy topmount lab 95mm	8 weeks	2 weeks
3.03.158	Lower part case Euro MFC	2 weeks	*Not applicable*

Appendix 4 ARIMA Forecast



Appendix 5 Ex-post forecast



Appendix 5 Monthly data

//Confidential//

Appendix 6 Data plot (OEMP & CLRP)

//Confidential//

Appendix 7 Regression analysis

ELSE

Regression Statistics	
Multiple R	0.377697
R Square	0.142655
Adjusted R Square	0.117439
Standard Error	349.2326
Observations	36

ANOVA

	df	SS	MS	F	Significance F
Regression	1	689986.834	689986.834	5.657325342	0.023143286
Residual	34	4146756.805	121963.4354		
Total	35	4836743.639			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	1901.149	118.879229	15.99227403	2.1837E-17	1659.557546	2142.740867	1659.557546	2142.740867
X Variable 1	13.32677	5.602983105	2.378513263	0.023143286	1.940137976	24.71340128	1.940137976	24.71340128

OEMP

Regression Statistics	
Multiple R	0.045137
R Square	0.002037
Adjusted R Square	-0.02731
Standard Error	123.6502
Observations	36

	df	SS	MS	F	Significance F
Regression	1	1061.243308	1061.243308	0.069410468	0.793787256
Residual	34	519839.0622	15289.38418		
Total	35	520900.3056			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	381.4698	42.09070035	9.063043334	1.36109E-10	295.9312466	467.008436	295.9312466	467.008436
X Variable 1	0.522651	1.983807305	0.263458664	0.793787256	-3.508930281	4.554232726	-3.508930281	4.554232726

CLRP

Regression Statistics	
Multiple R	0.558599
R Square	0.312033
Adjusted R Square	0.291798
Standard Error	108.5016
Observations	36

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	181544.6091	181544.6091	15.4209543	0.000399041
Residual	34	400268.1409	11772.59238		
Total	35	581812.75			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	252.119	36.93407348	6.826191207	7.43536E-08	177.0599796	327.1781157	177.0599796	327.1781157
X Variable 1	6.835907	1.740766587	3.926952291	0.000399041	3.298243998	10.37357067	3.298243998	10.37357067

Appendix 8 Quantitative time series forecasting methods

Technique	Quantitative Methods – Time Series				
	1. Moving Average method	**2. Exponential Smoothing**	**2. ARIMA**	**3. Trend Projection Method**	**4. Neural Network Models**
Description	The moving average method generates forecast based on the n-period average of consecutive points of the series. Limited n-number of data points are chosen so the effects of seasonality's are eliminated.	Exponential Smoothing Methods are a family of forecasting models. They use weighted averages of past observations to forecast new values. The idea is to give more importance to recent values in the series. As observations get older (in time), the importance of these values get exponentially smaller. This method combines Error, Trend, and Seasonal components in a smoothing calculation.	While exponential smoothing models are based on a description of the trend and seasonality in the data, Autoregressive integrated moving average (ARIMA) models aim to describe the autocorrelations in the data. Autocorrelation is the degree of similarity between a given time series and a lagged version of itself over successive time intervals.	Time projection fits a trend line to mathematical equations and then projects it into the future by means of this equation. The model assumes that past trends in the variable to be projected will continue in the future. The most popular variations include graphical method, Least Square Method, Box-Jenkins method.	Artificial neural networks (NN) are forecasting methods that are based on mathematical models of the brain. They allow complex nonlinear relationships between the response variable and its predictors. Neural networks contains layers made out of nodes. Nodes are places where computations happen that either amplify or reduce that input.
Advantages	▪ If the data does not have any seasonality, the MA-method can deliver good forecasting accuracy. ▪ A very simple, yet effective of forecasting ▪ Applicable to linear and non-linear trends	▪ Exponential smoothing gives higher weights to more recent observations. This is especially beneficial in environments where recent data is more relevant (e.g. inventory planning). ▪ Can produce accurate short term forecasts. ▪ Easy to understand and apply.	▪ ARIMA is usually superior to exponential smoothing techniques when the data is reasonably long and the correlation between past observations is stable. ▪ ARIMA models can generate a confidence interval for future prediction. These upper and lower bounds are especially useful in supply chain-related applications.	▪ Trend projection is the easiest time series forecasting method to compute. ▪ Effective for long-term forecasts	▪ Outperforms traditional forecasting methods in the short term for time series with noise and monthly/quarterly time series. ▪ Outperforms traditional forecasting methods for discontinuous and non-linear time series.
Disadvantages	▪ Moving averages can be spread out over any time period, which can be problematic because the general trend can be different depending on the time period used. For	▪ The required smoothing constant is somewhat arbitrary. ▪ Exponential smoothing is best used in absence of seasonality or trend. However, variations of exponential smoothing that	▪ Arima works best with non-seasonal time series without trend. However, it is possible to de-seasonalize the series before modelling. The model will transform the time series into a stationary one before the	▪ Historical data may not give a true picture of an underlying trend, making it hard to predict turning points. ▪ Long term projections need more data to support the trend projections, which may	▪ Without careful choice of architecture, functions and values may not converge or lead to inaccurate forecast. ▪ NN requires high data frequency and processing time.

