MASTER

Designing a forecasting framework with an improved accuracy at the operational level

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Designing a forecasting framework with an improved accuracy at the operational level

Master Thesis

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Abstract

This research project investigated the forecasting process and the possibilities for forecasting directly on component level in a build-to-order industry company selling trucks. This was done by investigating the current forecasting process, analyzing data, categorizing components and testing multiple forecasting methods. The results of forecasting directly on component level with historical data showed an improvement in forecasting accuracy compared to the current forecasting system in place. With the results obtained, a forecasting framework was developed that indicates which forecasting method to use based on article categories. Furthermore, a forecasting procedure was included that can be implemented as an application.

Management summary

When a manufacturing firm adopts a build-to-order strategy, it gives them the possibility to produce items specifically and personalised for their customers. However, It also comes with challenges regarding ordering parts on time to still deliver in a competitive time span. To enable the timely delivery of parts, forecasting plays a crucial role. The truck company that initiated this research currently has a forecasting system in place that forecasts on truck types, which is then translated to article quantities with a two-level MPS system. This means the required article quantities are based on percentage bills. The use of percentage bills can be very beneficial, but the truck company experienced a high forecast error resulting in problems with supplier deliveries. Because of this, the company asked to investigate whether the possibility of conducting a forecast directly on parts level. This gave rise to the research question:

"What forecasting system could be implemented at the operational level in the future at the truck company to improve forecast accuracy of the required article quantities produced and communicated to suppliers?"

To answer this research question, the research was divided into a number of sub questions focusing on the current forecasting process, the effects of this process, the forecasting methods fitting the production environment, the possible use of multiple methods, and whether the proposed new system actually improves the material availability.

Investigation of forecasting possibilities

The current forecasting process was not performing well enough for the truck company, which is why they asked for a forecast based on historical data of articles. This data was collected, visualized and studied. First of all different article categories were established:

- Steering code 2 and 3.
- Yellow Line 98 and 99.
- Fastmovers and slowmovers.

Here steering code 2 contains articles that are immediately registered when used, whereas steering code 3 articles are registered as batches when taken from the warehouse. Yellow Line 98 means the articles are assembly ready, whereas Yellow Line 99 means the articles are

used in pre-operations. Other conclusions that were drawn from the data included the two different type of forecasting methods that were applied in this research: a linear regression and level forecasting methods. Based on these conclusions a solution design was developed to test a selection of forecasting methods, and see whether they improved the forecast error at the truck company. A linear regression was performed for articles with a significant relation to the buildrate. For the other articles the following forecasts were produced per category:

- Steering code 2 and YL98
  - 1 step ahead forecasts.
  - Rolling forecast of 5 steps.
  - Long term forecast.
- Yellow Line 99
  - 1 step ahead forecasts (periodically).
  - Long term forecast (periodically).
- Steering code 3
  - 1 step ahead forecasts (periodically).
  - Long term forecast (periodically).

For the Yellow Line 99 and Steering code 3 articles, a choice was made to produce period forecasts instead of weekly forecasts. This choice was made, because of the fluctuations in the data of these types of articles, and a period forecast absorbs part of the variation. The forecasts produced were compared to either database forecasts or delivery schedule forecasts. The database data is more raw forecast data and thus a more realistic representation. However, for some of the articles only delivery schedule data was available, and these were used for comparison, because of a lack of other available options.

The articles on which a linear regression was performed all had a forecast error lower than 15% and showed improvement over the current forecasting system. These forecasts were generated with as independent variable the buildrate. Having the buildrate included in the forecast means article requirements are based on the planned daily production. All articles belonging to the Yellow Line 98 category also showed improvements over the truck-type forecasting system in place. All fastmovers even had a forecast error below 20%. Part of the articles also showed improvement over the delivery schedule errors, meaning the proposed system might not only improve the forecast error itself, but also the planning steps that follow. Due to the nature of The Yellow Line 99 articles, only had delivery schedule forecasts were available for the current system. Nevertheless, a selection of the articles showed improvements, where this selection included all slowmovers. Therefore, it was concluded the new framework positively impacted the Yellow Line 99 category. Lastly, the articles in steering code 3 category also showed improvements, but it was difficult to draw realistic conclusion, because of the minimum amount of articles in this category. For this category it is advised to focus more on a decent stock policy.

Forecasting framework

Based on the results of the best performing method per article category, a forecasting framework was developed. Here an article has a significant relation to production when the Pearson correlation coefficient is higher than 0.65 and when there is clearly a linear relationship visible when plotting the variables against each other. Assembly ready parts are parts that are directly used in the assembly lines. Furthermore, basic materials are very small cheap parts that are stored in batches in the wharehouse.

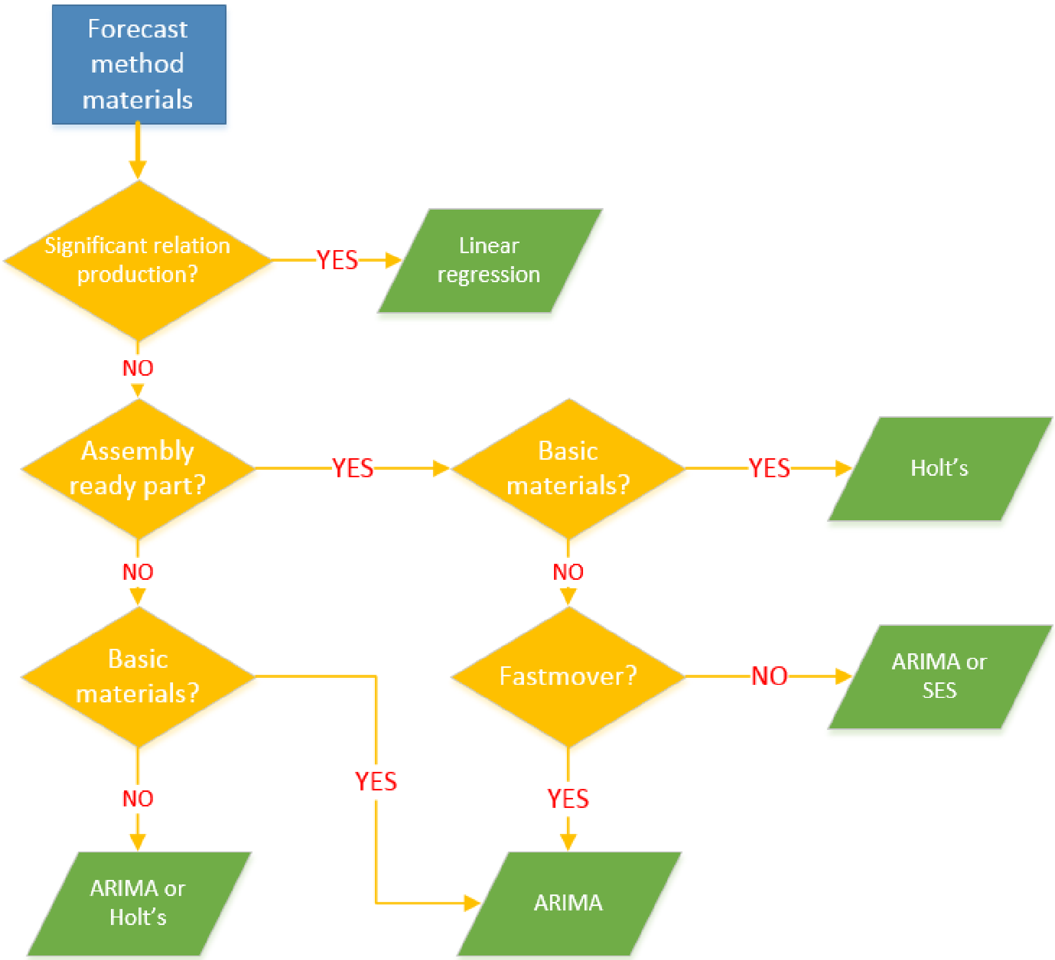

Figure 1: Forecasting framework

Conclusions and recommendations

Overall it was concluded the forecasting framework proposed can improve the forecasting accuracy of articles compared to the current system in place. It was however, quite difficult to obtain forecast and historical usage data of articles, meaning this should definitely be better maintained. Furthermore, due to a limited amount of data to work with, this framework was only tested on short-term planning. Possibilities to use the framework for a longer time horizon might be investigated in the future. Lastly, the comparison between the old and the new system was done with a different amount of observations and variations.

The following recommendations were made to the truck company based on the research:

- Save all forecast and historical usage data.
- Monitor forecast performance.
- Inform and educate users of the forecast about the framework.
- Use the forecasting framework for short-term planning.
- When implementing the framework let customer orders consume the forecast quantities.
- When forecasting new articles, use historical usage data of similar articles.
- Implement a stock policy for steering code 3 articles.
- Investigate whether the incorporation of actual material leadtimes into the forecast system can be beneficial.

The following areas for future research were proposed:

- Test the forecasting framework for long term.
- Compare the current and new forecasting system on the same amount of observations.
- Investigate the use of machine learning algorithms.
- Consider IT implementation.

Preface

This report is the result of a Master Thesis project, which I conducted as partial fulfillment of the Master Operations Management & Logistics at Eindhoven University of Technology.

First of all I would like to thank my primary supervisor, prof. dr. Ton de Kok, for his enthusiasm and his feedback he gladly provided throughout the project. During our mentor sessions he tried to answer all my questions as detailed as possible, and he guided my research in the right direction. Furthermore, before the research period, I also learned a lot from you during all the courses you taught. Secondly, I would also like to express my gratitude to dr. Karel van Donselaar, my second supervisor. H took the time to critically review my work and motivated me to look for the challenge during my research.

From the company, I would like to thank both Edwin van Walraven and Annette Tummers, who initiated the project and gave me the opportunity to conduct my thesis in this environment. They both offered me guidance, insights and support throughout the project. They did your best to provide me with all the information necessary, put me in touch with other employees and you made me feel welcome within the company.

Contents

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List of abbreviations

ARIMA Autoregressive Integrated Moving Average. 12, 15, 16, 40, 45, 52, 57, 60

CV Coefficient of Variation. 34, 39

ETS Exponential smoothing state space model. 14, 40

MAD Mean Absolute Deviation. 19, 21, 26, 27

MAPE Mean Absolute Percentage Error. 19, 20, 26, 28, 47, 48, 50, 51

MPS Master Production Schedule. 3, 4, 20, 32

OFTF Order Fill Time Fence. 2, 41, 59

POB Plan Order Document. 2, 3, 32

RMSE Root Mean Square Error. 19, 21, 26, 27

SES Single Exponential Smoothing. 12, 13, 40, 45, 52, 57

SMA Single Moving Average. 12, 13

SSE Sum of Squared errors. 40

VOB Sales Order Document. 2, 3

YL98 Yellow Line 98. 24, 25, 28, 52

YL99 Yellow Line 99. 24, 25, 30, 34, 37, 52, 57

Chapter 1

Introduction

A build-to-order strategy in a manufacturing environment gives firms the possibility to produce items specifically and personalised for their customers. The truck company has adopted this strategy to distinguish them from their competitors. In a build-to-order strategy, the final product is build when it is linked to a real customer order. To be able to adopt such a strategy and still deliver in a time span that is seen as competitive, parts need to be produced or ordered on time. This means for a build-to-order strategy to succeed, there is a need for forecasting. Forecasting is a challenging subject, because there is always uncertainty when trying to predict the future. This introduction section elaborates on the company in which the research is carried out in Section 1.1. Section 1.2 explains the forecasting process that is currently used at this company to gain a better understanding of the process that will be analyzed and improved. Section 1.3 discusses the problem for which this research project is carried out. This section also defines the research into the form of research questions.

1.1 Company introduction

This master thesis was motivated by a business problem taking place at a truck company. Here the company is introduced to give a better understanding of the research environment.

1.1.1 Truck company

The truck company is a technological truck manufacturing company, and is producing high-end trucks and services for transportation companies. The truck company achieved their success through their basic principles: lean organization, build-to-order, and mixed model assembly. With being a lean organization the truck company wants to minimize waste and improve continuously. Furthermore, they only build trucks that are already sold to customers, and on top of that every truck can be completely personalized by customers. The company places a very high value on the ability of customization, which distinguishes them from their competitors. They live up to the first time right principle according to the customer specifications. Lastly, they produce and assemble all their truck models over the same line.

1.1.2 Company scope

Since the truck company does more than just producing trucks, it is important to highlight in which organizational environment this research took place. This research was focused on the production of trucks by the company. This means it included all factories that produce main components for and do the final assembly of trucks. Furthermore, this research was specifically conducted for the operational level at the logistics department. Figure 1.1 shows the layout of the logistics engineering department. This research project was located in between Demand Management and the Material Requirements & Capacity Planning.

Figure 1.1: Research project placement

The next section explains how the forecast is currently done, and how this leads to the required quantity of articles.

1.2 The forecasting process

The truck company determines the amount of trucks they plan to sell on a 1 year horizon, or 13 periods (1 period equals 4 weeks). The first 5 weeks, relative to the current week, are fixed and thus assigned to customer orders. This is called the Order Fill Time Fence (OFTF), which is the minimal horizon consisting only of customer orders. The weeks that follow are a combination of customer orders and forecast orders. The customer orders can be found in the Sales Order Document (VOB) and the forecast orders can be found in the Plan Order Document (POB). This is shown in Figure 1.2. The red line shows the maximum amount of trucks the company can assemble in one day, and the blue line shows the division between customer orders and forecast orders. As can be seen in Figure 1.2, the amount of forecast orders increases over time, while the amount of customer orders decreases over time. The assembly limit is called the buildrate, which they plan to reach every day.

The forecasting process is a complex process that goes through multiple divisions. There are many different truck options for a customer to choose from, resulting in thousands of different set-ups and types for the trucks and millions of different articles and materials that are needed to build the trucks. The forecasting is done on multiple levels. The highest level forecast is done on truck level. This forecast is done with a multiple linear regression model, where economic indicators that influence the truck market are included. This forecast is done for both the long-term (multiple years) and the short-term (6-12 months), and is mostly used for strategic planning. The next forecast is done at demand management where the forecast is also done on truck level, but now the forecast is partly based on already known customer

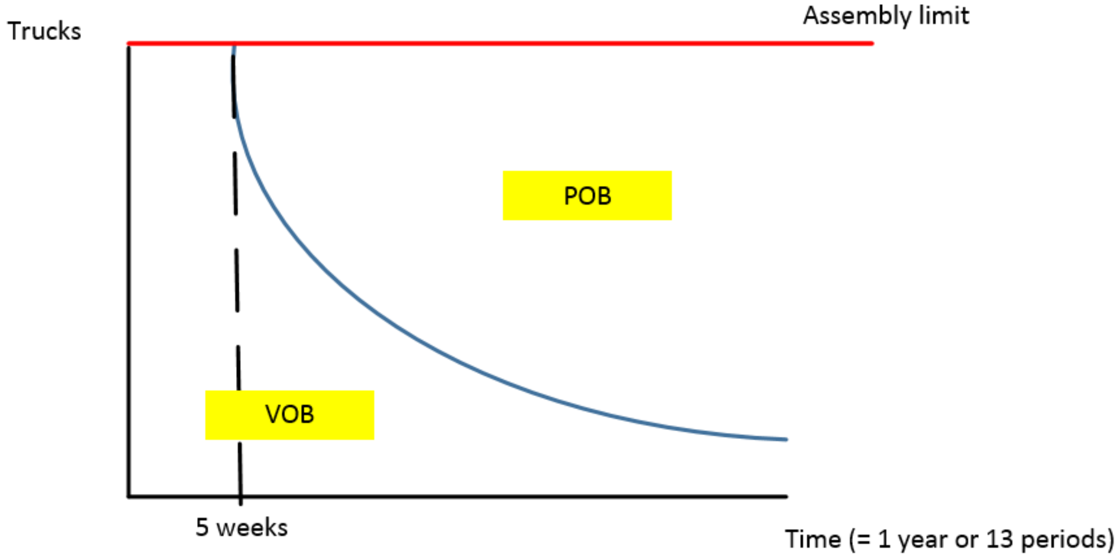

Figure 1.2: Division of customer orders and forecast orders.

orders. This forecast generates the POB. The POB takes into account the working days per period and the buildrate to decide how many trucks to produce every period. The forecast used by the operational level is done at Marketing & Sales and creates a forecast on truck-type. This is a collection of material types, and can be seen as a catalog from which options can be chosen. They create this forecast with help of the POB and the VOB. This forecast has to take into account the production restrictions of the factories, which are guarded by production control. A Master Production Schedule (MPS) is created with actual customer orders, meaning this schedule is on order level and filled with complete truck orders. From the forecast, the buildrate, the sales orders, and the MPS, Marketing & Sales develops a central planning for the factories, which is first checked by production control before communicating it to the factories. When this central planning is accepted, the system translates this to the required article quantities. Either these articles are ordered at suppliers or they are produced internally. An overview of this flow can be found in Appendix A.

Based on the required article quantities, the factories send out delivery schedules, but in these schedules changes are constantly being made. This is partly due to the changes that customers are still making, but also because the forecast errors seems to be high for certain articles. The system in which the forecast is seen automatically translates the truck-type forecast to article quantities based on user ratio (two-level MPS). When the user ratios are not accurate, delivery schedules do not include the correct quantities. For material planners it is difficult to see where the cause appears to be, because they cannot see the translation from truck-type to article quantity. There is a 'black box' present where the forecast is translated from truck-type to article quantities.

1.3 Problem statement

Multiple problems came to light during the inspection of the current forecasting process. The forecast outcomes were partly based on the experience of an employee, instead of solely on an automated formal forecasting method. Next to this, after the forecast was determined, all emerging changes were incorporated manually. According to multiple logistical managers, the forecast they received consisted of a certain forecast error that resulted in difficulties with production and/or suppliers. So the main incentive of this project was to propose an empirically validated forecasting framework to the truck company for the operational level to improve the forecast accuracy. They asked for a forecast on parts-level, instead of a forecast which is translated according to the two-level MPS approach. A cause and effect diagram of the current forecasting system can be found in Appendix B. As mentioned before, one of the causes of the high forecast error is that it was mainly based on experience from certain employees. This means that the knowledge of the forecasting method is limited to these employees. The part of the forecasting method which was based on data, was done with the moving average method and with a two-level MPS. This is not always reliable, since the market is dynamic and constantly changing. The user ratio is not always correct, since every customer can completely personalize its truck order. Moreover, whenever the forecast was created, all changes that emerged had to be modified manually. This is a lot of work and at the same time very perceptible to making mistakes. Effects of the current forecasting system include issues with suppliers and production. Suppliers receive delivery schedules (containing a forecast for a year) every week, but these quantities fluctuate heavily. These fluctuations can cause issues: deliveries arrive too late, higher costs due to emergency deliveries, weaker supplier relations due to unprofessional behavior, which can result in higher material costs, etc. Production at factories is also impacted by a high forecast error, because they might produce the wrong quantities, either too much or too little, resulting in higher inventory costs or production loss. Next to this, labor capacity can also be wrongly planned due to a wrong forecast.

The objective of this thesis was to investigate if forecasting at parts level improves the accuracy and proposing a forecasting framework at article level.

1.3.1 Demand forecasting challenges

Forecasting always brings challenges with it, therefore it is important certain objectives are defined such that the process can reach its objectives. Forecasting can be done on multiple levels (strategic, tactical, and operational), as is happening at the truck company. Different levels need different approaches, because forecasting trucks is a very different objective than forecasting articles. This research specifically focused on the short-term planning, because the problem that needed to be solved was happening at the detailed level. By investigating forecasting directly on article quantities instead of a two-level MPS approach, this research adds insights to which approach works better in this context.

1.3.2 Research questions

The problems that arise from the current forecasting methods used, result in the following main research question:

- What forecasting system could be implemented at the operational level in the future at the truck company to improve the forecast accuracy of the required article quantities produced and communicated to suppliers?

The sub-questions, that are needed to answer the main research question, are:

1. What does the current forecasting process look like?
2. What are the effects of the current forecasting process at the operational level?
3. Which type of forecasting methods fit the production environment of the truck company?
4. Should different forecasting methods be used for different type of articles?
5. Does the proposed forecasting system improve the material planning at the operational level?

The first sub-question explores the current forecasting problem to create a clear understanding of the problem at hand. The second sub-question empirically looks at the effects of the current forecasting process. The third sub-question looks closer at the data used and the literature to discover which type of forecasting methods are relevant for this context. The fourth sub-question reveals whether the difference between different types of articles require different forecasting methods. The fifth sub-question validates whether the proposed forecasting methods actually solve the initial problem at the truck company.

1.4 Thesis outline

The following section starts with the research design this thesis has followed. Chapter 3 elaborates on the forecasting methods used. This is followed by a diagnosis of the problem, which includes an accuracy overview of the forecasting performance of a selection of articles. Chapter 5 dives deeper into the article data to examine the current demand model, the data irregularities and the demand models inferred from the data. After the data analysis, a solution design is set up to test other forecasting methods. In Chapter 7 the results of the methods are evaluated, which is followed by the development of a forecasting framework and forecasting procedure in Chapter 8. The thesis ends with a conclusion and recommendations to the company in Chapter 9.

Chapter 2

Research design

Solving the forecasting problem at the truck company was done by following a research technique. [Van Aken and Berends, 2018] developed a problem-solving cycle specifically for business problems, see Figure 2.1. In the middle of the cycle a problem mess is present that is linked to all steps of the cycle. This problem mess is the reason for the project to be conducted. From this problem mess, the problem was clearly defined into a business problem. This business problem was then analysed and diagnosed to investigate the causes and the effects of the problem. The next step was designing a solution and implementing it in the intervention phase. lastly, the solution needed to be evaluated to learn whether the solution actually solved the problem defined.

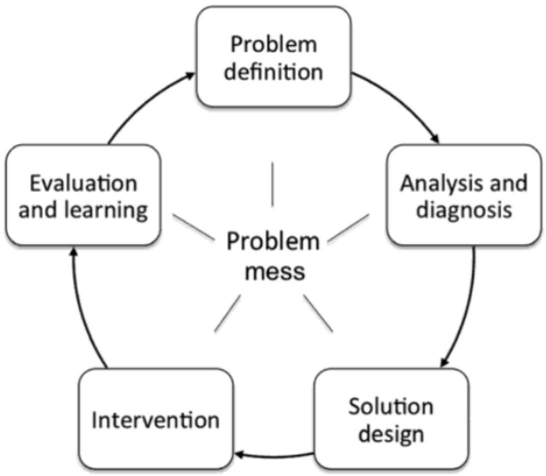

Figure 2.1: Problem-Solving cycle, *Retrieved from: "Problem Solving in Organizations: a methodological handbook for business students", by van Aken and Berends, 2018.*

This master thesis followed the steps of the problem-solving cycle shown in 2.1 [Van Aken and Berends, 2018]. At first the problem was defined, which equals explaining the problem mess that was present. During the problem definition phase the current forecasting process was mapped out. This step answered sub-question 1. The current forecasting process has certain effects at the operational level. These effects are shown by a calculation of the accuracy of the current forecasting method used. This gave an answer to sub-question 2. This step was part of the problem analysis and diagnosis phase. Another step in this phase was linking the literature to the problem at the company. An extensive literature review was done on forecasting methods and everything that influences the fit with the production environment of the company. The literature expressed how the choice of forecasting method is dependent on the type of data and its features. This step consisted of collecting past sales data from different factories. This data was then visualized graphically to discover its features (seasonality, trends, patterns, etc.) and was used as input for the forecasting process. Analysis of the data and the forecasting methods explained in the literature helped answer sub-question 3. The visualization of the data also gave insights to answers for sub-question 4, by comparing the datasets from different type of articles. The next step in the cycle was redesigning the process and designing a solution. This included making choices about how to solve the problem proposed in the first phase and testing multiple forecasting methods. This included a calculation of the accuracy of the used forecasting methods. The last step, evaluating the proposed solution, was done by evaluating the methods and proposing a new forecasting system. This final step gave an answer to sub-question 5.

2.1 Research Methods

The problem definition phase was approached by conducting interviews that were used to define the research problem and understand the current forecasting process. This is a qualitative approach to collecting information, which can provide in-depth information about the participant's experiences and viewpoints [Turner III, 2010]. For this particular situation the use of informal interviews was chosen. In informal interviews, no specific predefined questions are asked, but the conversation relies on the interaction between the participants and the interviewer goes with the flow [Turner III, 2010]. This type of interview allows a certain flexibility in its nature. In the beginning of the research project a lot of these type of interviews have taken place, with people from different divisions. With the help of all these informal interviews, the problem definition and the mapping of the current process was realized. This step answered the first sub-question: 'What does the current forecasting process look like?'

The first step in the analysis and diagnosis phase was collecting data with regards to the current forecasting system, which were then used to generate an empirical analysis about the forecasting accuracy. This accuracy calculation is a quantitative complementary input for the problems and effects that the interviewees describe. The accuracy calculation answered the second sub-question: 'What are the effects of the current forecasting process at the operational level?'

In the second step of the analysis and diagnosis phase past sales data of articles from different factories was collected. This data was visualized graphically. When visualizing the data, the flow of the data points can be seen and thus certain patterns can be noticed. As became clear in the literature review, the type of data that is used to forecast decides which forecasting methods will be the best fit for the problem. After visualisation of the data, the knowledge gained from the literature was linked to this data and the third sub-question was answered: 'Which type of forecasting methods fit the production environment of the truck company?' When data from different types of articles is visualized, it is possible that the patterns that emerge within the data differ. This could be an indication that multiple forecasting methods are necessary for forecasting in this production environment. This gave an answer to the fourth sub-question:'Should different forecasting methods be used for different type of articles?'

The third phase was the redesign phase. Here a set of solutions was defined to find the best fitting solution to the problem. The forecasting methods that fit the production environment, found in the analysis and diagnosis phase, were further explored and adjusted to the problem specific form. The answer to the fourth sub-question indicated whether this needed to be done for only one forecasting method or multiple forecasting methods. In this phase there was the possibility to alter the answers to the third and the fourth sub-questions, if it turned out a certain method was not feasible in the company's environment.

The last phase, the evaluation phase, consisted of evaluating the outcomes of the tested forecasting methods. The methods were applied on a historical period for which actual sales data was made available, and the accuracy was calculated. This was used for evaluating the outcomes of the methods. The results were compared with the outcomes of the accuracy calculation of the problem definition phase. A comparative analysis learned us whether the new forecasting methods show an improved over the current forecasting system employed. This answered the final and fifth sub-question: 'Does the proposed forecasting system improve the material planning at the operational level?'.

When all the sub-questions were answered, the main research question could be answered too: 'What forecasting system could be implemented at the operational level in the future at the truck company to improve the forecast of the required article quantities produced and communicated to suppliers?' A forecasting framework and system was developed. Based on this, the master thesis concludes with some recommendations on how to proceed.

Chapter 3

Literature

When talking about forecasting, it is important to make a distinction between demand models and forecasting methods. The demand model can be inferred from the data that will be used. The demand model is useful to discover the optimal forecasting method and to minimize forecasting error.

According to [Hyndman and Athanasopoulos, 2018] the basic steps in a forecasting task are:

1. Problem definition
    - By understanding the circumstances of the forecast (how will it be used, who will use it, etc.) the problem can be defined.
2. Gathering information
    - When forecasting statistical data and the expertise of the users of the forecasts is required.
3. Preliminary (exploratory) analysis
    - It is important to first explore the data by visualizing and analyzing it. During this exploration a demand model can be inferred from the data.
4. Choosing and fitting models
    - Forecasting methods can be chosen according to the demand model from the previous step. Choosing the correct method depends on the availability of historical data and the possible influence of other variables. The models belonging to the forecasting methods can be fitted, where a model is a construct that is based on a set of assumptions and includes parameters that need to be estimated.
5. Using and evaluating a forecasting model
    - When the model is used for making forecasts, its performance should be closely monitored.

Section 3.1 gives an overview of the forecasting methods used in this research. Section 3.2 explains how to evaluate forecast performance.

3.1 Forecasting methods

According to [Abraham and Ledolter, 2009] a quantitative forecast system consists of two phases: the model building phase and the forecasting phase, see Figure 3.1. In the first phase a model is constructed based on the available theory and the past data. At the end of this phase, the adequacy of the model must be checked. In the second phase, the actual forecasting with the final model is done. During this phase the stability of the model is assessed, and there is a possibility to go back to the first phase. Figure 3.1 does not include the choice of forecasting method anywhere, which should be placed in between the model building phase and the forecasting phase. After the model building, a corresponding forecasting method can be used and a forecast can be generated.

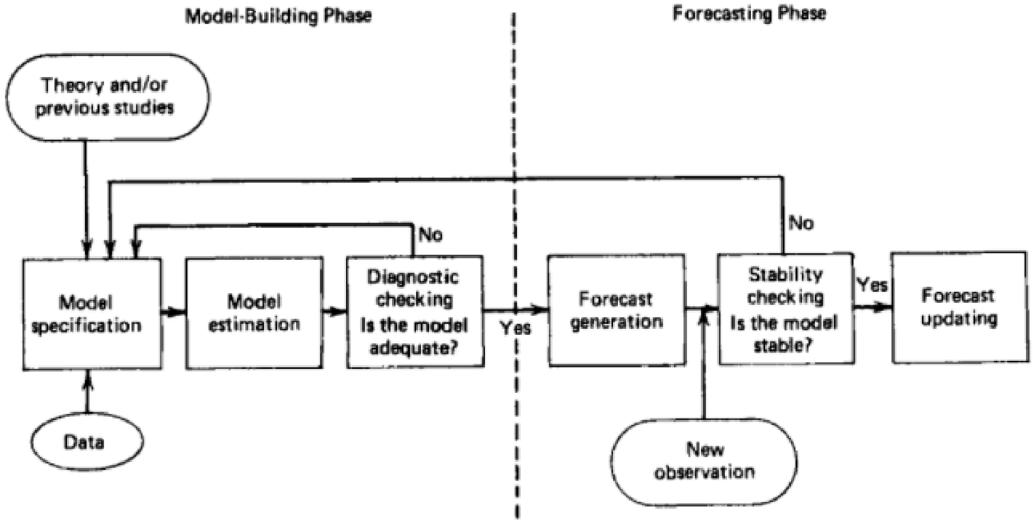

Figure 3.1: Conceptual framework of a forecasting system, *Retrieved from "Statistical methods for forecasting", by Abraham and Ledolter, 2009.*

Statistical models use extrapolation techniques to generate forecasts [Morlidge and Player, 2010]. They are widely used and generally outperform complex models. The variable that is to be forecasted, can be seen as a combination of signal and noise, or a predictable component and a statistically independent unpredictable component [Nau, 2015]. When forecasting, the signal that is buried in the noise should be captured, and extrapolated in the appropriate way.

Time series

In this research, the data occurred in time-ordered sequences, which is also called time series [Abraham and Ledolter, 2009,Box et al., 2015]. There are different variations that occur in time-series: seasonality, trends, cyclic changes, and other irregular fluctuations [Chatfield, 2013]. A trend is present when there is a long-term increase or decrease in the data. Seasonality means a time series is affected by seasonal factors. A cycle occurs when the data rises and falls while these fluctuations are not of a fixed frequency [Hyndman and Athanasopoulos, 2018]. If there is no systematic change in the mean (trend) or there is no systematic change in the variance, then a time series is said to be stationary.

The previous named patterns will be explained in more detail now [Hyndman and Athanasopoulos, 2018, Silver et al., 1998]:

- Level (a)
  - When the data points hover around the mean, the data consists of a level which is most of the time a constant value.

$$x_t = a + e_t$$

- Trend (b)
  - The data contains a trend when there is a long-term increase or decrease present.

$$x_t = a + b * t + e_t$$

- Seasonality (F)
  - When the data is affected by seasonal factors, it is said a seasonal pattern occurs. A seasonal pattern is always of a fixed and known frequency. Mix level-seasonality model:

$$x_t = a * F_t + e_t$$

    Mix level-Trend-Seasonality model:

$$x_t = (a + b * t) * F_t + e_t$$

The remainder of the variability of the other components is called random fluctuations (e_t). These are irregular and unpredictable variations.

When data consists of patterns it is said to be non-stationary. When data is stationary, it means its values are constant over time. This type of data is relatively easy to forecast. Most data, however, is not stationary itself. Some series might show a long stable trend, which can be transformed by de-trending, and can be seen as trend-stationary series [Nau, 2015]. If de-trending does not solve the non-stationarity, the data series can be transformed into a series of period-to-period differences, which can be seen as difference-stationary. A logarithmic transformation can also be used to adjust the data. Logging data can convert multiplicative to additive relationships and it can also (simultaneously) convert exponential trends to linear trends [Nau, 2015].

This chapter describes the forecasting methods used for forecasting the time series in this research.

3.1.1 Naïve Method

A very simple forecasting method is the naïve method, also called the random walk model. This method assumes that every period the value of the variable takes a random step up or down [Nau, 2015]. It is predicted there will be no change from one period to the next period. The random walk period can include a certain drift, which incorporates a value in the formula that assumes the mean step size is a nonzero value. The naïve model is as follows, where the first line represents the naïve model without drift and the second line represents the naïve model with drift:

$$\begin{aligned} \hat{Y}_t &= Y_{t-1} \\ \hat{Y}_t &= Y_{t-1} + \alpha \end{aligned} \tag{3.1}$$

Here $\hat{Y}_t$ is the predicted value in period t, Y_{t-1} is the actual value in previous period and α is the mean step size. The amount of change over time (or the mean step size) is set to be the average change seen in the historical data. Advantages of this model are the ease of use and the capability to generate forecasts when only short historical series data are available, but the disadvantage of this model is not being based on scientific mathematical theories [Chen et al., 2003]. This kind of model is commonly seen in speculative markets, such as stocks and currencies, and is often used as a benchmark model when comparing forecasting methods. The random walk model is also a special Autoregressive Integrated Moving Average (ARIMA) case, which can be seen in subsection 3.1.4.

3.1.2 Moving average

The moving average method is a technique to determine the overall trend in a data set. It is useful for predicting short-term trends. Single Moving Average (SMA) is a very basic forecasting method and is widely used in practice. This popularity comes from the simplicity of the method; it can be easily understood and used [Svetunkov and Petropoulos, 2018]. Due to its simplicity, simple moving average does not really have a concise statistical model. Beforehand, the order (= the length) of the moving average has to be determined. Simple moving average is usually considered in inventory control context and is very often used on low level and intermittent data. SMA and Single Exponential Smoothing (SES) are considered competitors. The demand model for moving average is:

$$y_t = a_t + \epsilon_t \tag{3.2}$$

Where ϵ_t is normally distributed.

The basic model for SMA is as follows [Nau, 2015, Svetunkov and Petropoulos, 2018]:

$$\hat{y}_t = \frac{1}{k} \sum_{i=1}^{k} y_{t-i} \tag{3.3}$$

where $\hat{y}_t$ is the forecast value for the period t, y_t is the actual value for period t, and k is the length of the SMA. This is however without an error term, which can be included: $\epsilon_t \sim N(0, \sigma^2)$. This formula could be extended with adding a weight factor to combine moving averages, which will then result in weighted moving averages [Hyndman and Athanasopoulos, 2018].

[Sani and Kingsman, 1997] found that SMA(k=12) outperforms the SES on low level and infrequent data. SMA, however, tends to lag behind the turning points in the data and when used for a long term forecasting, SMA assumes there is no trend present in the data [Nau, 2015]. The SMA is also not an applicable method when seasonality is present in the data.

Another form of a moving average model is the exponential moving average (or exponential weighted moving average). This model is the same model as the single exponential smoothing model, and is explained in Section 3.1.3.

The moving average approach will not be used in this research, but is explained here, because the current forecasting process in place is a moving average approach.

3.1.3 Exponential smoothing

Exponential smoothing uses weighted averages of past data sets to forecast new values. It is comparable with moving average, but differs in placing a different weight on recent and actual observations instead of placing equal weight on all observations. It is a useful technique for forecasting seasonal demand as it combines error, trend, and seasonal patterns.

Single (or simple) exponential smoothing SES is a popular method for forecasting demand. It is simple to use, because it requires only two pieces of data: the last forecast and the observation of the latest period [Sani and Kingsman, 1997]. It is also flexible, because the smoothing constant that is used can be changed. Moreover, this model responds quickly to new information and thus reacts with high specificity and intensity [Kim et al., 2020]. The demand model for exponential smoothing is:

$$X_t = X_{t-1} + \epsilon_{t(lag-1)} \tag{3.4}$$

The formula for single exponential smoothing is as follows [Gardner Jr, 2006,Holt, 2004,Nau, 2015]:

$$S_t = \alpha \cdot X_t + (1 - \alpha) \cdot S_{t-1} \tag{3.5}$$

where S_t is the forecast value of the demand in period t, X_t is the actual demand value of period t, and α is the smoothing constant between zero and one. The level parameter α should be estimated beforehand, which can, for example, be done by averaging the demand for the first several periods. It is generally well known that simple exponential smoothing is optimal for an ARIMA(0,1,1) or a random walk model containing noise [Chatfield et al., 2001].

This simple approach, however, cannot cope well with patterns. It is typically used in short-term predictions and in the absence of seasonal or periodic fluctuations. To solve this problem, [Holt, 2004] showed how this formula can be extended to be able to cope with seasonality and trends. He also stated: "the flexibility of the method combined with its economy of computation and data requirements make it especially suitable for industrial situations in which a large number of forecasts are needed for sales of individual products." [Holt, 2004, p. 5]

[Gardner Jr, 2006] provides a table in his article containing all different smoothing methods with regards to the presence of trends or seasonality. Here he makes a difference between additive and multiplicative trends or seasonality, which can be seen as decomposing the time

Symbol	Definition
α	Smoothing parameter for the level of the series
γ	Smoothing parameter for the trend
S_t	Smoothed level of the series
T_t	Smoothed additive trend
X_t	Observed value of time series
$X_t'(m)$	Forecast for m periods ahead of t

Table 3.1: Notations exponential smoothing, *Based on "Exponential smoothing: The state of the art - Part 2", by Gardner, 2006.*

series into different components. The methods used in this research will be shown below and Table 3.1 contains the notations of the variables used in the equations.

The formula that contains an additive trend but no seasonality, is called Holt's method:

$$\begin{aligned} X_t'(m) &= S_t + m \cdot T_t \\ S_t &= \alpha \cdot X_t + (1-\alpha)(S_{t-1}) + T_{t-1} \\ T_t &= \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1} \end{aligned} \tag{3.6}$$

Here the parameters α and γ should be estimated beforehand, which can be done by finding a best fit linear equation from the initial data of using least squares regression of the demand for several periods. Holt's method is optimal for an ARIMA(0,2,2) [Chatfield et al., 2001].

State space models

Exponential smoothing state space model (ETS) are exponential smoothing methods which incorporate stochastic models, likelihood calculation, prediction intervals and procedures for model selection [Hyndman et al., 2002]. So when using the same parameters, the models generate the same point forecasts, but the state space models can produce an entire different forecast distribution [Hyndman and Athanasopoulos, 2018]. Each model describes the observed data through a measurement equation and describes how the unobserved components change over time through state equations. For every method there are two models: one with additive errors and one with multiplicative errors.

Just like with the regular exponential smoothing methods there are many different versions available, this section will only show the same methods as before to indicate the difference. All of the notations used in this section correspond to Table 3.1. The additive error model for single exponential smoothing is as follows:

$$\begin{aligned} X_t' &= S_{t-1} + \epsilon_t \\ S_t &= S_{t-1} + \alpha \cdot \epsilon_t \end{aligned} \tag{3.7}$$

Here the first part of the equation represents the measurement equation and the second part represents the state equation. The error term is normally distributed white noise with mean 0 and variance σ^2, or $\epsilon_t \sim NID(0, \sigma^2)$. These equations and the statistical distribution of the errors form a fully specified statistical model.

For the model of Holt's method the errors are also normally distributed white noise with mean 0 and variance σ^2, or $\epsilon_t \sim NID(0, \sigma^2)$. The equations are:

$$\begin{aligned} X'_t &= S_{t-1} + T_{t-1} + \epsilon_t \\ S_t &= S_{t-1} + T_{t-1} + \alpha \cdot \epsilon_t \\ T_t &= T_{t-1} + \gamma^* \cdot \epsilon_t \end{aligned} \tag{3.8}$$

Where $\gamma^* = \alpha\gamma$.

3.1.4 Autoregressive integrated moving average

Autoregressive integrated moving average, or ARIMA, aims to describe the autocorrelations in the data [Hyndman and Athanasopoulos, 2018]. Exponential smoothing and ARIMA are the two most widely used forecasting approaches when forecasting time series. The I in ARIMA stands for integrated, and makes stationary time series out of non-stationary time series. This procedure is called differencing [Box et al., 2015]. When working with ARIMA and differencing, the concept of lags (or backward shift) has to be introduced:

$$L_{y_t} = y_{t-1}$$

where L stands for the lag and y_t for the variable of interest. This equation is useful for describing differences, a d^{th} order difference can be written as:

$$(1 - L)^d y_t$$

If the time series are already stationary, it is also possible to use the ARMA approach instead of ARIMA. ARIMA is a combination of an autoregressive model and a moving average model, to understand it the two models will first be explained individually.

The term autoregression means that it is a regression of the variable itself [Hyndman and Athanasopoulos, 2018]. In such a model, the dependent variable is forecasted using a linear combination of the variable against itself. An autoregressive model of order p, or AR(p) model, can be written as [Box et al., 2015, Chauvet and Potter, 2013, Hyndman and Athanasopoulos, 2018]:

$$\Delta y_t = c + \phi_1 \Delta y_{t-1} + \phi_2 \Delta y_{t-2} + ... + \phi_p \Delta y_{t-p} + \epsilon_t \tag{3.9}$$

where y_t is the variable of interest, $\Delta = 1 - L$, L is the lag operator, ϕ is the parameter that has to be estimated from the data, and ϵ is the white noise (or pure random series) that looks like $\epsilon_t \sim WN(0, \sigma^2)$.

AR models can handle a wide range of different time series patterns. Changing the parameters ϕ result in different time series patterns. Changing the error term will not change the patterns, but will only change the scale of the patterns [Hyndman and Athanasopoulos, 2018].