	this reasons the trend cannot be extended to forecast longer horizon. ▪ Cannot compute confidence intervals.	can handle strong trend (Holt's Model) or strong trend and seasonal patterns (Winter's Model). ▪ Long term and new product forecasting are not possible ▪ Cannot compute confidence intervals	ARIMA can be used to forecast. ▪ ARIMA forecasting is generally performed in R or Python, which makes the development process hard to understand/execute. ▪ Long term and new product forecasting are not possible	not always be available (e.g. new product line). ▪ The accuracy of reliability will depend on external conditions such as market changes or the work environment.	▪ NN can be very complex and hard to understand. Expertise is required to carefully design the system.
Accuracy Short term (0-3 months) Medium term (3 months-2 years) Long term (2+ years)	Poor to good Poor Poor	Fair to very good Poor to fair Poor	Fair to very good Poor to good Poor	Poor to good Good Good	Poor to excellent Poor to very good Poor to very good
Data requirements	The data requirements depend on the *n* number of periods the moving average are calculated for.	In general, for data with m seasons per year, m+5 observations is the theoretical minimum number for estimation: that is, 9 observations for quarterly data and 17 observations for monthly data. This minimum is not necessarily adequate to deal with randomness in the data.	A seasonal ARIMA model has p+q+P+Q parameters, if differencing is required, a total of p+q+P+Q+d+mD parameters are used in the model. Consequently, at least p+q+P+Q+d+mD+1 observations are required to estimate a seasonal ARIMA model.	Depends on the variation, generally accepted rule of thumb is to use 5+ years of historical data. However, the entire data is preferred for long term forecast.	Depends on the required NN architecture
Development time	1 Day	1 Day	Less than 1 week *(with programming experience)*	1 day	Depends on the required NN architecture
References	- Hyndman &Athanasopoulos (2018) - Chopra & Meindl, (2016)	- Hyndman, Koehler, Ord & Snyder (2008) - Chopra & Meindl, (2016)	- Hyndman &Athanasopoulos (2018) - Hyndman & Kostenko (2014)	- Hyndman &Athanasopoulos (2018)	- Hyndman &Athanasopoulos (2018) - Harvey, R. L. (1994)