A moving average model in a regression-like model does not use past values, but uses past forecast errors. A moving average model of order q, or MA(q) model, can be written as [Box et al., 2015, Hyndman and Athanasopoulos, 2018]:

$$y_t = c + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + ... + \theta_p \epsilon_{t-q} \tag{3.10}$$

Model	Name	Formula
ARIMA(1,0,0)	First-order autoregressive model	$\hat{Y}_t = \mu + \phi Y_{t-1} + e_t$
ARIMA(0,1,0)	Random walk	$\hat{Y}_t = \mu + Y_{t-1} + e_t$
ARIMA(1,1,0)	Differenced first-order autoregressive model	$\hat{Y}_t = \mu + Y_{t-1} + \phi(Y_{t-1} - Y_{t-2}) + e_t$
ARIMA(0,1,1) without constant	Simple exponential smoothing	$\hat{Y}_t = Y_{t-1} - \theta e_{t-1} + e_t$
ARIMA(0,1,1) with constant	Simple exponential smoothing with growth	$\hat{Y}_t = \mu + Yt - 1 - \theta e_{t-1} + e_t$
ARIMA(0,2,1) or (0,2,2) without constant	Linear exponential smoothing	$\hat{Y}_t = 2Y_{t-1} - Y_{t-2} - \theta_1 e_{t-1} - \theta_2 e_{t-2} + e_t$
ARIMA(1,1,2) without constant	Damped-trend linear exponential smoothing	$\hat{Y}_t = Y_{t-1} - \phi(Y_{t-1} - Y_{t-2}) - \theta_1 e_{t-1} - \theta_2 e_{t-2} + e_t$

Table 3.2: Commonly encountered nonseasonal ARIMA models

where y_t is the variable of interest, θ is the parameter that has to be estimated from the data, and ϵ_t is the white noise. The values of ϵ_t are not really observed, so it is not a regression in the usual sense. Here a change in the parameters θ will also result in different time series, and changing ϵ_t will only change the scale of the series.

By combining the previous explained models, a non-seasonal ARIMA model is obtained [Hyndman and Athanasopoulos, 2018, Zhang, 2003]:

$$y'_t = c + \phi_1 y'_{t-1} + ... + \phi_p y'_{t-p} + \theta_1 \epsilon_{t-1} + ... + \theta_p \epsilon_{t-q} + \epsilon_t \tag{3.11}$$

where y'_t is the differenced series, ϕ and θ are the parameters, and ϵ is the white noise. This is called an ARIMA(p,d,q) model, where p is the order of the autoregressive part, d is the degree of first differencing involved needed for stationarity, and q is the order of the moving average part [Anne, 2020].

An overview of some commonly encountered nonseasonal ARIMA models is given in Table 3.2 [Nau, 2015]. A question that might arise is whether to add an AR or MA term when correcting for autocorrelation. A rule-of-thumb for this is when a positive autocorrelation is present, this is usually best managed by adding an AR term whereas if a negative autocorrelation is present this is usually best managed by adding an MA term. ARIMA can also model seasonal data by including additional seasonal terms in the model [Hyndman and Athanasopoulos, 2018].

ARIMA has been applied before in the automotive industry for forecasting linear time series. Even though ARIMA models can represent several different time series, one of the disadvantages of applying an ARIMA model is the assumption of a linear correlation structure among the time series values [Zhang, 2003]. Nonlinear patterns cannot be captured by this model [Winkowski, 2019].

Causal methods

Causal methods assume that the variable that needs to be forecasted has a certain cause and effect relationship with one or more independent variables, which is also called econometrics. So causal methods take into account all factors that might impact the forecasted variable, instead of only relying on past data. This can be used when a time series approach does not suffice [Beutel and Minner, 2012].

3.1.5 Regression

Regression analyzes the underlying factors that may influence the variable being forecasted. It compares a dependent variable with one or more independent variables.

Linear regression is a widely used method. It is the study of linear, additive relationships between variables [Nau, 2015, Hyndman and Athanasopoulos, 2018]. The formula for linear regression is:

$$Y_t = b_0 + b_1 X_{1t} + b_2 X_{2t} + ... + b_i X_{it} + \epsilon_t \tag{3.12}$$

where Y_t is the dependent variable which will be predicted, X_{it} are the independent variables, b_0 is the intercept, b_i represent the slope of the line, or the co-coefficients of the variables, and ϵ_t is the error term that captures everything that may affect Y_t other than $X_i t$. This is a multiple regression model due to the numerous independent variables. If there is only one independent variable, it is called a simple regression model and it looks like this:

$$Y_t = b_0 + b_1 X_t + \epsilon_t \tag{3.13}$$

For estimating the co-coefficients, least squares estimation can be used by minimising the sum of the squared errors [Hyndman and Athanasopoulos, 2018]:

$$\sum_{t=1}^{T} \epsilon_t^2 = \sum_{t=1}^{T} (Y_t - b_0 - b_1 X_{1t} - b_2 X_{2t} - ... - b_i X_{it})^2$$

When using linear regression for forecasting, the error term is mostly ignored to obtain predictions of the dependent variable [Hyndman and Athanasopoulos, 2018].

The corresponding assumptions associated with linear regression are [Hyndman and Athanasopoulos, 2018, Nau, 2015]:

1. Linearity and additivity of the relationships between dependent and independent variables;
2. Homoscedasticity (constant variance of the error term);
3. Independent variables independent of the error term;
4. Normality of the error distribution.

The correlation coefficient between each pair of variables measures the strength of the linear relationship between the variables, and should be calculated. This is done best with standardized variables. Standardizing variables is putting the variables on the same scale. This can be done by:

$$X_t^* = \frac{X_t - \mu}{\sigma}$$

where X_t^* is the standardized variable, X_t is the variable, μ is the mean and σ is the standard deviation. Now the the correlation coefficient can be calculated with the following formula [Nau, 2015]:

$$r_{XY} = \frac{(X_1^* Y_1^* + X_2^* Y_2^* + ... + X_n^* Y_n^*)}{n}$$

where r_{XY} is the correlation coefficient, X_n^* and Y_n^* are the standardized variables, and n is the number of observations.

When using linear regression, the coefficient of determination, or R^2, can be used to see how well the model fits the data. R^2 shows how much of the variance is explained by the model [Hyndman and Athanasopoulos, 2018]:

$$R^2 = \frac{\sum(\hat{y_t} - \bar{y_t})^2}{\sum(y_t - \bar{y_t})^2}$$

where y_t are the observed values, $\hat{y}_t$ are the predicted values and $\bar{y}_t$ is is the mean. Another way of measuring how well the model has fitted the data, is the standard deviation of the residuals, or the residual standard error:

$$\hat{\sigma_e} = \sqrt{\frac{1}{T-k-1}\sum_{t=1}^{T} e_t^2}$$

where k is the number of predictors.

The advantage of linear regression is the linearity, which makes the estimation procedure simple, and the properties of the model are well understood. At the same time, the assumption of a linear relationship between the inputs and the outputs is also a disadvantage. Most data often exhibit some nonlinearity which cannot be captured by a linear regression model [Aminian et al., 2006]. If nonlinear effects are present, a better suited model would be a neural network. However, it would also be possible to transform the data with the help of non linear functions. An example of this would be using the log function to achieve linearity in the data.

3.2 Evaluating forecast performance

"However good our model, it does not guarantee success. It simply helps reduce the chance of failure." [Morlidge and Player, 2010, p. 126]. This means that, in order to successfully forecast, it is important to measure the performance of the model continuously and correct the forecast where necessary. Forecasting methods can be evaluated by either their input or their output [Armstrong, 2001].

Steps that need to be taken in the forecasting evaluating process are as follows:

1. Infer the demand model from the data.
2. Determine the forecasting method that fits the demand model.
3. Initialize the forecasting method with part of the data.
4. Optimize parameters of the method with another part of the data.
5. Start forecasting and monitoring the model.

3.2.1 Error measures

Forecasts can be evaluated by error measures. It is of high importance to keep track of the forecast error, since a high forecast error can negatively affect the business operations. The choice of error measure depends mostly on the the data used to create the forecast. There are already a lot of error measures available in the literature, from which a small selection is chosen to use. This research uses the Mean Absolute Percentage Error (MAPE), the Mean Absolute Deviation (MAD) and the Root Mean Square Error (RMSE). Table 3.3 shows their formulas. In this table y_t is the measured value at time t and f_t is the forecasted value at time t.

Error measure	**Formula**
Mean Absolute error (MAE) or MAD	$mean(\|(y_t - f_t)\|)$
Root Mean Square Error RMSE	$\sqrt{mean((y_t - f_t)^2)}$
Mean Absolute Percentage Error MAPE	$mean(100 \cdot \|\frac{\|(y_t - f_t)\|}{y_t}\|)$

Table 3.3: Error measures

Using absolute error measures (MAD and RMSE) can be useful when comparing methods applied tot the same set of data, but should not be used when the scale of the data differs [Armstrong, 2001, Hyndman and Koehler, 2006, Prestwich et al., 2014, Shcherbakov et al., 2013]. Other shortcomings of these type of measures, especially applicable to RMSE, include a high influence of outliers in the data and a low reliability. [Armstrong, 2001] also points out RMSE should not be used when comparing forecast performance across series. Percentage errors (MAPE), however, are known to be scale-independent and can be used for comparing forecast performance across different data sets [Hyndman and Koehler, 2006]. Disadvantages of percentage errors include a division by zero when the actual value is equal to the predicted value, they have a non-symmetric issue, they assume a meaningful zero, and the error measures are biased [Armstrong, 2001, Hyndman and Koehler, 2006, Shcherbakov et al., 2013].

Chapter 4

Problem diagnosis

During the problem definition phase the current forecasting process in place was mapped out. This process is described in Section 1.2 and answers the first sub-question: 'What does the current forecasting process look like?'. This forecasting process uses the two-level MPS approach that results in a planning for individual article quantities. This process is also described and visualized in model form in Section 5.1 and Figure 5.1. This chapter elaborates on the individual article forecasts and its effects. This is done by presenting the forecast accuracy of a number of articles. The articles studied were selected by material planners at the factories, they decided on the mix of different kind of articles. This differed per factory. This chapter discusses the factories included in this research and per factory the article numbers and corresponding accuracy is presented. The second sub-question: 'What are the effects of the current forecasting process at the operational level?' is answered in this chapter.

The data presented in this chapter was collected from delivery schedules and a database. A delivery schedule includes the required quantities of an article for a one year horizon. The database consists of raw forecast data, before planning gets involved. The accuracy for both of these forecast data was calculated. The accuracy of the database data is the best representation of the actual forecast performance, however, database data was not available for all articles. This was mostly applicable to articles that are used in operations before assembly. Therefore, the primary source for performance evaluation was the database data, and when this was not available the delivery schedules were used. In this chapter the average percentage or absolute error of the available forecast data is presented. For the database this consists of observations once every 4 weeks, where the range differs between themselves. Some articles contain observations for two years (once every 4 weeks), while other articles contain observations for less than a year. Furthermore, the variation decreases over time, since there are less observations closer to the end. This is why it was chosen to calculate an average to inspect the forecasting performance of the current system. For the delivery schedules the difference in observations and decreasing variation is also present. Some articles contain forecast observations for half a year, while others only contain a few weeks, and some articles also miss weeks in between. The accuracy calculation for all available weeks per article, both for the database and the delivery schedules can be found in Appendix C. The chosen accuracy measures are explained in Section 3.2.1. The standard used measure is the MAPE, but when an article has a demand with multiple zeros, the MAD and the RMSE were calculated, because a percentage error was not representable.

Due to Covid the truck company had to close unexpectedly between week 13 and 17 of 2020 and had to start up again in the weeks 18 till 21. The forecast for these weeks was normal, but because of suddenly closing down, the error was extremely high. This is why these weeks were removed from the accuracy calculation.

4.1 Truck Plant

The Truck Plant is the last stop of a truck in production, it is the end assembly. If a truck finishes at the Truck Plant the truck is ready for shipping. The Truck Plant consists of one long line with a number of areas. Every area is specifically meant for assembling a part of the truck. The data from articles that is collected from the truck plant can be divided in different categories, see Table 4.1.

	Fastmover	**Slowmovers**
Steering code 2	1849492, 1878677, 2121022	0506834, 2157776, 2184214
Steering code 3	0090861, 1377743, 2208021	1257443, 1377785, 1881839

Table 4.1: Article numbers per category from Truck Plant

The biggest distinction is between the fastmover and the slowmover, which is the distinction between articles that are ordered in big quantities mostly due to being on most of the trucks, and articles that are ordered less often, because they are less required. An article can be categorized as a fastmover when it consumes more than 70 pieces a day, and as slowmover when it consumes less than 70 pieces a day. Furthermore, there is a distinction made between steering code 2 and 3. Articles from steering code 3 are mostly small parts for which the stock keeping method can only be done manually. Articles from steering code 3 are mostly small and cheap items that are stored in boxes, for which consumption is registered in batches. When an article from steering code 2 is collected, this is written off at the factory, while articles from steering code 3 are written off at the warehouse. Furthermore, an article from steering code 2 is written off per article, while articles from steering code 3 are written of as batches.

4.1.1 Delivery schedules

Figure 4.1 shows the average of the MAPE of a number of articles of the Truck plant. What can instantly be seen is the two slowmovers, article 2184214 and 1257443, have the highest percentage error with respectively 44.11% and 31.90%. The forecast of the fastmovers perfoms generally pretty well, except for article 0090861 which is the only fastmover with a percentage error higher than 10%. Overall the forecast performance of these articles is good.

Article 0506834, 1377785 and 1881839 were not suitable for using the MAPE calculation due to containing zeros. This is due to the fact these articles have a package quantity, but are slowmovers, so there are weeks where there is no need to order more of these articles. The

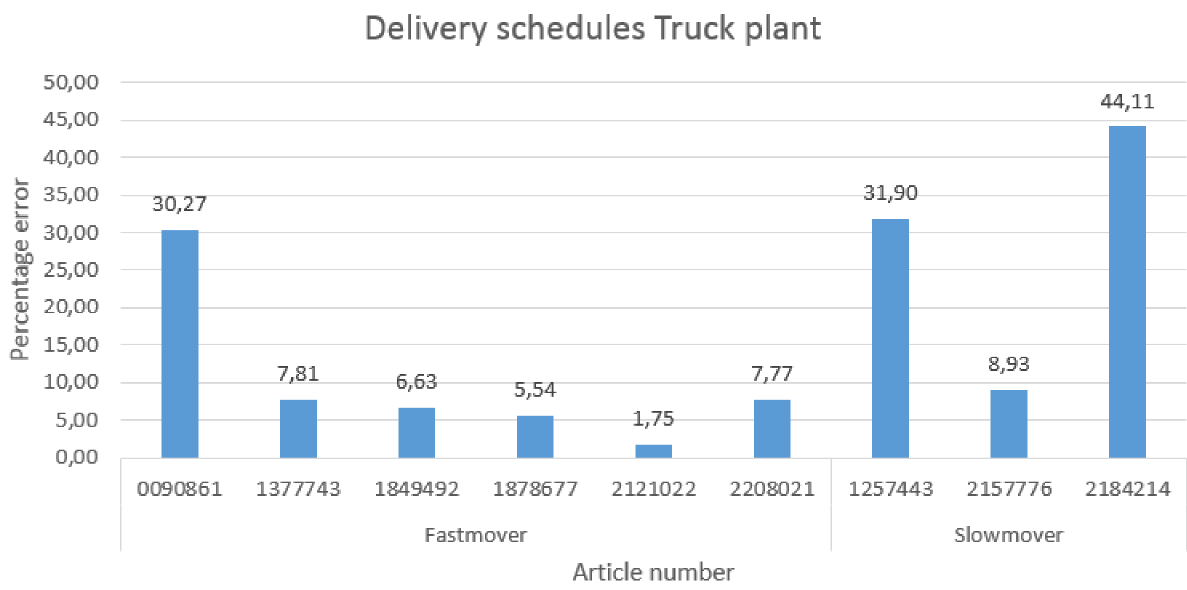

Figure 4.1: Average percentage error of delivery schedules of Truck plant

average MAD and RMSE of these articles is shown in 4.2. Article 0506834 has a package quantity of 96 and is ordered once every couple of weeks. Article 137785 has a package quantity of 50, and is ordered more often. Article 1881839 has a package quantity of 750 and is also ordered once every few weeks. The package quantities explain the differences in MAD and RMSE for the article quantities.

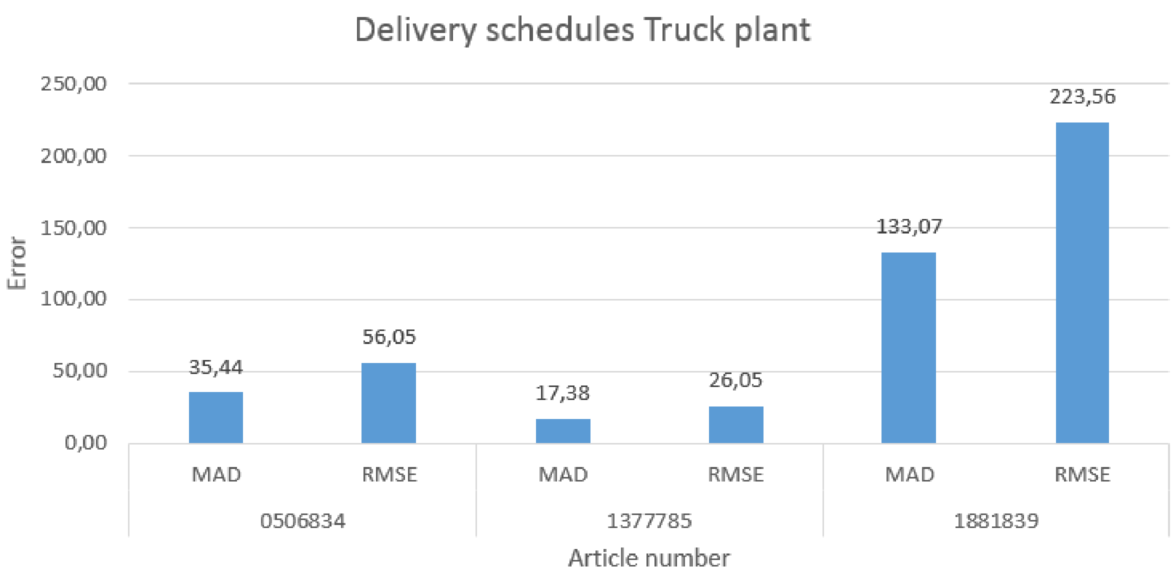

Figure 4.2: Average error of delivery schedules of Truck plant

4.1.2 Database

The non available article numbers of the truck plant are article 0090861 and 1881839, the rest of the articles were all available in the database data. The overview of the average percentage error can be seen in Figure 4.3. The first thing that can be seen is the higher overall percentage error when looking at the database data in comparison to the delivery schedules data. This mean planners positively impact the forecast of the article numbers, and thus the original forecast (database) gives a higher error than the delivery schedule forecast. Furthermore it is clearly visible slowmovers give a much higher error than fastmovers. Especially article 0506834 and 2157776 have a high error, namely 144.01% and 149.92%. Article 2184214 has an error of 74.16%, which is still very high but at least lower than 100%. The fastmovers all give an error of about 20% which is higher than the error in the delivery schedules. For article 0506834 the MAPE could also be calculated for the database data due to not being constrained with packaging quantities.

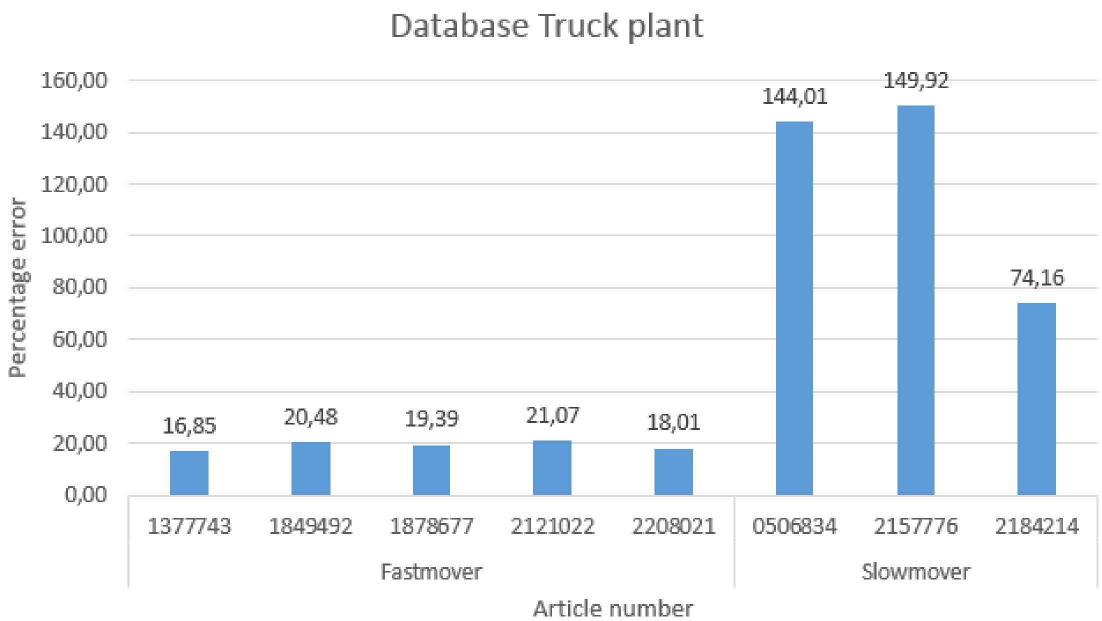

Figure 4.3: Average percentage error of database data of Truck plant

When looking at Table 4.2 it can be seen that all of the articles represent negative errors. This means that all articles are under forecasted.

Article number	MPE
1377743	-10,07
1849492	-12,9
1878677	-12,16
2121022	-9,19
2208021	-10,24
0506834	-127,82
2157776	-122,11
2184214	-59,16

Table 4.2: Forecast bias of database Truck plant

Article 1257443 contains lots of zeros in the database data, and thus the MAD and the RMSE were calculated instead of the MAPE. The articles for which the MAD and the RMSE were calculated are shown in Figure 4.4. The MAD of Article 1377785 is lower for the database data than for the delivery schedules, because the database data is not restricted to packaging quantities, and thus the demand forecast could be less drastically changed.

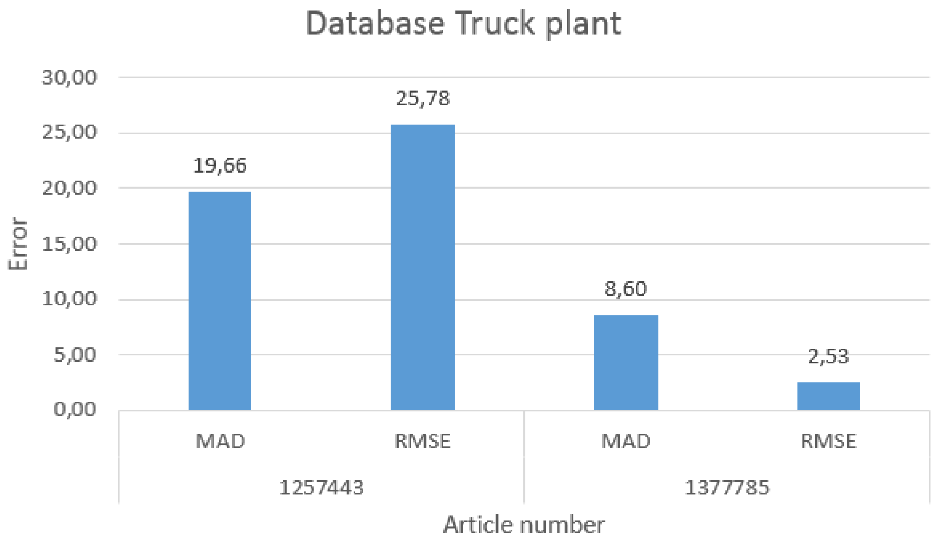

Figure 4.4: Average error of database data containing zeros of Truck plant

4.2 Axle Plant

In the Axle Plant, employees work on about 475 axles a day. These axles are then transported to be assembled. According to the logistical manager of the Axle Plant, the problem of sending out fluctuating numbers to suppliers is very active here. This is also because they have suppliers that are very far away. Here a distinction is made between Yellow Line 98 (YL98) and Yellow Line 99 (YL99), and fastmover and slowmover, see Table 4.1. Yellow line 98 means the articles are assembly ready, while articles in Yellow line 99 still need to undergo several operations before being assembly ready. What should be noted, as Table 4.6 shows, the articles 0964061, 0966541 and 0966542 are ordered at a supplier located far away. This means the forecast for these articles is more critical due to having a much longer travel time. The travel time is estimated at about 16 weeks.

	Fastmover	**Slowmovers**
Yellow Line 98	1287859, 1849780	-
Yellow Line 99	0964061, 2048982	0966541, 0966542

Table 4.3: Article numbers per category from Axle Plant

4.2.1 Delivery schedules

As can be seen in Figure 4.5, the two slowmovers articles 0966541 and 0966542 have the highest percentage error compared to the others articles. The percentage errors are 34.48% and 44.10%. These articles are ordered from India, so their error is more critical. Article 2048982 also shows a higher error compared to the other articles, namely 32.11%, which is possibly due to the fact it is a YL99 item. Its demand consists of fluctuations, because it is used in pre-operations. The low percentage error of article 0964061, 6.16%, is remarkable, because it is a YL99 item and it is ordered from a supplier in India, however it is also a fastmover. The last two articles show a low percentage error due to being a YL98 item and being a fastmover.

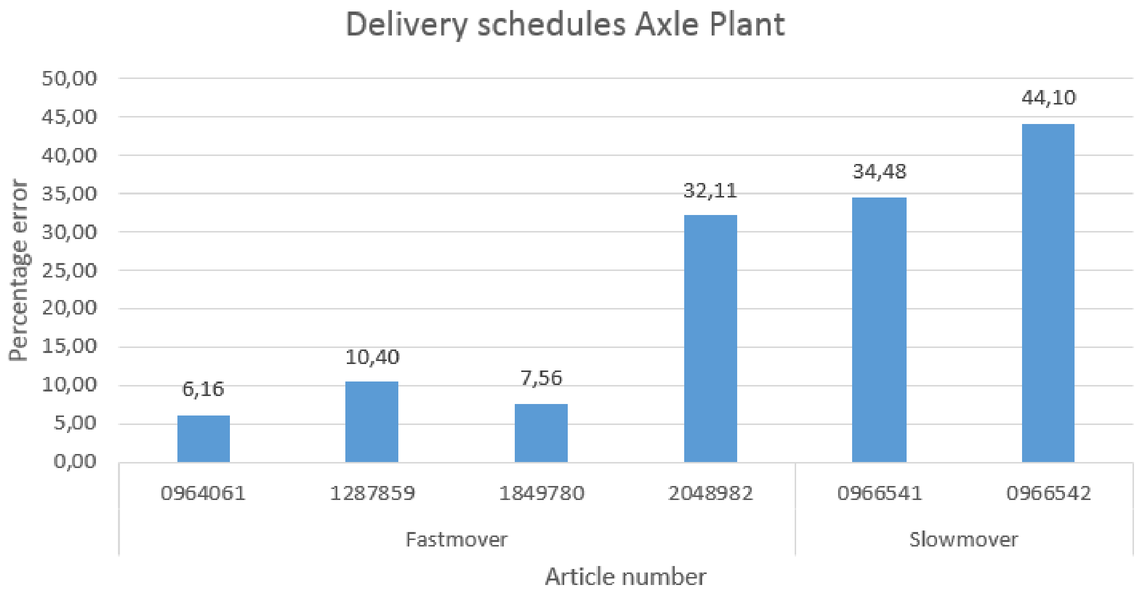

Figure 4.5: Average percentage error of delivery schedules of the Axle plant

4.2.2 Database

Unfortunately, for the Axle plant only two articles were available in the database: article 1287859 and 1849780. The other articles are all part of the YL99 category, and were not available in the database. The average percentage error of the two articles is shown in Figure 4.6. Compared to the delivery schedules, the two articles give a higher error when looking at the database data. When looking at the database data the error of article 1849780 is higher than article 1287859, while in the delivery schedules this is the other way around.

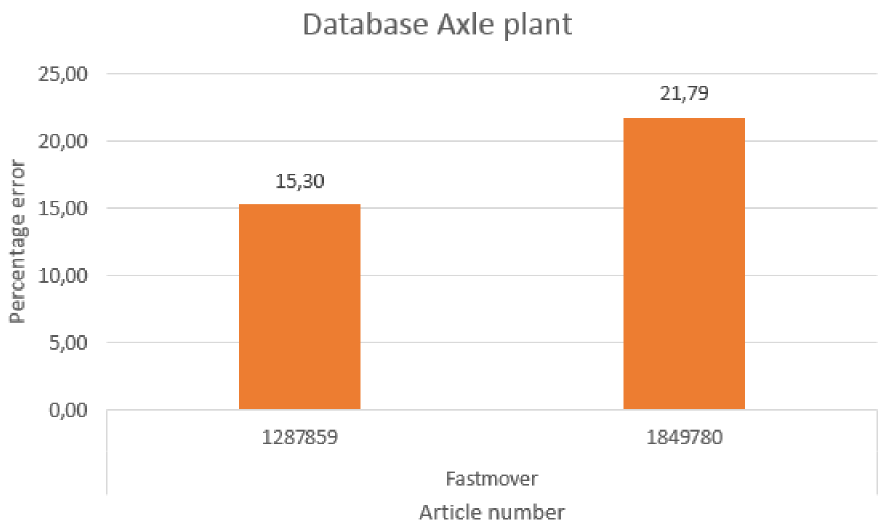

Figure 4.6: Average percentage error of database data of the Axle plant

4.3 Engine Plant

The complete engine of a truck is build in the Engine Plant. The Engine Plant has a completely automated production line where a bare engine block is transformed to a complete engine. This plant consists of both production operations and assembly. The articles that are used in the engine plant are divided in fastmovers and slowmovers, and like the Axle plant, in Yellow line 98 and Yellow line 99.

	Fastmover	**Slowmovers**
Yellow Line 98	2126626, 2258740, 2258745	2126790, 2258742, 2258743
Yellow Line 99	2245292, 2245294	2262314

Table 4.4: Article numbers per category from the Engine Plant

4.3.1 Delivery schedules

The overview of the average percentage error of the delivery schedules for the engine plant can be seen in Figure 4.7. Overall the percentage error for the articles at the Engine plant is higher than for the other plants. The articles with the highest error, article 2126790 with 45.62% and 2258742 with 47.20% are once again slowmovers. The fastmovers, however, also have a relatively high error. Article 2126626 has an error of 34.81% and article 2258740 has an error of 32.83%. The other fastmovers have a percentage error between 15% and 25%, which is higher than for the other plants. For article 2245292 and 2245294 this might be due to being a YL99 item and having fluctuating demand.

Article 2261324 and 2258743 were not suitable for using the MAPE calculation due to containing zeros. This is due to the fact these articles have a package quantity, but are slowmovers, so some weeks there is no need to order more of these articles. The average MAD and RMSE

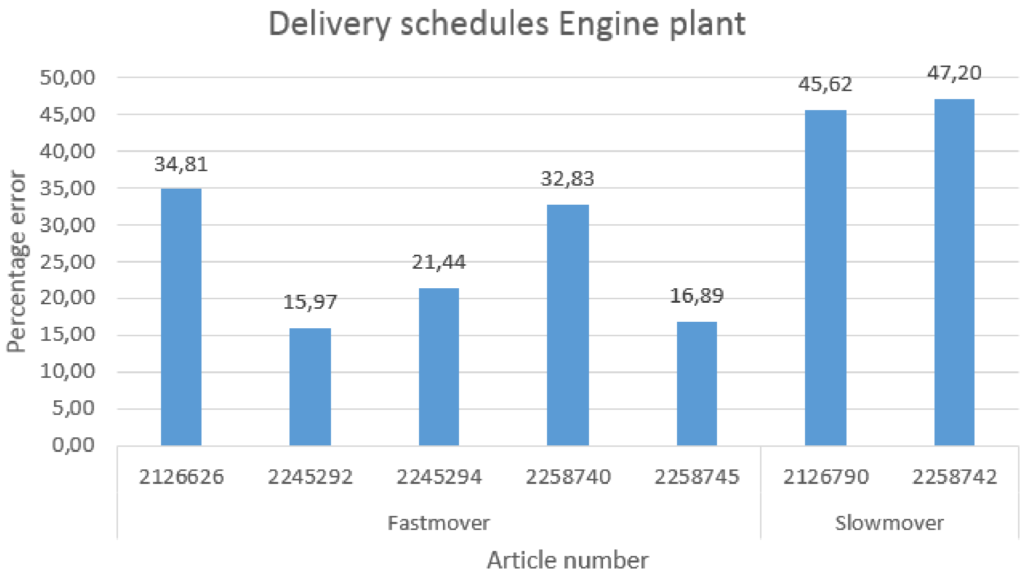

Figure 4.7: Average percentage error of delivery schedules of Engine plant

of these articles is shown in Figure 4.8. Article 2261324 has a package quantity of 36 and is ordered very little. Article 2258743 has a package quantity of 3, is mostly ordered in a multiple of 3 but is ordered sporadically. The package quantities explain the differences in MAD and RMSE for the article quantities. It can be noted the error of article 2258743 is only 4.62 and thus performing quite well. The absolute error of article 2261324 is 119.16 and is performing worse.

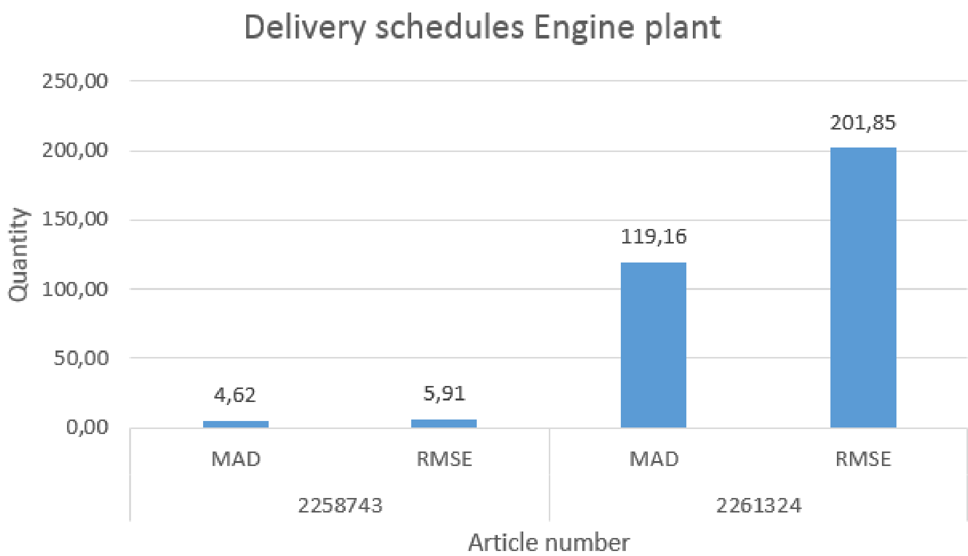

Figure 4.8: Average error of delivery schedules containing zeros of Engine plant

4.3.2 Database

The available articles in the database for the engine were the YL98 articles. An overview of the average percentage error is shown in Figure 4.9. It can be noted the overall percentage error is a lot higher compared to the delivery schedules. Especially the slowmovers have a high error. Article 2258743 has an error of 171.73%, which is extremely high. This is caused by the bias of the MAPE when dealing with very small numbers. Article 2126790 has an error of 62.86%, which is higher than than the delivery schedule, while article 2258742 has a lower error with 35.73%. The percentage error of the fastmovers are fairly similar with the error in the delivery schedules.

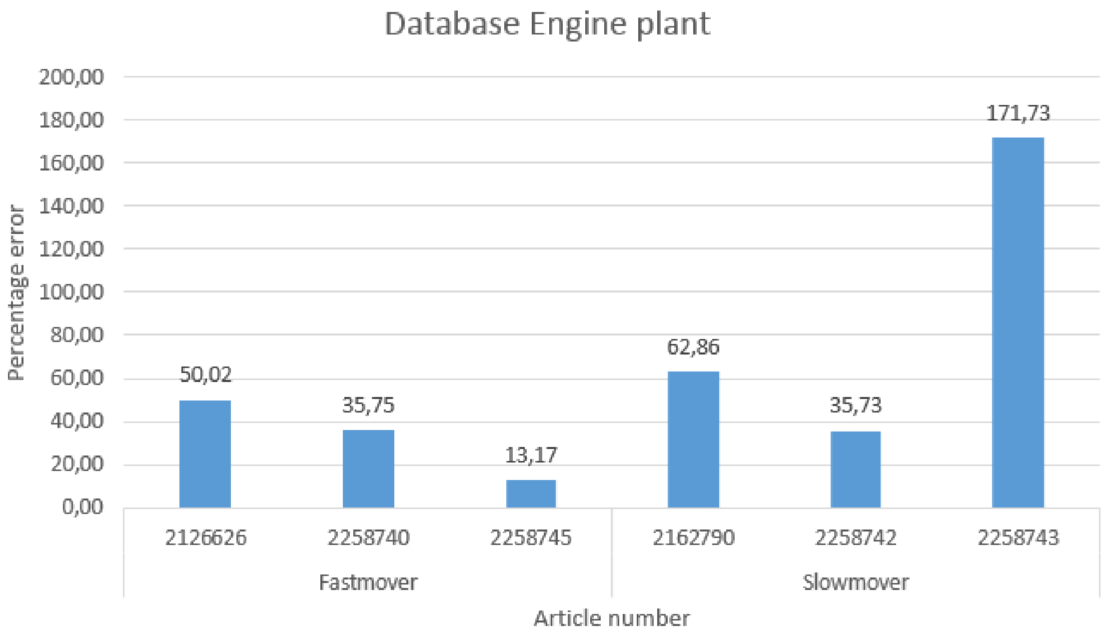

Figure 4.9: Average percentage error of database data of the Engine plant

Article number	MPE
2126626	-47,36
2258740	-26,37
2258745	12,6
2162790	-59,1
2258742	35,73
2258743	-135,82

Table 4.5: Forecast bias database Engine plant

Looking at Table 4.5 there are two articles that present a positive error and the other articles present a negative error. So most of the articles at the Engine plant are being under forecasted.

4.4 Article properties

Table 4.6 describes the article properties to give a better overview of the articles that are included in this research.

Article number	Price zone	Supplier location	Weight (kg)	Safety stock (items)
0090861	Very cheap	Close by	0.025	0
0506834	Cheap	Close by	2.036	0
0964061	Expensive	Far away	103	520
0966541	Expensive	Far away	98.9	40
0966542	Expensive	Far away	108	20
1257443	Very cheap	Very close	0.197	0
1287859	Affordable	Close by	4.187	0
1377743	Very cheap	Close by	0.028	1800
1377785	Very cheap	Close by	0.089	175
1849492	Medium ranged	Very close	34.5	24
1849780	Cheap	Close by	2.771	1500
1878677	Affordable	Close by	3.16	0
1881839	Very cheap	Close by	0.012	0
2048982	Affordable	Close by	12.705	400
2121022	Cheap	Medium distance	0.41	10
2126626	Medium ranged	Close by	6.92	0
2126790	Medium ranged	Close by	6.635	0
2157776	Medium ranged	Medium distance	0.108	0
2184214	Very expensive	Very close	70.407	0
2208021	Very cheap	Very close	0.006	4000
2245292	Medium ranged	Close by	23.85	500
2245294	Medium ranged	Close by	23.64	900
2258740	Very expensive	Medium distance	13.022	0
2258742	Expensive	Medium distance	15	0
2258743	Expensive	Medium distance	11.82	0
2258745	Very expensive	Medium distance	14.69	0
2261324	Medium ranged	Close by	23.64	700

Table 4.6: Article properties

When looking at the price zones of the articles, it can be seen that the articles that are very cheap belong to the steering code 3 category. These are very small and light articles that are easily stored and moved around. It is weird that not all of these articles have a safety stock in place. These items would be better suited for a stock policy instead of solely relying on a forecasting method. Only three of these items have a safety stock, while the other three do not.

When further inspecting the articles and looking at which do and do not have a safety stock (excluding the steering code 3 articles), it looks like the YL99 articles have a safety stock in place, while YL98 articles do not. This seems like a logical choice, since YL98 are only used at assembly and are easier to forecast, while YL99 articles are used in multiple operations and are more difficult to forecast.

As can be seen in Table 4.6, all suppliers are locaArticleed not too far away from the company, except for three articles which are located far away. The articles that need to come from far away all have a safety stock in place, because the travel time is very long.

4.5 Overall conclusion

Overall it can be concluded the forecast of the delivery schedules generally perform better than the database forecast. At the truck plant the performance of the delivery schedules do not necessarily show a distinction between fast- and slowmovers. here one fastmover has a significantly higher error, while one slowmover has a significantly lower error. The database forecast does show this distinction, where fastmovers have a much lower forecast error than slowmovers. The axle plant has mostly data available from the delivery schedules due to having a lot of YL99 items at this plant. The fastmovers do all perform better than the slowmovers, but one of the fastmovers has a forecast error that is more similar to the slowmovers. At the engine plant, the performance is very spread out. Even though fastmovers generally perform better for both delivery schedules and database, it is very close to each other and the forecast error is quite high. So overall it can be said fastmovers do show a lower error than slowmovers, nevertheless there are also fastmovers that do not perform that well. Therefore it is important to improve the forecast errors of both categories in this research.

Chapter 5

Data analysis

The data analysis phase consisted of collecting data, visualizing it, and analyzing the patterns to support the choice of forecasting methods. As explained in Chapter 4 there were two sources from which data could be collected. For the collection of data that was used for producing forecasts only the database was used as a source. In the database usage data of articles was available. Usage data is the actual quantity of the article numbers that was used in production. Whenever a part is taken from the warehouse, it is registered. This data was chosen to use in the forecasting process, because it represents the actual quantity used. The control charts for every article can be found in Appendix D. Furthermore, analysis of the data provided a current demand model and a demand model that was initiated from the article data. The data analysis phase answered the third sub-question: 'Which type of forecasting methods fit the production environment of the truck company?'.

During the data understanding phase, the articles that were studied were categorized:

- Steering code 2 and 3.
- Yellow Line 98 and 99.
- Fastmovers and slowmovers.

The category steering code 2 consists of articles that are registered whenever a single part is used in production, whereas steering code 3 is registered as batches when taken from the warehouse. For articles in the category steering code 3 a forecast is not really necessary since these are very cheap and small articles that only need a stock policy. Yellow line 98 means the articles are assembly ready, while articles in Yellow line 99 still need to undergo several operations before being assembly ready. Both of these type of articles need a forecast, because both are ordered at suppliers, but their usage differs due to their nature. Lastly, a distinction is made between fastmovers, of which more than 70 pieces a day are used in production, and slowmovers, of which less than 70 pieces a day are used. In the following sections steering code 3 and Yellow Line 99 will be actively indicated, meaning the remaining articles belong in the steering code 2 and Yellow Line 98 categories.