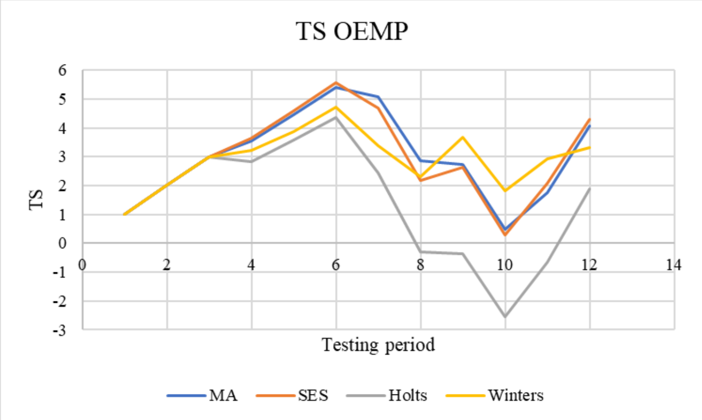
Technique	**A. Qualitative Methods (Company Deliverable)**			
	1. Delphi Method	**2. Market Research**	**3. Executive Opinions**	**4. Sales force polling**
Description	The aim of the Delphi method is to construct consensus forecasts from a group of experts in a structured iterative manner. Contrary to regular panels, with direct communication, the participants remain anonymous at all times.	Using customer input related to future purchasing plans to predict future events. This can be done using questionnaires, customer panels and interviews. Other forms of market research include analysis of external influences (such as customer and market behaviour).	Subjective views of high level experts or managers are pooled to generate a forecast about future sales. With preferably, one representative per company department (e.g. sales, production, finance). There is no secrecy and communication is encouraged.	Regional salesperson provides necessary sales estimates. These forecasts are reviewed for reliability and pooled at different levels to obtain an overall forecast. Sales force polling can also be utilized to modify other quantitative or qualitative forecast that have been developed
Advantages	• Effective in shorts, medium and long term forecasting. • Seeks to aggregate opinions from a diverse set of experts. • No need for physical meetings. • Eliminates peer pressure.	• Easy to conduct . • Good short term forecast accuracy • Allows for broader analysis of external factors.	• Forecast is done quickly and easily without the need of elaborate statistics.	• It utilizes information/knowledge of those closest to the customer. • Information can be broken down easily by region, product and customer.
Disadvantages	• Long response times. • Not all responses will provide added value. • No face-to-face problem solving. • Possible communication and/or interpretation problems.	• Future purchasing plans of customer might change overtime, making it less compatible fore long term forecasting (unless high accuracy not required).	• Strong leadership fosters group pressure for unanimous opinion. • Forecast may be influenced by social factors. The group might become more conforming through group pressure.	• Overly optimistic of pessimistic salespersons can cause inaccurate forecast. • Variable beyond the control of salespersons (e.g. economic changes, market behaviour) are hard to include whilst making estimations.
Accuracy Short term (0-3 months)	Very good	Excellent	Poor to fair	Very good to excellent
Medium term (3 months-2 years)	Very good	Good	Poor to fair	Fair

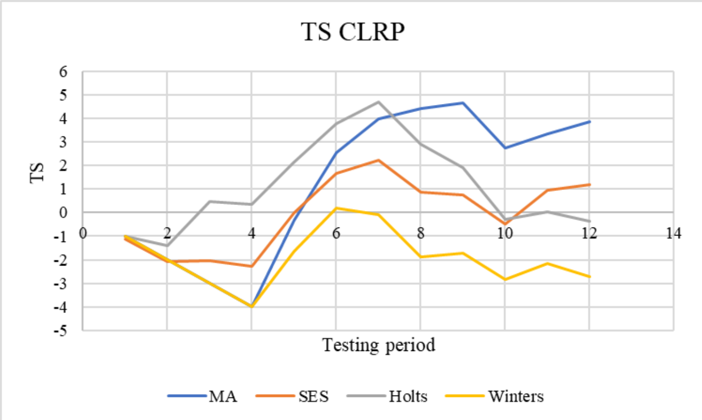
Long term (2+ years)	Very good	Fair to good	Poor	Poor
Common applications	Long term sales forecast, new product sales forecast	Long term sales forecast, new product sales forecast, short term sales forecast	Long term sales forecast, new product sales forecast	New product sales forecast, short term sales forecast
Data requirements	A coordinator need to select a group of experts that can contribute to the forecast of a selected variable	Minimum of two sets or reports over time per variable, to determine the reliability of input. Sufficient amount of information about market variables.	A panel of experts need to come to an forecast agreement through group meetings. The frequency of the meeting is dependent on the forecast horizon.	Salesperson that is responsible for the variable to be forecast needs to estimate future sales using his/her experience and expertise.
Time required for development	2 months +	2 months +	2 weeks+	3 weeks+
References	Linstone, Harold A. and Murray Turoff. 1975. The Delphi Method : Techniques and Applications. Reading, Mass.: Addison-Wesley. Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: principles and practice (2nd ed.).	-	-	-