5.1 Current demand model

For the forecast on truck-type, they are currently using a moving average approach. Marketing & Sales uses the last 6 periods (=24 weeks) of actual customer orders as input for calculating the forecast orders at truck-type level. They calculate the average of these past sales and the system checks the percentage of a truck-type relative to the total amount of orders. This can also be seen as a two-level MPS. In such an approach, product families are master scheduled and the user ratio of individual products is calculated. Then the bill of material is used to calculate the requirements of the individual items. A two-level MPS is commonly used in companies that have a build-to-order or assemble-to-order approach. Other input for the forecast is the POB, which consists of production numbers that are calculated by multiplying the amount of working days with the buildrate per period. Since the company has a build-to-order system, customers can personalize their trucks, and are able to make changes until 5 weeks before delivery. Demand at the truck company is made up of:

$$D_t = C_t + F_t$$

Where D_t is the truck demand for period t, C_t are the customer orders for period t, F_t are the forecast orders for period t. The truck production for a period is always equal to the buildrate, which can consist of customer orders and forecast orders, but might differ from the actual truck demand. Whenever a customer orders comes in, it consumes a forecast order, which makes sure the production level stays the same. The forecast is generated with a moving average of the past 24 weeks based on truck-types. The detailed forecast is generated by percentage usage of articles in truck-types. This is done with the use of percentage bills, which are bills that use expected sales percentages [Cunningham et al., 1996]. These percentages are calculated based on past data and estimates of customer preference in the planning period. The use of percentage bills might enhance product forecasting and scheduling efficiency, because forecasting and planning on higher level is generally more accurate [Stonebraker, 1996].

At article level there are two models that are important:

$$A_{td} = D_t * x$$

and

$$A_{tb} = B_t * x$$

Where A_{td} is the article demand for period t based on the customer orders, A_{tb} is the article demand for period t based on the buildrate, D_t is the truck demand for period t, B_t is the buildrate for period t, and x is the quantity of articles needed for a truck as indicated by the bill of material. Figure 5.1 is a visualization of how the article requirements are determined.

An important note to make here, is the dynamic percentage bill and buildrate. The percentage usage of certain articles changes regularly. This is due to the fact the percentage bill is based on what customers actually buy every year and is updated whenever the percentage ratio changes. These percentages can also be seen as a forecast of itself, since it is partly based on expected customer preferences in the coming planning period. The buildrate is reviewed manually by management, but is also based on the amount of working days, irregularities in certain weeks and might be increased/decreased if the truck company wants to change its daily production. The buildrate cannot be seen as a forecast, because once it is set it is the

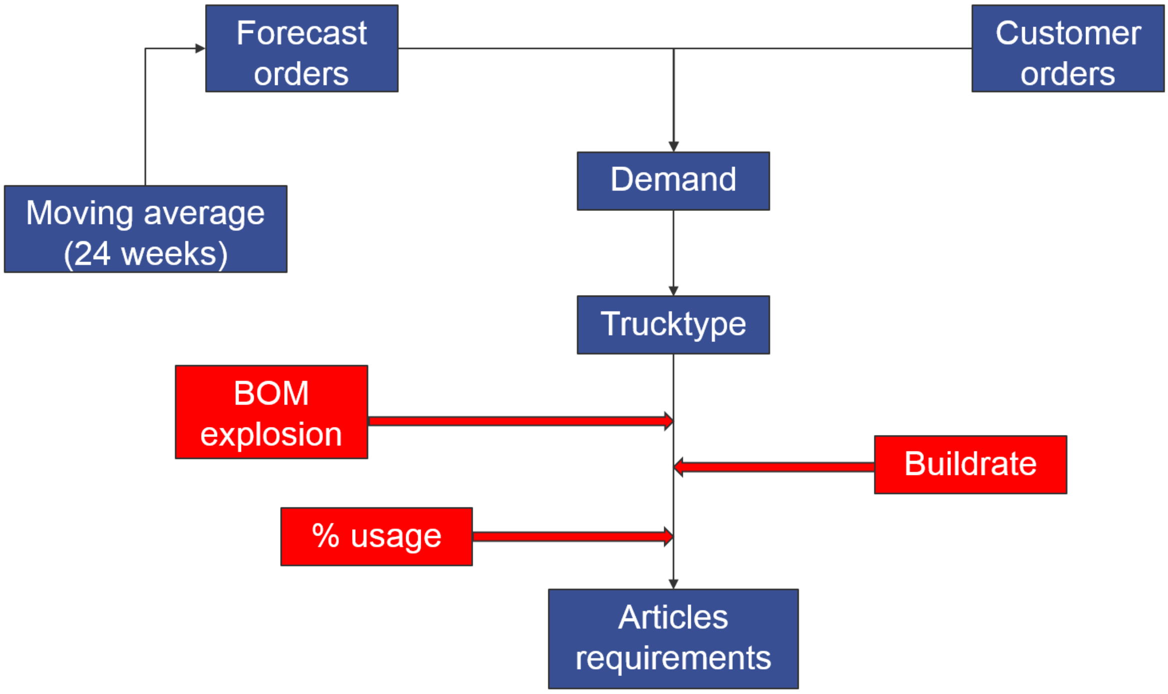

Figure 5.1: Visualization of current demand model

quantity the company aims to achieve every day, instead of predicting the quantity they think they will assemble.

5.2 Data

The data described in this chapter corresponds to the visualizations shown in Appendix D. Furthermore, the Coefficient of Variation (CV) was calculated for every article number and is described in this chapter. The formula of the coefficient of variation is as follows:

$$CV = \frac{\sigma}{\mu} \tag{5.1}$$

The higher the CV, the greater level of dispersion around the mean. [de Kok et al., 2018] explains when a component is present multiple times at different levels in the BOM, its CV can be significantly higher than the CV of the end item, even though this end demand is stable. The components are sensitive to demand mix changes. A higher CV will make it more difficult for forecasting methods to successfully pick up and forecast the signal in the data [Morlidge et al., 2013]. Furthermore a high CV can indicate a cumulative forecast might be better suited for an article, since this absorbs some of the variation in the dataset. Table 5.1 shows the mean, the standard deviation and the coefficient of variation of all article numbers. The CV's were calculated after removal of outliers. These outliers are described in the following subsection.

Figure 5.2 shows the frequencies of the CV values of the articles. Fastmovers generally have a lower CV than slowmovers. All fastmovers had a CV below 0.35, except for two YL99 articles that have a CV of 0.55 and 0.58. The CV values of the slowmovers are above 0.35, except for one article with a CV of 0.26. Other slowmover values range from 0.35 to 1.26. So in this histogram the fastmovers mostly represent the lef part and the slowmovers mostly represent the right part. The range that contains the most frequencies is a combination of fastmovers and slowmovers.

Subsection 5.2.1 will further elaborate on the irregularities found in the datasets.

5.2.1 Irregularities

Two important factors that may influence the usage of the articles are the buildrate and the working days per week. The working days, however, are incorporated beforehand into the buildrate. At the truck company, the maximum production is always equal to the buildrate, meaning they want to assemble the amount of trucks that is equal to the buildrate everyday. In the time span for this research there are three moments the buildrate was increased: Week 25 of 2020, which already got in motion in week 24, Week 41 of 2020, and week 10 of 2021.

Some of the irregularities in the data of the articles can be explained by the buildrate and the working days. The first few weeks of usage for most of the articles is quite low, not only due to weeks having less working days, but also due to production needing to start up again after unexpectedly stopping because of Covid. There was no production in weeks 30 till 32, because of the summer break. Weeks 52 and 53 are low due to including Christmas and 2020 being a leap year (meaning week 53 was half a week). The rest of the weeks containing less than 5 working days, also have a lower buildrate. Week 30 till 32 of 2020 were removed from the dataset, because it influences the forecasting process while the company already knows they will be closed for three weeks. This happens every year, and thus can be incorporated in

Article number	**Mean (μ)**	**Standard deviation (σ)**	**CV**
0090861	2483.96	839.69	0.34
0506834	20.79	10.68	0.51
0964061	738.16	408.17	0.55
0966541	69.18	35.88	0.52
0966542	43	21.99	0.51
1257443	70	29.69	0.42
1287859	811.34	193.28	0.24
1377743	31527.76	7955.56	0.25
1377785	59.26	25.72	0.43
1849492	675.2	172.71	0.26
1849780	1663.2	399.15	0.24
1878677	764.28	195.13	0.26
1881839	348.66	144.06	0.41
2048982	784.02	453.61	0.58
2121022	574.82	160.64	0.28
2126626	161.5	40.7	0.25
2126790	46.98	16.22	0.35
2157776	9.85	7.97	0.81
2184214	10.6	7.41	0.70
2208021	29284.4	8321.77	0.28
2245292	277.29	93.31	0.34
2245294	1035.25	354.06	0.34
2258740	87.07	24.65	0.28
2258742	47.54	12.59	0.26
2258743	7.46	5.2	0.70
2258745	784.35	79.62	0.10
2261324	119.21	150.54	1.26

Table 5.1: CV of article numbers

the planning after the forecast has been produced. Week 52 and 53 were also removed from the dataset, because these values heavily influence the forecast produced, while these weeks do no represent a normal week.

Other irregularities

Multiple articles contained outliers that were established by looking at values that exceeded the control limits. It was studied how long before these values were incorporated in the forecast, whether a mistake was made when registering a value or if there was another reason. After this, the outliers that could be safely removed were removed.

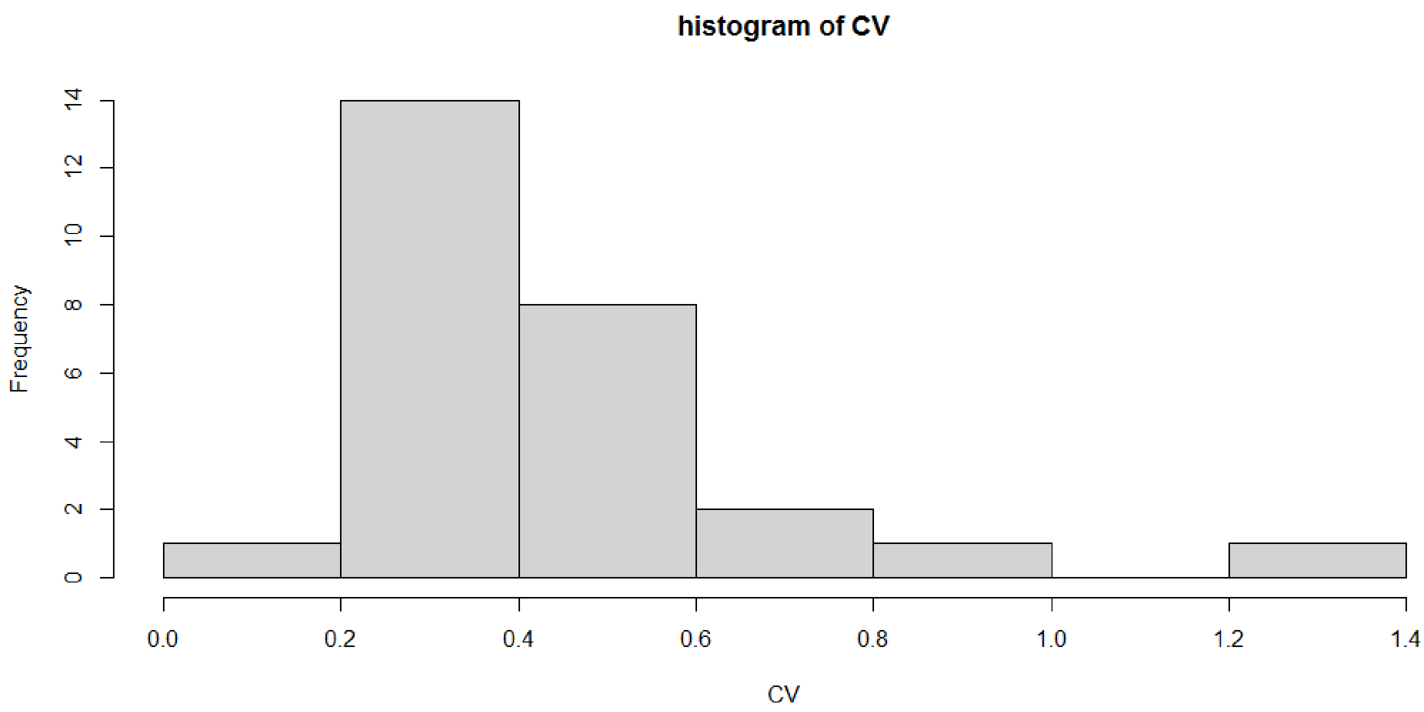

Figure 5.2: Histogram of CV

5.2.2 Missing values

Next to irregularities, there were also missing values for certain weeks in the dataset. Before removing or replacing missing values in the dataset, it is important to understand the different types of missing data [Kang, 2013, Acock, 2005]:

1. Missing Completely at Random (MCAR)
    - Data is defined as missing completely at random when it is not related to observations and the missing values are randomly distributed throughout the observed values.
2. Missing at Random (MAR)
    - Data is regarded as missing at random when the probability that the values are missing depends on the observations, but not on the specific missing values.
3. Missing not at random (MNAR)
    - If it does not fall in one of the previous category, the data can be defined as not missing at random.

After investigating why some articles contained missing values, it was concluded there were no underlying reasons. The weeks 30 till 32 were missing for all articles, because of the summer break, as explained in the previous section. Other missing values could be attributed to the database not registering any value for a specific week, and thus these could safely removed from the dataset.

5.3 Basic demand models

During inspection of the data of the articles, two basic demand models were found.

$$Y_t = ax_t + b \tag{5.2}$$

Where Y_t is the article demand, a is the slope, x_t is the buildrate and b is the intercept. This demand model is applicable to articles that are present at every truck and thus have a linear relationship with the buildrate. For these articles a linear regression was applied as forecasting method because of this linear relationship.

For the articles that had a linear relationship with the buildrate the following changes were made to the data:

- The usage values of weeks 30 till 32 were converted to 0 instead of removing these weeks, because the buildrate of these weeks was also equal to 0.

For the articles of which the usage did not show a significant relation to the buildrate, another forecasting approach has been used. After closely analyzing the data and its patterns, it was concluded these articles contain a level model that includes a lot of randomness. Seasonality could be not be investigated, since there was only usage data for 1 year, which is not enough to investigate seasonality effects. Thus, for data that contained a level with randomness the following equation was found:

$$Y_t = a + b_t + \epsilon_t \tag{5.3}$$

Where Y_t is the article demand, a is the level of the data, b_t is the trend present in the data, and ϵ_t is the error term or randomness. For the articles that do not have a linear relationship with the buildrate, this demand model was used. The trend component included was only applicable to articles containing a trend.

For article numbers belonging in the YL99 category and having to follow the level forecasting approach, a decision was made to produce period forecasts instead of weekly forecasts. These articles showed very fluctuating demand values and some of the articles belonging to this category also contained a lot of missing values. For the forecasts produced with periods, missing values were not removed from the dataset. If only a few datapoints are available, a period forecast is more reliable than a weekly forecast. Another reason why a period forecast is more reliable is the absorption of the variation when producing forecasts periodically.

Chapter 6

Solution design

6.1 Forecasting methods

As explained in the previous chapter, two demand models were inferred from the data. Different kind of forecasting methods fit these demand models. For the articles with a relationship to the buildrate, a linear regression was performed. This relationship was established by calculating the Pearson correlation coefficient and plotting the usage against the buildrate. All articles in this category had a correlation coefficient above 0.65 and had a clearly visual linear relationship in the graph. For the level demand model, multiple (level) forecasting methods were applied and inspected to choose the best performing method for the article categories.

6.1.1 Linear regression

Articles that have a linear relationship with the buildrate belong to the category of fastmovers. These particular fastmovers are found in almost every truck. As explained in Chapter 3 linear regression is a widely used forecasting method that studies the linear additive relationships between variables and helps explain what causes the variation in demand [Nau, 2015,Hyndman and Athanasopoulos, 2018]. In this particular case, since there is only one independent variable, a simple linear regression model was used which is shown in Equation 3.13. When forecasting the error term is mostly ignored to obtain predictions of the dependent variable [Hyndman and Athanasopoulos, 2018]. Furthermore, the co-coefficients were estimated using least squares and the coefficient of determination (R^2) was used to see how well the model fits the data.

When using linear regression, some assumptions need to be satisfied, which can be seen in Section 3.1.5. For every article these assumptions have been tested before applying linear regression. These assumptions have been tested with the following [Hyndman and Athanasopoulos, 2018]:

- An ACF plot of the residuals was created to find possible autocorrelations in the residuals. The Breusch-Godfrey test was also applied to check for possible autocorrelations. The null hypothesis of the Breusch-Godfrey test is that there is no serial correlation.

So a small p-value indicates significant autocorrelation in the residuals.

- To check for homoskedasticity (constant variance of the error term) the Breusch-Pagan test was applied, where the null hypothesis is homoskediasticity and the alternate hypothesis equals heteroskedacity. A small p-value indicates the presence of heteroskedacity.
- The residuals were plotted against the independent variable to investigate whether this plot shows a pattern (meaning there may be a nonlinear relationship).
- Even though it is not strictly necessary for forecasting, it was checked whether the residuals are normally distributed. This was done by generating Q-Q plots. It is not essential, but it does make the calculation of prediction intervals easier.

No articles showed significant autocorrelations in the residuals, both on the ACF plot and the Breusch-Godfrey test (all p-values above 0.05). Furthermore, for all articles the p-value of the Breusch-Pagan test was also above 0.05, indicating homoskedasticity. When plotting the residuals against the buildrate for all of the articles, no patterns were identified and all Q-Q plots showed a normal distribution. It was concluded all the relevant assumptions, explained in Section 3.1.5, were satisfied and thus a linear regression could be reliably applied to all of the articles in this section. The results of the tests can be found in Appendix E. The linear regression was fitted with the training set, which is approximately 70% of the complete dataset [Siami-Namini et al., 2018,Siami-Namini and Namin, 2018]. The remaining 30% was the test set, which was used to evaluate the forecast error.

Week 18 of 2021 had a high buildrate, but a very low usage while week 19 of 2021 had a very low buildrate (due to its 3 working days), but the usage of articles is nevertheless high. For all articles either one or both of these weeks were deleted from the linear regression.

Table 6.1 shows the fitted linear regression model for every article and the corresponding coefficient of determination. This regression model consists of the dependent variable, y, the independent variable, x, the slope of the line, and the intercept. the independent variable is the buildrate. The linear regression model is fitted by using only the training set. All models show a coefficient of determination that is equal to or higher than 0.89. All of these articles have a relative low CV in comparison to the other articles, which can be explained by the nature of the articles. The articles on which a regression was applied, are articles that are commonly used on all trucks. Therefore, their usage is very similar to the buildrate resulting in a high coefficient of determination. This shows that all models have a good fit.

Article	**Model**	R^2
1287859	$y = 1.069 * x + 12.835$	0.95
1377743	$y = 43.162 * x - 381.723$	0.98
1849492	$y = 0.919 * x - 8.503$	0.96
1849780	$y = 2.196 * x + 20.813$	0.96
1878677	$y = 1.046 * x - 13.386$	0.99
2121022	$y = 0.760 * x - 11.216$	0.97
2208021	$y = 39.810 * x - 568.345$	0.89

Table 6.1: Linear regression models and fit

6.1.2 Level forecasts

For the articles where a level forecast is appropriate, a selection of forecasting methods was tested and evaluated afterwards. The methods that were tested are:

- The Naive method (as benchmark method).
- Single exponential smoothing (SES).
- Holt's model.
- Exponential smoothing state space model (ETS).
- ARIMA.

The methods above were explained in Chapter 3. The Naive method was included in this research to investigate if the other forecasting methods performed better than this easy forecasting principle. If forecasting methods do not perform better than the naive method, the question should be if implementing a forecasting system is even useful at all.

The forecasts have been generated with the forecast package in R. This package contains forecasting functions that also include an optimization tool to estimate the optimal value for the parameters. This is applicable to the exponential smoothing methods and the ARIMA method. The parameters of the exponential smoothing methods are optimized by the tool, by minimizing the Sum of Squared errors (SSE):

$$SSE = \sum_{t=1}^{T} e_t^2$$

The automatic ARIMA modelling function in R determines the ARIMA model by using a variation of the Hyndman-Khandakar algorithm [Hyndman and Khandakar, 2008]. This algorithm combines unit root tests, minimisation of the akaike information criterion and maximum likelihood estimation to obtain an ARIMA model. The parameter optimization of R was used as a starting point. The optimization tool does not always provide the best values for the parameters due to overfitting on the training set. This is why, the parameters were manually adapted with the validation set to find the optimal values.

Steering code 2 and YL98

Different types of forecasts were produced to investigate the performance on multiple aspects:

- 1 step ahead forecasts.
  - The 1 step ahead forecasts were produced with a training set, validation set, and test set. The training set was 50% of the data, and the validation and test set were both 25% of the data [Rácz et al., 2015]. The forecasting model was fitted to the training set and the parameters were estimated (if necessary). Then the validation set was used to start up the forecast, evaluate the model fit, and possibly tune some of the parameters. Lastly, the test set was used to evaluate the performance of the produced forecasts by calculating forecast error.

- Rolling forecast of 5 steps.
  - The choice of the amount of steps for the rolling forecasts was based on the OFTF. This is also shown in Section 1 and Figure 1.2. In practice, no real changes are made in these 5 weeks, which is why a rolling forecast of 5 steps was chosen to include in the evaluation. The forecast was generated in the validation set 5 periods before the test set starts.
- A long term forecast.
  - The long term forecast was evaluated on the validation plus test set. In this case the validation set was included in the evaluation to have a longer forecasting horizon available. The horizon was 21 weeks for this forecast.

The rolling forecast of 5 steps can be seen as the leadtime based forecast. At this company they work with a non-change period with regards to placing and changing orders. This is often equal to 2 or 3 weeks, but in practice no real changes are made in the 5 weeks before order delivery. Therefore, the choice to generate a forecast over these 5 weeks has been made. For articles that take longer than 5 weeks to produce and transport, suppliers have a safety stock in place to make sure they can adhere to the 5 weeks leadtime.

By producing different type of forecasts, the performance could be evaluated on multiple aspects. However, all forecasts were produced with a model fitted on the training set, and the parameters have the same values for all forecasts. The parameter values of the forecast methods can be found in Appendix F. As explained in Chapter 5 for a selection of articles outliers were removed if they negatively impacted the forecast.