Appendix 9 Forecast values over actual demand (ELSE)

//Confidential//

Appendix 10 Tracking signals (OEMP & CLRP)





Appendix 11 Supply chain coordination

Similar to other organizational and supply chain processes, forecasting needs to be flexible to be most effective in times of change (Zsidisin & Richie, 2009). Due to the uncertain nature of product demand of products at Bronkhorst High-Tech, statistical forecast alone cannot guarantee accurate prediction of future demand in fast-changing environments, since historical demand can become irrelevant. Managerial forecasts, in combination with statistical forecasts, however, have been shown to improve forecast accuracy (Sanders, 1995). This because managers and representatives usually can factor in relevant external variables that cannot be captured by statistical forecasting methods. One option to better utilize knowledge is to select forecasting methods that allow managers to make adjustments when new information is available. Manual input does, however, require a better understanding of major factors that influence the demand forecast. One approach to gaining a better understanding of demand patters is to implement causal forecasting methods.

Forecasts are also more successful when it relies on coordination and collaborative forecasting efforts with all supply chain stages, rather than developing the forecast alone (Zsidisin & Richie, 2009). A lack of coordination generally comes from conflicting objectives amongst supply chain stages or because the flow of information between stages is distorted or delayed. If actions within different stages are focused on maximizing its own profits, the overall supply chain profits will diminish. As discussed in Section 1.2, material planners at Bronkhorst High-Tech indicated that poor cross-department communication increased demand uncertainty. The lack of coordination at Bronkhorst negatively impacts product availability and requires higher levels of inventory than would be required if the supply chain were coordinated.

The first step towards better coordination within the supply chain is by aligning goals and incentives so that the efforts of all stages are directed at maximizing total supply chain profits. Next, managers can improve information flow by improving the visibility and accuracy of the information available in different parts of the supply chain (Chopra & Meindl, 2016). By sharing point-of-sale (POS) data across the supply chain, accurate and timely data can be made available to each entity in the supply chain (Stadtler, 2009). POS data measures how much product the end-users purchase (Simon, 2008). Using POS data, multiple demand forecast can be avoided, which means that ordering and planning decisions will always be based on ultimate customer demand. Using the POS data, different stages of the supply chain must forecast and plan jointly if complete coordination is to be achieved. Sharing POS data alone does not guarantee complete coordination, therefore collaborative planning is required.

The key is to ensure that the entire supply chain is operating with a common forecast (Chopra & Meindl, 2016). One such effort is Collaborative Planning Forecasting and Replenishment (CPFR), which is a process between two trading partners that establish formal guidelines for joint forecasting and planning (Zsidisin & Richie, 2009). The purpose of CPRF is that companies can be more successful by joining forces to bring value to their customers, share risks of the marketplace and improve their performance. The CPFR is built on the concept of synchronised data and the exchange of information amongst different supply chain partners. At Bronkhorst High-Tech the CPFR can be implemented between the suppliers of product components and the "retailers" of the products. On the retailers' side, which are the customers that use the final products of Bronkhorst High-Tech as a component of their own products, shared information about customer demand can improve forecasting accuracy. Ideally, these customers would need to share historical sales data of products that consisted of flow meters produced by Bronkhorst High-Tech. Especially on the suppliers' side, the lead times and the responsiveness of the supply chain could be improved significantly if component-level demand is estimated timely using a shared demand forecast. A more radical approach is to centralize the decision-making process for the entire supply chain is to completely diminish information distortion (Stadtler & Kilger, 2008). Several practices such as continuous replenishment programs (CRP) and vendor managed inventory (VMI) provide centralized control over replenishment. Although Bronkhorst High-Tech does take the role of the supplier for a majority of its customers, the products delivered to these customers are not the final product that is sold to their end-user. Therefore the replenishment cannot be determined by Bronkhorst High-Tech, making the CRP and VMI systems not applicable for the current business model.

Appendix 12 Resistance to change

A large factor that influences the effectiveness of forecasting at Bronkhorst High-Tech is the resistance to change the current planning processes (Håkansson & Waluszewski, 2002). A technically strong system can be abandoned because members of the organization resist adopting the new system or because the system is inconsistent with the constraints of a particular situation (Miller, 1985). A large obstacle in the implementation of the proposed forecast development process is the resistance to change current processes. Explanations of resistance are important because, they guide the behaviour and influence the action taken by the managers and system analysts concerned with implementing computer-based applications (Markus, 1983).