YL99

For articles belonging to the yellow line 99 category, period forecasts were produced instead of weekly forecasst. This is due to the fact that the usage of these articles fluctuates, because the articles are used in pre-operations. This means that when a YL98 article is needed, for example, the need for a YL99 article can suddenly rise. Furthermore, the usage write off of YL99 articles sometimes produces missing values or usage of 0 due to this fluctuating demand. For the period forecasts, no data has been removed. If data would be removed there would not be enough values to produce a reliable forecast. Furthermore, it is not necessary to remove datapoints, since the forecast is done for periods and not for single weeks.

For the Yellow Line 99 items, two different type of forecasts were produced:

- 1 step ahead forecasts.
  - The 1 step ahead forecasts were produced with a training set and a test set, where the split was respectively 70% and 30% [Siami-Namini et al., 2018, Siami-Namini and Namin, 2018]. In this case, the 1 step ahead was equal to 1 period ahead, resulting in already multiple steps ahead and less data, which is why a rolling forecast with multiple steps was not done for this type of article. The training set was used for fitting the model, and the test set was used to evaluate the performance of the methods.

- A long term forecast.
  - The long term forecast was generated for and evaluated on the test set. The forecasting horizon was 4 periods, which is equal to 16 weeks.

The parameter values of the forecast methods can be found in Appendix F.

Steering code 3

The articles in steering code 3 are difficult to forecast. They are stored in bulk and their usage is registered as batches, resulting in numbers that indicate when a batch was taken instead of a single article. For the slowmovers this causes a lot of missing values and zeros. One of the slowmovers is also a YL99 item. Due to the missing values, the storage in bulk and including a YL99 item, a period forecast was applied to the articles in this category. The forecast produced were the same as for the Yellow Line 99 items. The parameter values of the forecast methods can be found in Appendix F.

6.2 Procedure

Figure 6.1 shows the steps taken in this research. Here the linear relationship was established by calculating the Pearson correlation coefficient and plotting the usage and the buildrate against each other. To be able to develop a more generalized forecasting framework, the articles were classified into categories. This categorization was based on the nature of the articles. Taking into account the nature of the articles and the visualization of the historical usage, method were allocated to the categories.

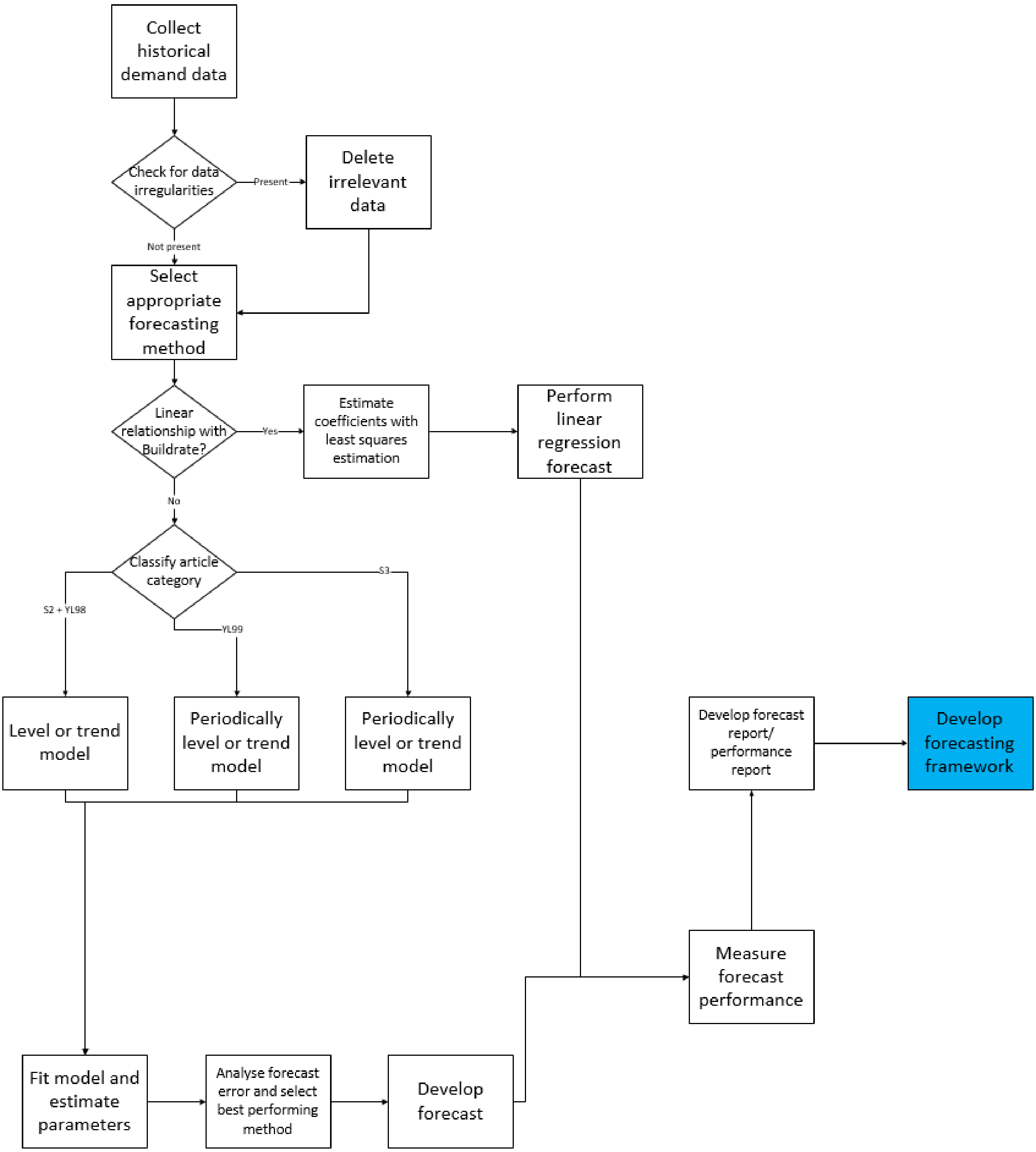

Figure 6.1: Research process flow

Chapter 7

Evaluation and Learning

In this chapter the performance of the forecasting methods applied to the usage data is compared to the performance of the current forecasting system in place at the truck company. The current forecasting system is done at truck-type level, while the methods used in this research are applied to the historical article data directly. As explained in Chapter 4, the forecast error of the current forecasting system is an average of the available observations of the articles. The amount of observations and the variation differs between themselves. The comparison is made nevertheless, to indicate whether the new forecasting methods show improvements over the current forecasting method. Furthermore, the best performing methods per categories are investigated in this chapter to answer the fourth sub-question: 'Should different forecasting methods be used for different type of articles?'.

The performance of the articles with forecast data available in the database was evaluated with the performance of the database forecast, because this is the most similar process. For articles where the forecast data was only available in the delivery schedules, this performance was compared. It should be noted, however, that when comparing the performance of a forecast applied to the usage data of articles with the forecast of the delivery schedules, it might not be a reliable benchmark. This is because there are planning steps in between producing a forecast and sending delivery schedules to suppliers; delivery schedules include package quantities and potential third parties. However, since there is no forecast data available in the database for these articles, it is the only method of evaluating the performance.

7.1 Linear regression

The results of the linear regression can be seen in Figure 7.1. It can be seen all articles show an improvement in comparison to the current forecasts retrieved from the database. All linear regressions errors were below 15%, meaning they all performed very well. The steering code 3 articles performed slightly worse than the rest, which is logical because of the different registering method.

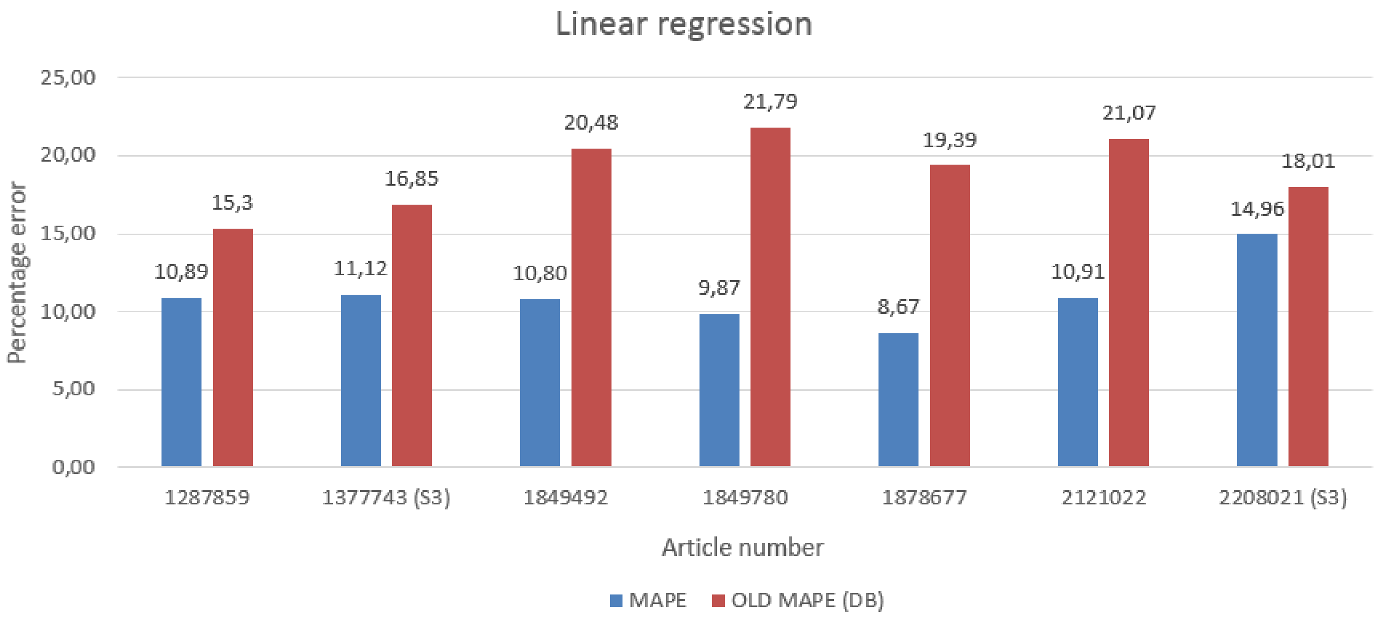

Figure 7.1: Results linear regression

7.2 Level forecasts

The outcome of the level forecasts were compared with the current forecasting system, and split up in the article categories to be able to make a distinction between forecasting methods for different categories.

7.2.1 Steering code 2 and YL98

Figure 7.2 and 7.3 show the three forecasts produced compared to the database data.

It can be seen all forecasts show an improvement in comparison to the current forecasting system in place. For the fastmovers the best performing method was ARIMA, except for article 2245745 regarding the 1 step ahead, where it was Holt's method. However, ARIMA has an error percentage of 8.21% for this forecast, which is very close to the 5.94%. So generally said, ARIMA performs very well for every article here. The best performing method for the slowmovers was either SES or ARIMA, with an exception for article 2258743. Here Holt's method performed best for the 1 step ahead, and the Naive method performed best for the long term forecast. Choosing the SES method, however, gives a percentage error of 105,47% for the 1 step ahead and 111,41% for the long term forecast. These values still show an improvement over the current percentage error and are close to the value for the multiple steps ahead. It can also be noted that the 1 step ahead forecast is the least important, since this only forecasts the value for the week after, while the long term and multiple steps forecast are of greater importance.

The two best performing methods in this category are ARIMA and SES. Furthermore, the error values for the three different forecasts lie close together, with the exception of article

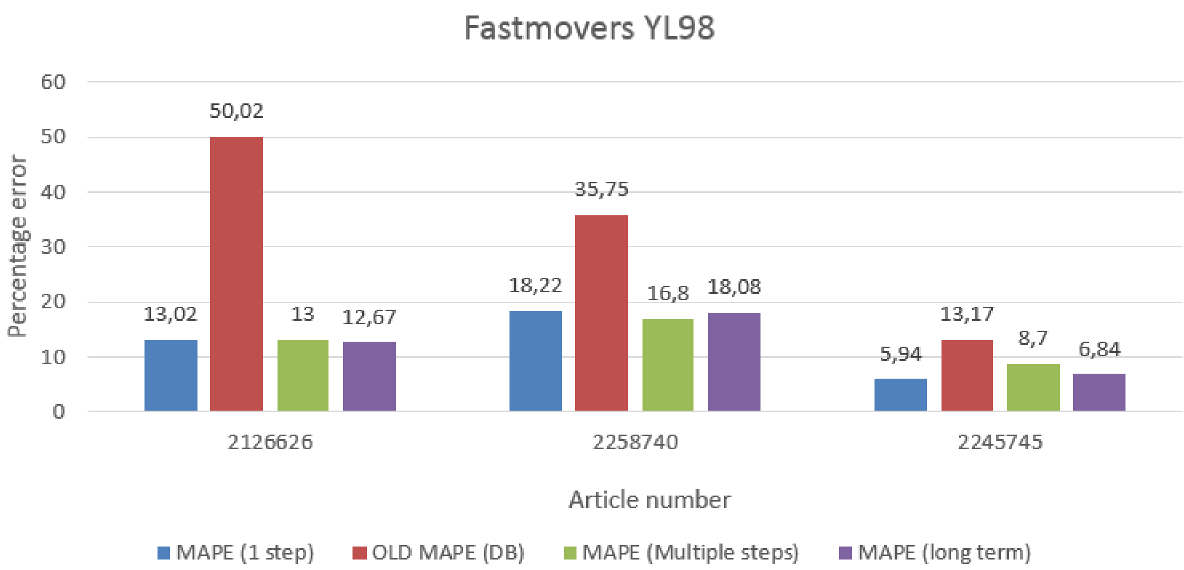

Figure 7.2: Results fastmovers Yellow Line 98

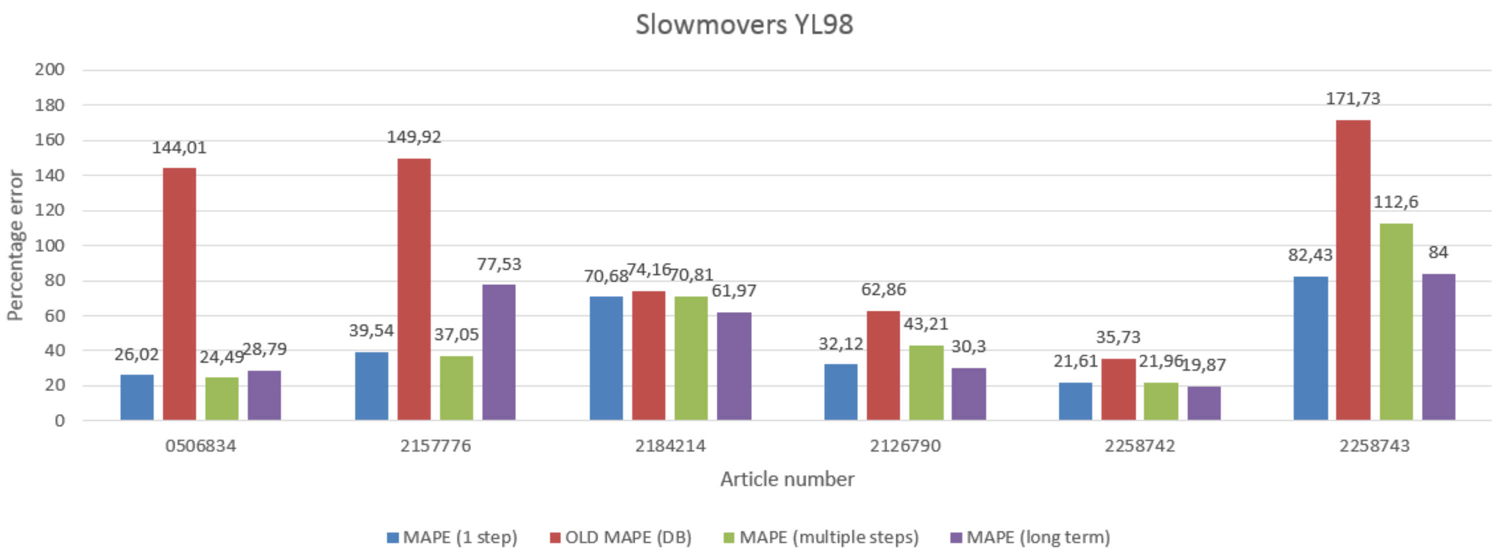

Figure 7.3: Results slowmovers Yellow Line 98

2157776, which means the forecasting horizon does not significantly impact the performance, nor the choice of method.

7.2.2 YL99

For articles belonging in the category YL99, there is only past forecast data available from the delivery schedules. This means that the performance of the forecast methods is compared with the accuracy of the forecast on the delivery schedules. This is not completely compatible, because the delivery schedules also include planning decisions, packaging sizes and possible inclusion of third parties. Nevertheless, this comparison was still made, due to the lack of availability of other data. Furthermore, the calculated MAPE for the delivery schedules was based on a weekly error, while the results shown in Figure 7.4 and 7.5 were based on a periodically error. This is because the company currently forecasts these articles on a weekly basis. By showing the comparison between the weekly forecast error and the newly derived periodically forecast errors, the difference between the new and old system can be seen instantly. The delivery schedule accuracy and results shown in Figure 7.6 are both based on a periodically error.

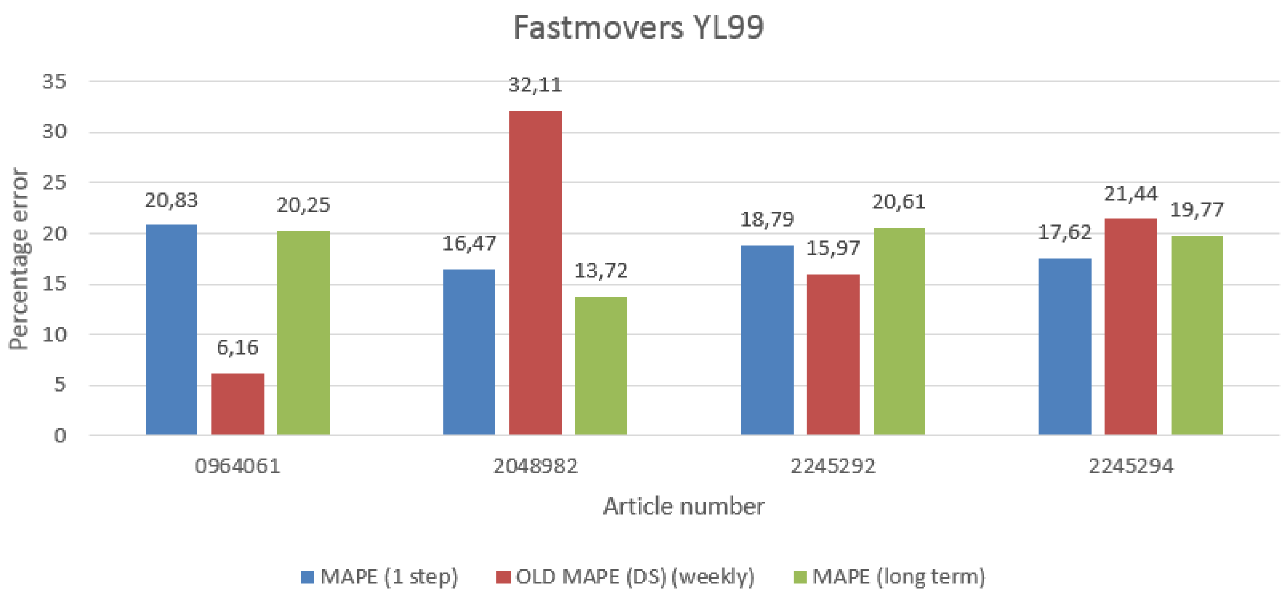

Figure 7.4: Results fastmovers Yellow Line 99

In comparison to the delivery schedules the results of the forecast outcomes differ. For the fastmovers, some of them perform better than the delivery schedules and some of them perform worse. Whereas, for the slowmovers all articles show improvements over the delivery schedules. The fact that some of the outcomes are an improvement over the accuracy of the delivery schedules indicate this new way of forecasting might also improve the planning, instead of only the forecasts produced. The best performing method was similar for almost all of the articles, namely Holt's method. This is due to the fact that the period values showed a trend in 2021, in comparison to 2020. Only for two articles, article 2245292 and 0966542 did ARIMA perform the best. For article 2245292 this was only the fact for the 1 step ahead forecast, while for article 0966542 this was the fact for both of the situations.

As can be seen in the three figures, for all articles the 1 step ahead and the long term forecast perform quite similar, which means the forecasting horizon does not significantly impact the forecast performance of the methods.

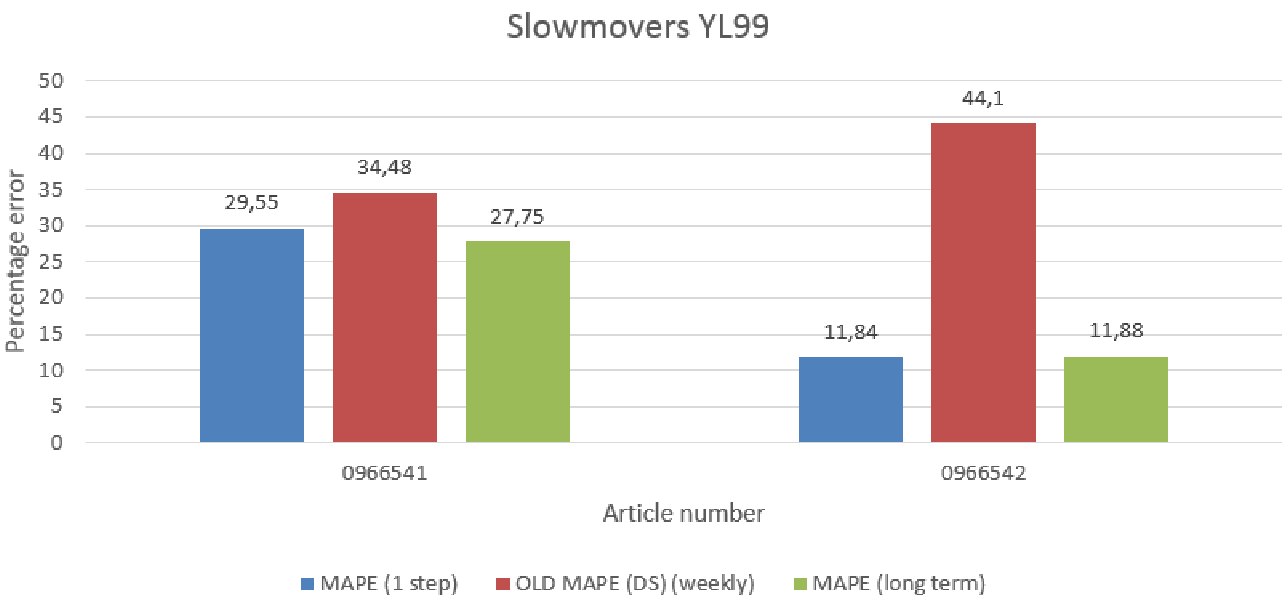

Figure 7.5: Results slowmovers Yellow Line 99

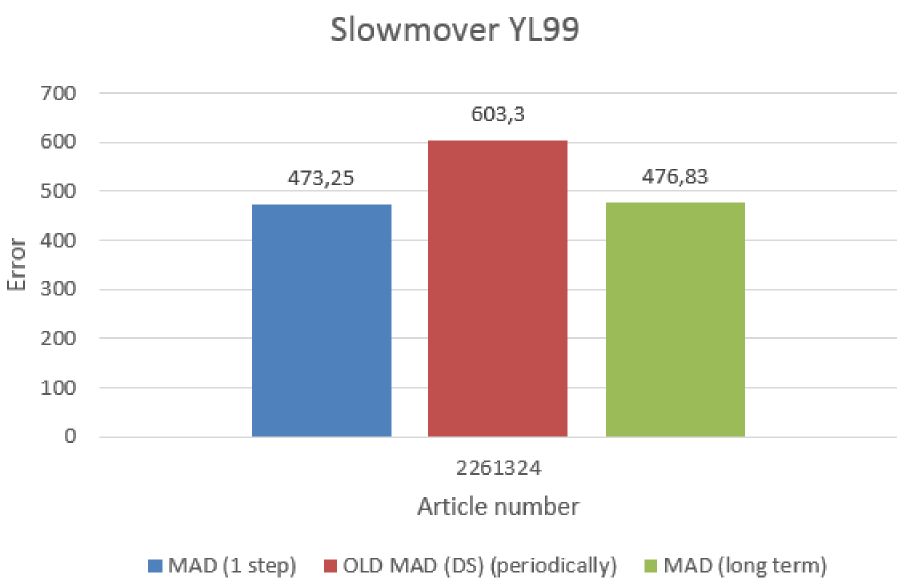

Figure 7.6: Result slowmover Yellow Line 99 (MAD)

7.2.3 Steering code 3

For the articles belonging to the category of steering code 3, the availability of data in the database differs. For two articles there is data from the database, while for the other two articles there is only data from delivery schedules. Once again, the calculated MAPE for the delivery schedules was based on a weekly error, while the results shown in Figure 7.7 were based on a periodically error. The results shown in Figure 7.8 and 7.9 are not a percentage, but an absolute error and here the results of the current system are a periodically deviation too.

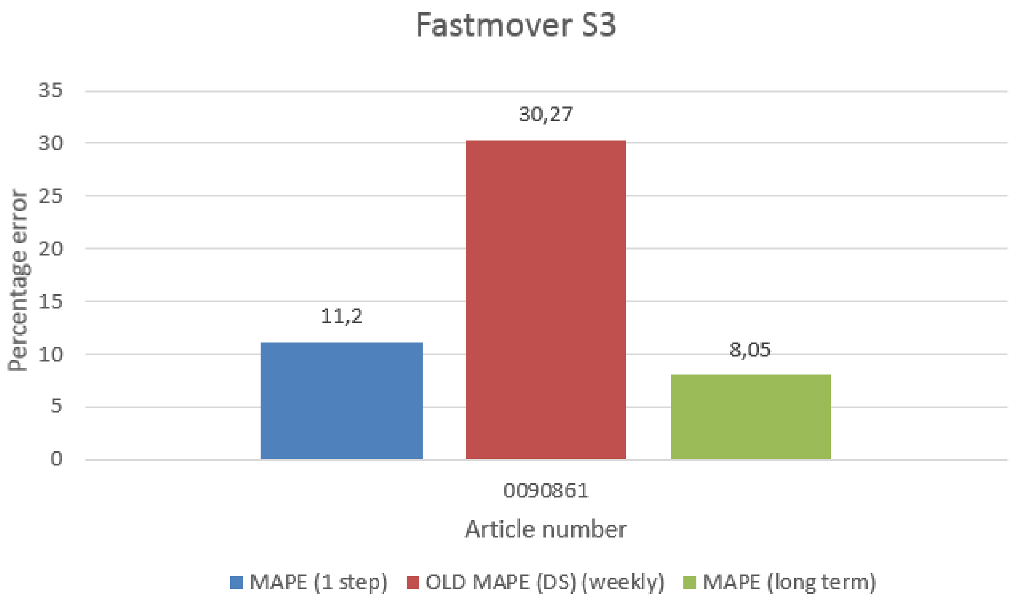

Figure 7.7: Fastmover steering code 3

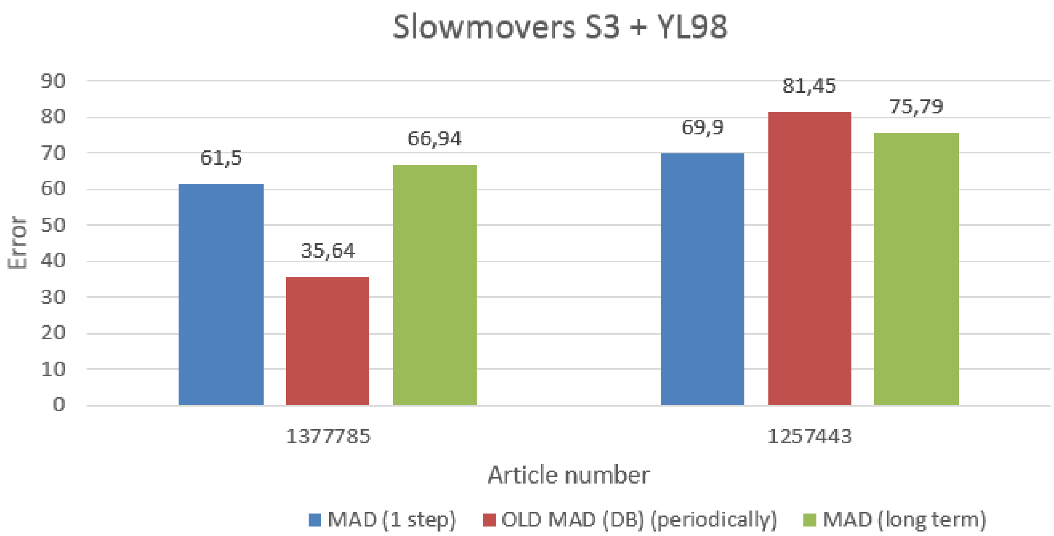

Figure 7.8: Slowmover steering code 3 and Yellow Line 98

It is difficult to draw any real conclusions for this category, because there are few articles available in this category. The periodic forecast of the fastmover shows an improvement in comparison to the delivery schedules. The slowmovers in the Yellow Line 98 category, however, do either perform worse or only show a slight improvement compared to the database. The best performing method for the previous mentioned articles turned out to be Holt's method, due to the presence of a trend. The last article, a Yellow Line 99 article, performed best with

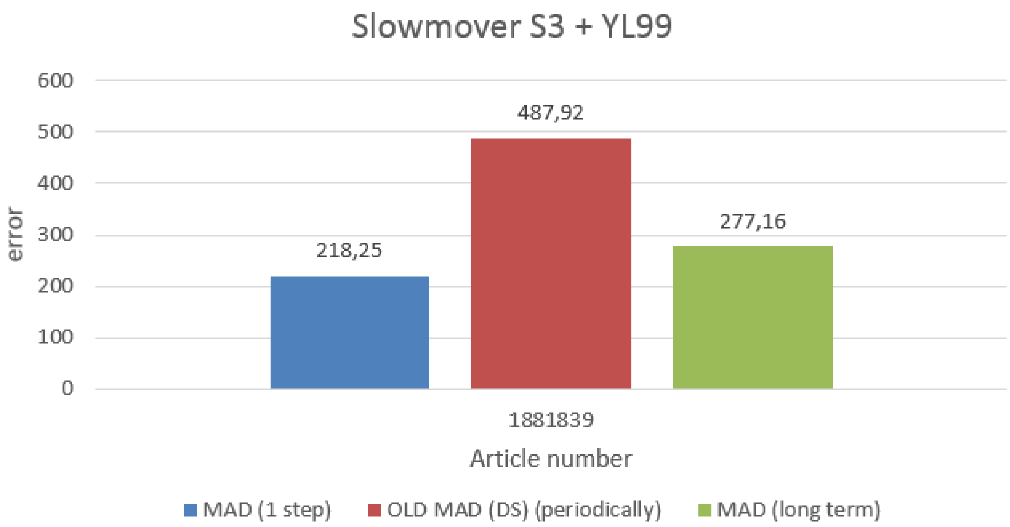

Figure 7.9: Slowmover steering code 3 and Yellow Line 99

the ARIMA method and showed an improvement in comparison to the delivery schedules.

Also for these articles, the forecast of the 1 step forecast and the long term forecast performed quite similar, meaning the forecast horizon does not significantly impact the forecast performance of the methods.

7.3 Overall performance

The articles on which a linear regression was performed all had a forecast error lower than 15% and lower than the current forecasting system in place. The decrease in error ranged from 4% to 10%. Furthermore, by incorporating the buildrate in the forecast, any changes made in production will automatically activate changes in article requirements.

For articles belonging in the Yellow Line 98 category, all articles show an improvement over the current forecasting system in place. Some improvements are remarkably big, while others are smaller. All fastmovers show a forecast error of below 20%. For the slowmovers some outcomes do have a very high MAPE, which is caused by the low usage and the bias of MAPE. When inspecting the delivery schedule errors, the new forecast of the articles belonging to the engine plant even show an improvement over these errors. This means the new forecasting methods cannot only improve the forecast, but also the planning steps that come after.

The articles from the category Yellow Line 99 are visualized next to the errors gained from the delivery schedules. This is not a completely realistic comparison, also because the current error percentages are calculated for weekly values. Nevertheless, it can be seen that some of the articles show an improvement over these delivery schedules. All slowmovers show an improvement, meaning the new forecasting methods also positively impact the Yellow Line 99 items. For the fastmovers, all errors are below 21% and for the slowmovers they are below 30%. Once again, MAPE is always higher for slowmovers, due to the low usage quantities.

By forecasting Yellow Line 99 items in periods instead of weeks, part of the variation due to fluctuations decreases and thus improves the forecast generated. Due to the slowmovers showing improvements over the delivery schedules, it can be said the new forecasting methods can improve the forecast and the planning steps leading to the delivery schedules.

All articles, except for one, in steering code 3 show an improvement in forecast error. However, the errors of the new forecasting methods are still quite high. For the articles in steering code 3 it is advised to only use the forecast as input for a good stock policy and regularly updating it, since steering code 3 articles are cheap, small and stored in bulk. Forecasting steering code 3 articles in periods, instead of weeks can improve the forecast for certain articles.

Overall it seems that implementing a new forecasting system on article level can improve the general forecast that is currently produced by the company. Not every article shows the same improvements or even improvements at all, but when looking mostly at the comparison with the database data, almost every one of these articles benefit from the tested methods. It should be noted, as said before, that the average MAPE of the current forecasting system contains a different amount of observations and differing variations. So these conclusions are drawn while keeping this in mind.

Chapter 8

Forecasting framework

This chapter presents the developed framework and new forecasting procedure after evaluating the performance of the forecasting methods applied to the historical usage data. This chapter answers the main research question: 'What forecasting system could be implemented at the operational level in the future at the truck company to improve the forecast accuracy of the required article quantities produced and communicated to suppliers?'. The first section shows the division of best performing forecasting methods per article category and the next section shows a flowchart of the new forecasting procedure.

8.1 Forecasting framework

Figure 8.1 shows the flow of forecasting methods to the article categories. Generic terms have been chosen to include in this framework, to be able to also possibly apply this framework in other companies. A significant relation to production can be established by calculating the Pearson correlation coefficient and/or plotting usage against production to find a linear relationship. Assembly ready part is the distinction between YL98 and YL99, but in more generic terms. Furthermore, basic materials is in this research the difference between steering code 2 and steering code 3 articles. So basic materials are very cheap and small parts that are mostly stored in batches in wharehouses.

As explained in the previous chapter, the best performing methods were not the same for all articles in a category, but the overall best performing method was chosen per category. For some categories two methods have been chosen, because the performance differed in between the forecasts produced and the method might depend on the forecast horizon required. For these categories it would be good to conduct another investigation with more articles and more data available. This forecasting framework can be used for the new forecasting procedure, which is presented in the following section. As can be seen, especially ARIMA turns out to be best performing in lots of categories. Next to ARIMA, also SES and Holt's method come out as well performing methods. If Holt's method is going to be used, it is important to keep in mind that this method assumes there is a trend present in the data.

Next to the fact that the article forecast for some of the Yellow Line 99 and steering code 3

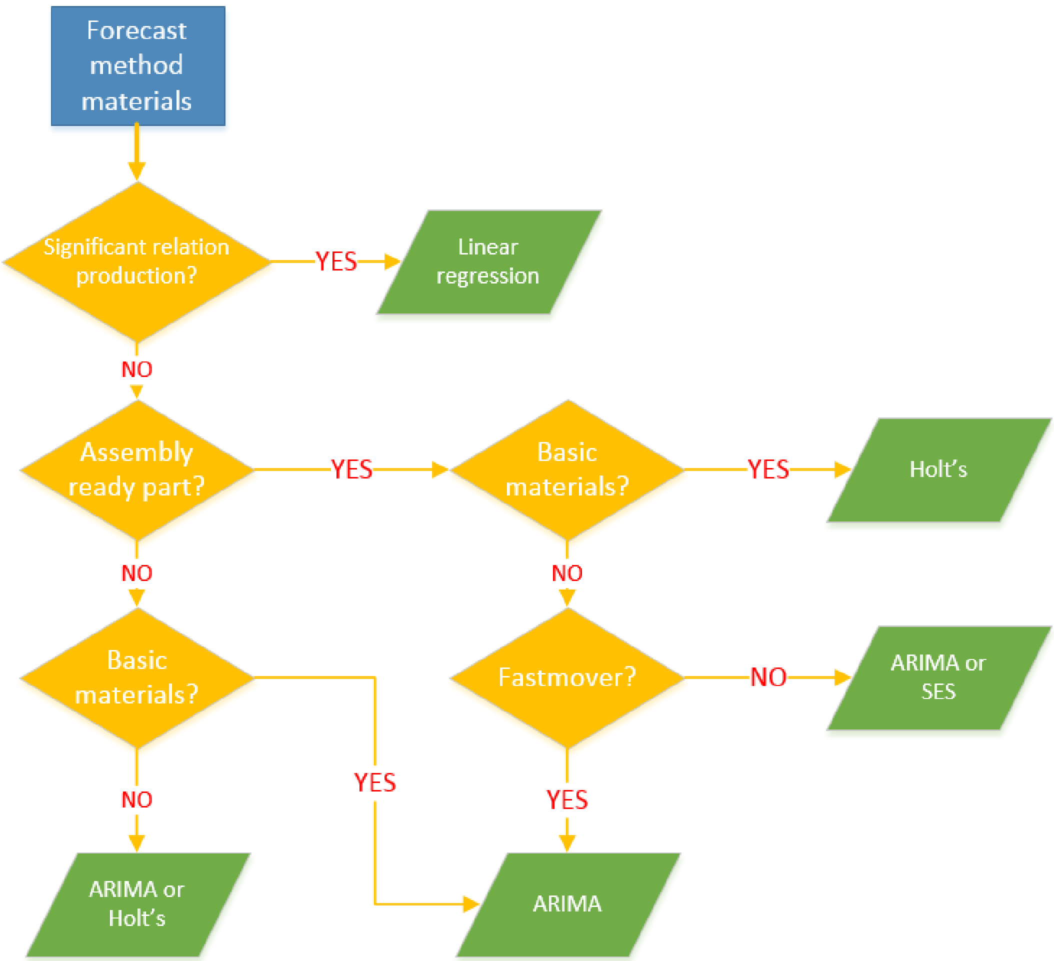

Figure 8.1: Forecasting framework

items perform better than the delivery schedule forecast, the periodic forecast can certainly benefit the material planning. Forecasting is just an aid and input for the actual material planning. The material planning is often moved around the weeks, meaning they do not always match the forecast values. By generating a periodic forecast, it gives the planners the availability to plan the material quantities throughout the period. This gives an answer to sub-question 5: 'Does the proposed forecasting system improve the material planning at the operational level?'.

8.2 New forecasting procedure

Figure 8.2 shows how to perform the forecast on article level in the future. First the historical data should be collected and cleaned. Moving on, the corresponding forecasting method and period can be chosen based on the article category and the forecasting framework. The coefficients or parameters can be estimated after this and the forecast can be developed. It is very important to keep track of and monitor the forecast error, because it might be necessary to review and revise the forecasting framework from time to time. A useful method to monitor forecast performance is CUSUM. This makes sure the forecast values stay within limits. Moreover, this research was conducted on short term forecasting (less than 6 months), meaning this procedure was developed with a research done on a short forecasting horizon. When implementing this procedure, the developing and monitoring of the forecast can be done in a separate application, which can feed the forecast values to the mainframe every week. In this way, the implementation does not change the usage of the forecast values in the main IT system, but only changes the forecasting procedure which is done in a different application. Furthermore, it would be preferred this procedure to be automatic. When the forecast report is developed and communicated to the material planners, they can continue with the next planning steps. If the application indicates the forecast performance to be out of bounds, people need to step in and inspect whether the forecasting framework and procedure is still working as it should. Apart from this, the procedure should be automatically executed.

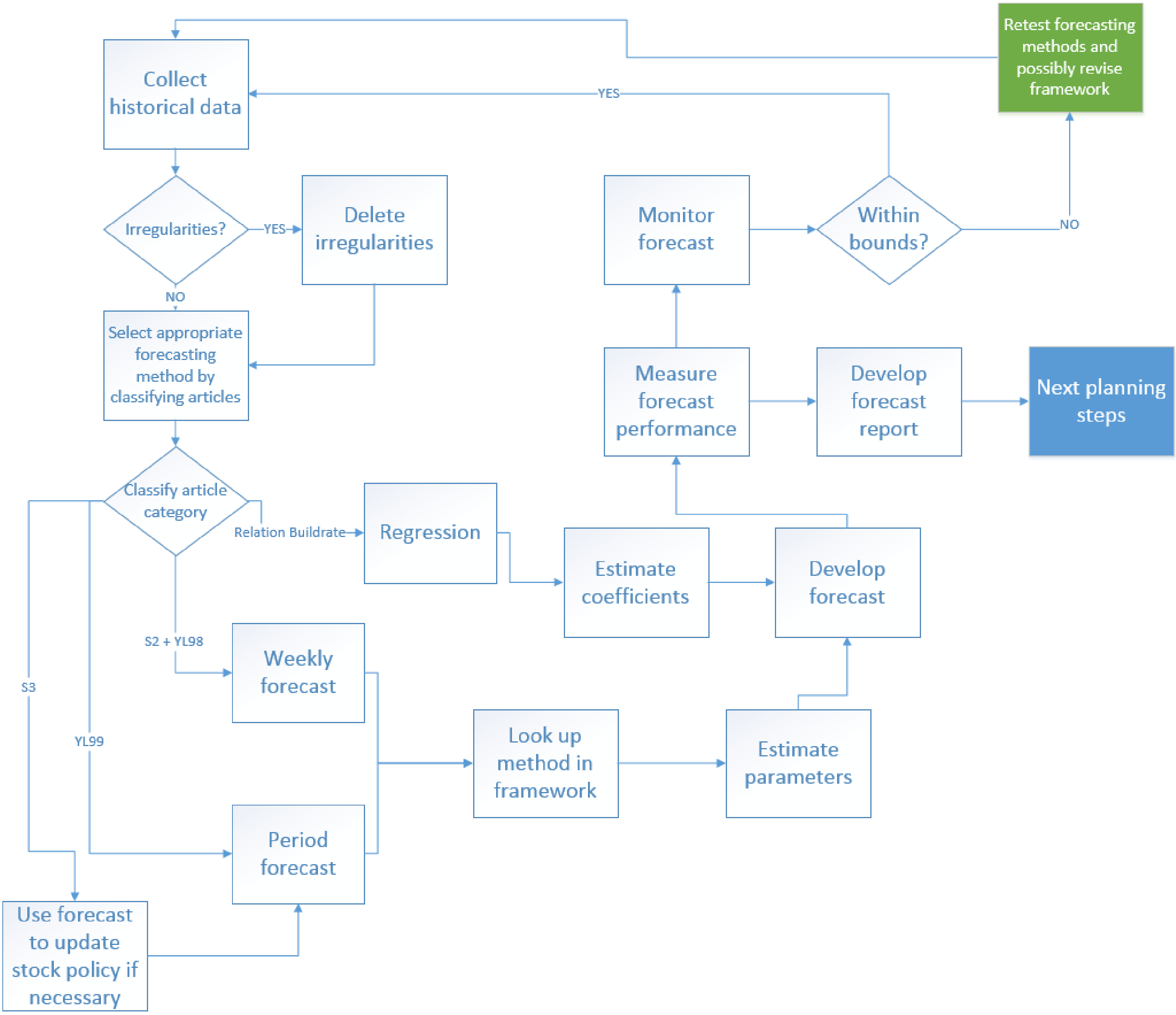

Figure 8.2: New forecasting procedure

Chapter 9

Conclusions and recommendations

9.1 Conclusions

The objective of this research was investigating the effectiveness of forecasting at article level in comparison to the current forecasting system at truck-type level. Furthermore, another objective was developing a forecasting framework for different type of articles. The effectiveness of forecasting at article level and the development of a forecasting framework was investigated through a main research question: “What forecasting system could be implemented at the operational level in the future at the truck company to improve the forecast accuracy of the required article quantities produced and communicated to suppliers?”