Kling (1980) identifies six distinct theoretical perspectives on technological resistance: Rational, Structural, Human Relations, Interactionist, Organization Politics and Class Politics. Markus (1983) builds upon Kling's theory by exploring these perspectives because the perspectives relate to a small aspect of the introduction and implementation of computer-based information systems and the human resistance that comes with it. According to Markus (1983), the supply chain manager of Bronkhorst High-Tech, responsible for the implementation of the demand forecast, may hold on to the three theories about why resistance occurs: (1) People-Determined (2) System-Determined and (3) Interaction Theory. The people-determined resistance relates to the resistance caused by a person or a group of people because of factors internal to the person or group. For example, people at Bronkhorst High-Tech with analytic cognitive styles may accept the new forecasting system, while intuitive thinkers resist it. Secondly, employees may resist the system because of aspects of the application or the system being implemented. For example, the forecast methodology might be deficient or forecasting system might not be user friendly. Lastly, the interaction theory relates to the resistance due to an altered balance of power in the organization. In the context of the demand forecast, the new information system may result in an altered division of roles and responsibilities. These variations in existing roles and may be perceived as a means for organizational change. The greater the organizational change, the more probable the resistance.

The three theories lead to predictions, often made by managers, of possible solutions to eliminate resistance. The person-determined theory generally leads to the predictions that replacing resisting employees or allowing them to suggest improvements to the forecasting method might reduce or eliminate resistance. The system determined-theory predicts that if technical features are changed, then the all resistance will be eliminated, assuming that people determined resistance does not occur. The interaction theory predicts that neither changing the people nor fixing the technical issues will eliminate the resistance to change, as long as the conditions which gave rise to it persist. Case studies (Markus, 1983) show that these predictions when implemented, do not completely remove the resistance. Accordingly, Markus (1983) recommends several solutions to reducing the resistance of change. These recommendations are summarized in Table 9.

Based on interviews and meetings with Bronkhorst High-Tech multiple assumptions are made with regards to the implementation of the demand forecast. First, all employees involved with the design and application of the demand forecast showed a positive attitude towards the development of a demand forecast. Secondly, all employees, both top management as well as material planners, are motivated to better understand forecasting methodologies and are willing to explore different forecasting techniques. Lastly, employees of the supply chain department are sceptical about the accuracy and the added value of the selected forecasting method. Using the three perspectives, a general approach to reducing future resistance to demand forecasting can be designed. First of all, the system developers need to be given the time and resources to optimize the forecasting system and methodology. To create a sound forecasting system, the forecaster needs to gain a strong understanding of available forecasting methods and their appropriate applications. Moreover, the managers and forecaster need to involve the user in the design process of the forecasting system. By conforming to the way employees think, work or do business, the implemented change is minimized. The less change is required, the less resistance will be present. If none of these measures decreases the resistance to change, the manager needs to review the root of resistance.

	People-Determined	**System-Determined**	**Interaction Theory**
Facts needed in real-world case for theory to be applicable	System is resisted, resistors differ from non-resistor on certain personal dimensions	System is resisted, system had technical problems	System is resisted, resistance occur in the context of political struggles
Predictions derived from theories	Change the people involved, resistance will disappear	Fix technical problems, resistance will disappear	Changing individuals and/or fixing technical features will have little effect on resistance
General predictions derived from theories	Job rotation among resistors and non-resistors eliminates resistance	Improve system efficiency and improving data entry eliminates resistance	Resistance will persist in spite of time, rotation, and technical improvement Interaction theory can explain other relevant organization phenomena in addition to resistance

Recommendations for implementation	Educate users (training) Coerce users (edicts, policies) Persuade users Use participation (to obtain commitment)	Educate designers (better technology) Modify packages to conform to organization procedures User participation (to obtain better design)	Fix organization problem(s) before introducing systems Restructure incentives for users Restructure relationships between users and designers User participation is not always appropriate