In order to answer this question the first step was mapping out the current forecasting system in place and looking at its performance. After having difficulty finding forecast data, the conclusion was made that monitoring the forecast and its performance was not done at all. Furthermore, the forecast produced by the current system in place did not only contain a high error, it also involved a lot of manual changes. Therefore this research investigated whether a direct forecast at article level would positively impact the forecast error. The collection of historical data was also quite difficult, meaning this could really need some improvements. After analyzing the historical data, two demand models were found: a regression model and a level model. Forecasting methods were chosen based on these models. The data analysis also provided the following article categories:

- Yellow Line 98 and Yellow Line 99
- Steering code 2 and steering code 3
- Fastmovers and slowmovers

After testing and evaluating the forecasting methods, some conclusions were drawn:

- Linear regression performed really well, however, the articles on which a linear regression was performed are not the critical articles, since these are fastmovers that are found on almost every truck. The initial forecast error of these articles was already quite low.

- Articles in the category of Yellow Line 98 and steering code 2 benefit from weekly forecasts generated by ARIMA or SES. All of the articles in this category showed improvements over the current forecasting system.
- Articles in the category Yellow Line 99 and steering code 2 were forecasted with period quantities, but the results differed throughout the category. They might benefit from the new framework, but this cannot be concluded with certainty. It can be concluded, however, that the articles in this category benefit from a period forecast over a weekly forecast, due to the absorption of part of the variance that is present in the usage of these articles. The best performing methods were ARIMA and Holt's method for both fastmovers and slowmovers.
- Articles in the category of steering code 3 also give different results. The amount of articles was also a bit small to really draw conclusions. It seems the new forecasting system can benefit some of these articles, but this was mostly applicable to the fastmover and YL99 article, but there is only one article available in both of these categories. Therefore, it is not reliable to base this conclusion on only one article in a category. The best performing methods were Holt's method for Yellow Line 98 and ARIMA for Yellow Line 99.

The aforementioned forecasting methods have some weaknesses nevertheless. Single exponential smoothing cannot cope well with patterns, and is typically used in short-term predictions and in the absence of seasonal or periodic fluctuations. Holt's method is applicable if a trend, but no seasonality is present. ARIMA has been applied before in the automotive industry for forecasting linear time series. Even though ARIMA models can represent several different time series, one of the disadvantages of applying an ARIMA model is the assumption of a linear correlation structure among the time series values. Nonlinear patterns cannot be captured by this model. If a nonlinear pattern should be captured, a neural network model might be more appropriate or the variables should be transformed beforehand.

Overall it can be concluded the forecasting framework for forecasting at article level can improve forecasting accuracy for articles. However, it should be noted the forecasts produced in this research were evaluated on a short horizon (less than 6 months) and therefore any conclusions made are only made for a horizon of maximum 6 months. Furthermore, as mentioned before, these conclusions are drawn while keeping in mind the difference in observations and variations between the current forecasting system and the proposed forecasting system.

9.2 Recommendations

This section describes the recommendations made to the truck company based on this research.

Save all forecast and historical usage data

During this research it became clear the current forecasting values are not saved and monitored. Moreover, the collection of historical usage data was quite a difficult task. When forecasting on article level, it is very important to have as much as possible historical usage data. Therefore, it is recommended to start saving all forecast and historical data. Not recording this data will result in loss in information and will impact the accuracy future forecasts.

Monitor forecast performance

Complementing the previous recommendation, the current forecasting system is not being monitored at all. There was no knowledge available about how well the forecast was performing and/or how big the error was. It is, however, very important to monitor the forecast to be able to see whether it is performing well and whether changes should be made. Monitoring the forecast can reveal any problems, which will result in investigating reasons why it is not working and thus eventually finding solutions to solve the problems.

Inform and educate users of the forecast about the new framework

When implementing a new system, it is of utmost importance to not encounter resistance. By including some change management in the implementation of the forecasting framework, the users of the forecast are given the opportunity to learn and positively embrace the framework.

Use the forecasting framework for short-term planning

This research had as limitation the amount of available historical data, resulting in a maximum forecast horizon that could be forecasted and evaluated. Therefore, the framework developed is especially useful for short-term forecasting and planning, since it has been evaluated on this horizon.

When implementing the framework let customer orders consume the forecast quantities

If the forecasting framework is to be implemented, the consumption by customer orders should be taken into account. This means that whenever a customer orders comes in and is translated to article quantities, these order quantities should consume the forecasted article quantities. This consumption was out of scope for this research, but it is important to include it when implementing the forecasting framework. When including this consumption the forecasted quantities are balanced with the actual customer orders.

When forecasting new articles, use historical data of similar articles

If the company introduced a series of new trucks, there will be new articles that need to be forecasted. New articles can be forecasted by using the historical data of a similar article belonging to the older truck series. This is due to the fact that the new trucks will probably have similar sales to the old trucks. Furthermore, when sales are a couple of months in for the new trucks, the new historical data of the new articles can be used for forecasting. Forecasting with similar articles is also applicable to items that reach end of life cycle and are replaced with similar articles with a different name.

Implement a stock policy for steering code 3 items

A period forecast was generated for the articles belonging to the steering code 3 articles. A forecast for this category can be used as input, but it is especially important for these articles to have a good stock policy. Steering code 3 articles are very small, cheap, and stored and collected in bulk. Therefore it is advised to base the quantities in the delivery schedules on the stock policy and the usage of the articles, while using the forecast as input for a possible update of the stock policy.

Investigate whether the incorporation of actual material leadtimes into the forecast system can be beneficial

When forecasting it can be very helpful to take into account the real leadtime of the articles, instead of the non-change period the company is working with at the moment. Right now they only work with the OFTF and the delivery schedules. However, it might be beneficial to work with the real leadtimes indicated by suppliers. This might result in less extra costs and better supplier relations. Therefore, it is advised for future research to investigate whether incorporating these leadtimes into the forecast might be an improvement over the current way of working.

9.3 Future research

Test the forecasting framework for long term (e.g. 1 year)

This research had only access to limited data, meaning the maximum horizon of the forecasts produced was equal to 20 weeks. For a short term forecast, conclusions could be drawn about the improvement on article level, but for a long term forecast no real conclusions could be drawn. Therefore it is advised to also test this framework for forecasting on a longer time horizon, such as a full year. This is only possible when there is enough data available to not only forecast a year ahead, but also to be able to evaluate this yearly forecast.

Compare the current and new forecasting system on the same amount of observations

As explained in Chapter 4, the amount of forecast observations of the current forecasting system differs per article. This results in a difference within the forecast performance of articles, different variations throughout the forecast observations, and a less reliable comparison between the current and new forecasting system. Therefore, it would be advised for future research to perform a research where these two systems are compared with exactly the same amount of forecast observations, and thus the same amount of variation present.

Investigate the use of machine learning algorithms

If the recommendation about saving all historical data is followed up, it can be investigated whether the use of machine learning algorithms can be of use. This research only investigated more classical forecasting methods, that do not need a whole lot of data to be able to work. As concluded previously, the classical methods have some drawbacks, that might be solved by using a machine learning algorithm or a hybrid approach (such as neural networks and smoothing methods). However, for a machine learning algorithm to work, it needs a huge amount of data. This can be investigated in the future, if there is enough historical data available.

Consider IT implementation

When the company is planning to implement the forecasting system, it is advised to make it a stand alone application that feeds the forecast values to the main IT system. Future research could investigate the use of forecasting in SAP. SAP contains a forecasting function where historical data is used to calculate forecast values. In this function single exponential smoothing and linear regression are readily available. Other simple forecasting methods are also available. There is even an automatic model selection forecast strategy that lets the system elect the forecast model that best fits the trend of the historic data. However, as seen in the previous chapter, ARIMA is one of the forecasting methods in the framework. SAP also contains a HANA predictive analysis library. For this, the SAP HANA platform should be installed, together with an application fuction library. In this library, a lot of algorithms are available, including ARIMA. Here the exponential smoothing methods and linear regression are available too. For the future, it is advised to first test these available methods in SAP, before actually using the forecasts produced by SAP.

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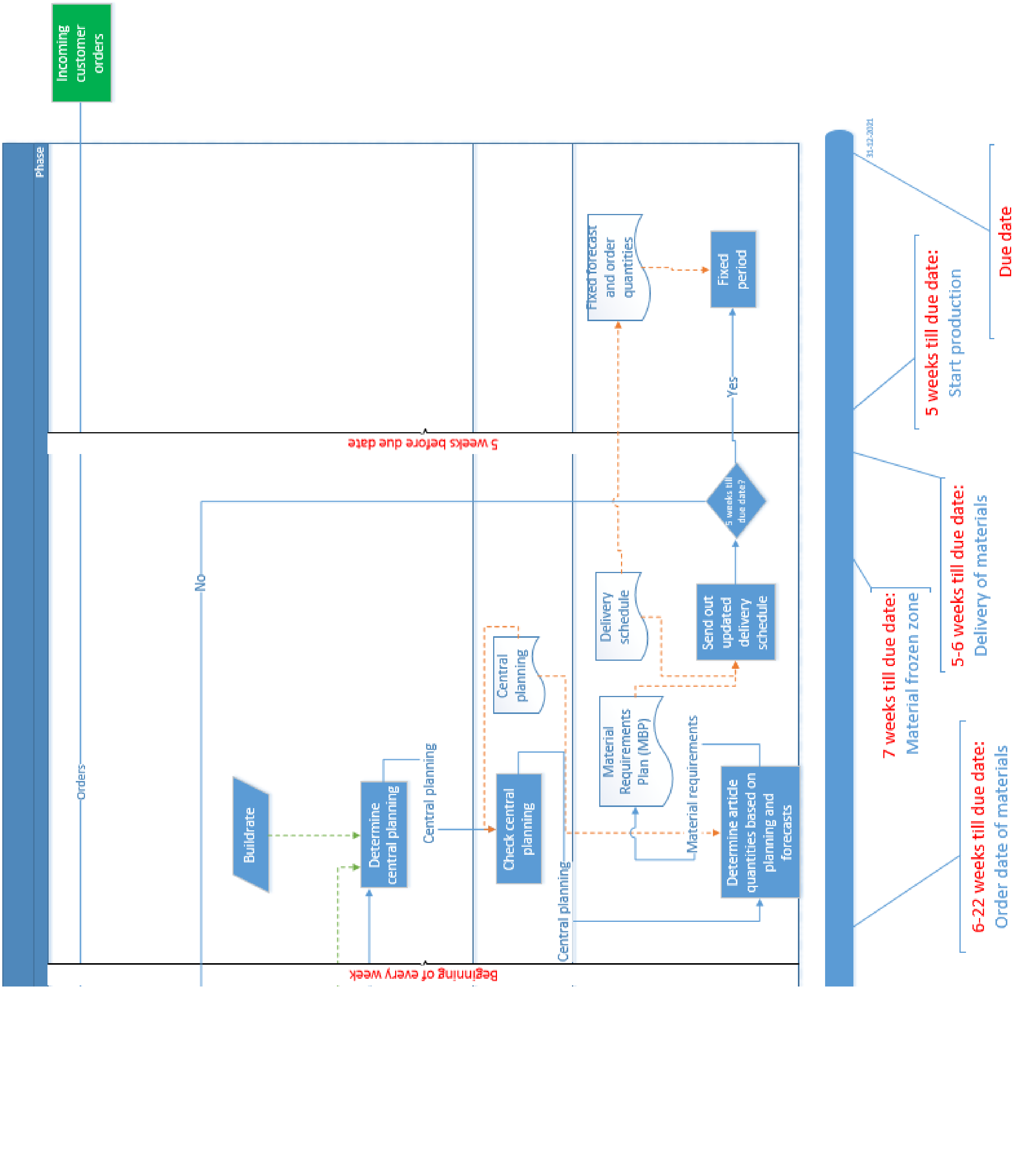
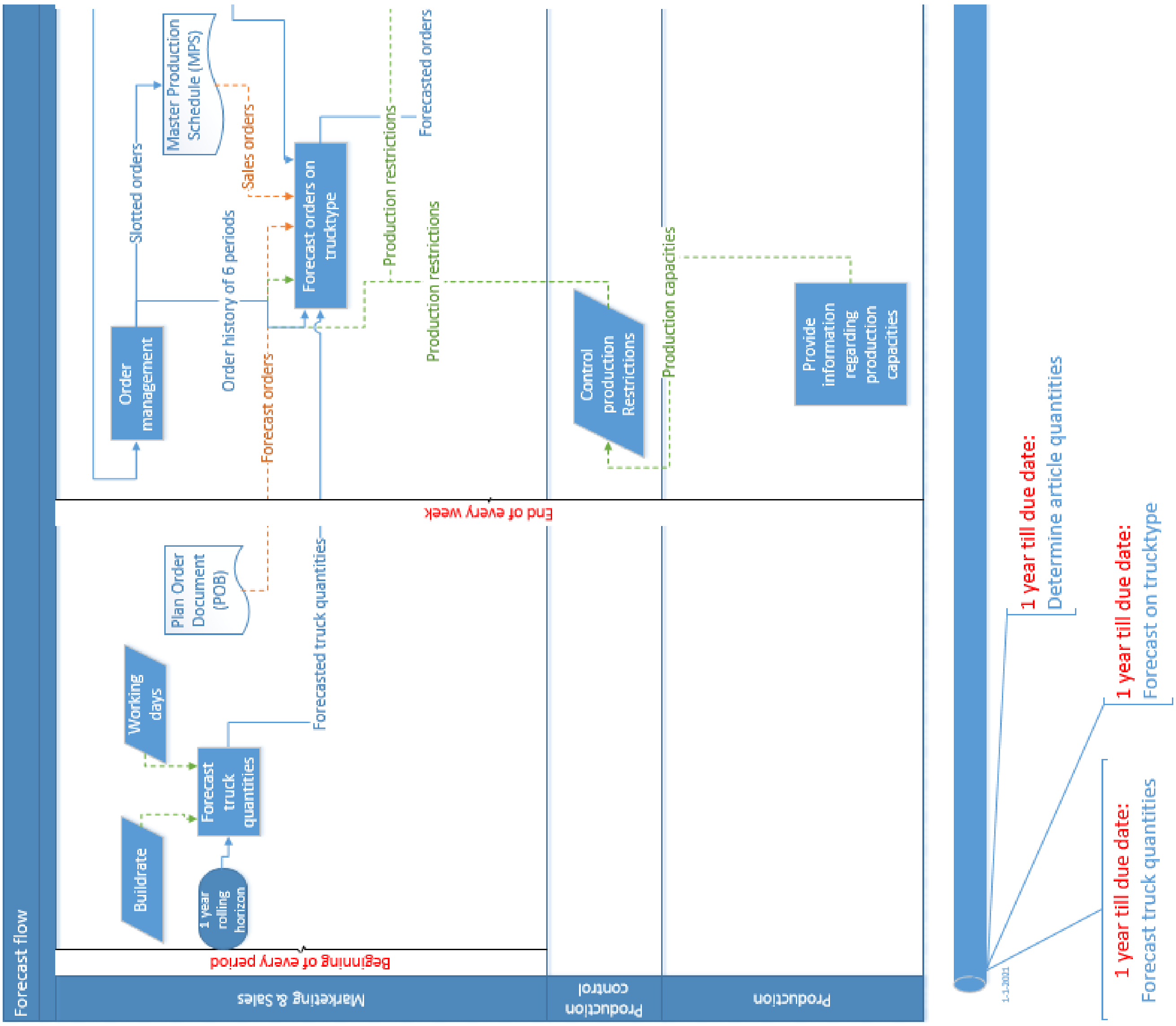
Appendix A

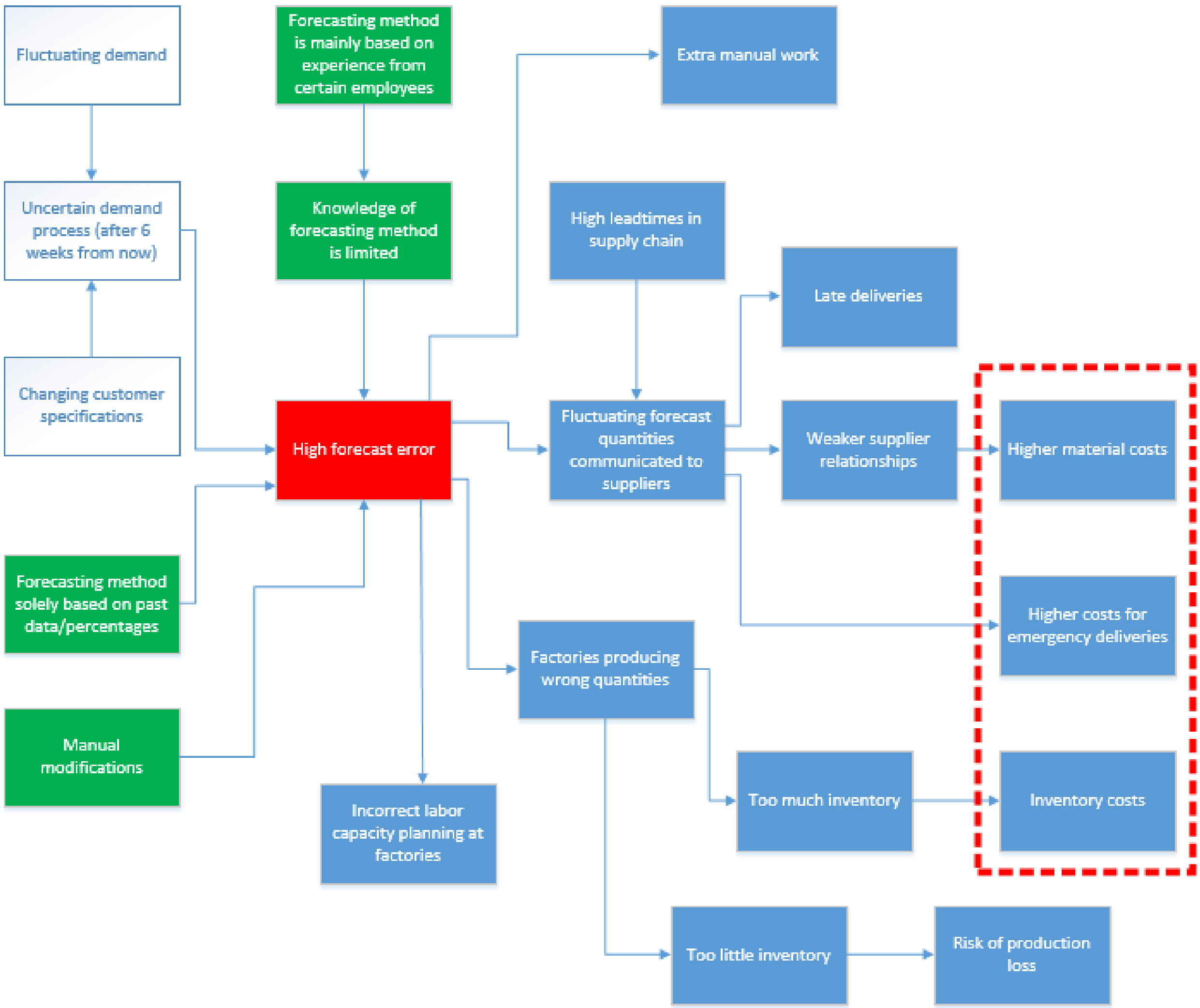
Forecasting process


Incoming customer orders
Phase
Orders
No
Buildrate
Determine central planning
Central planning
Check central planning
Central planning
Central planning
Material Requirements Plan (MBP)
Material requirements
Determine article quantities based on planning and forecasts
Delivery schedule
Send out updated delivery schedule
5 weeks till due date?
Yes
Fixed forecast and order quantities
Fixed period
5 weeks before due date
Beginning of every week
Due date
5 weeks till due date:
Start production
5-6 weeks till due date:
Delivery of materials
7 weeks till due date:
Material frozen zone
6-22 weeks till due date:
Order date of materials


Forecast flow
Marketing & Sales
Production control
Production
Beginning of every period
End of every week
1 year rolling horizon
Buildrate
Working days
Forecast truck quantities
Plan Order Document (POB)
Forecasted truck quantities
Order management
Slotted orders
Master Production Schedule (MPS)
Sales orders
Order history of 6 periods
Forecast orders
Forecast orders on trucktype
Production restrictions
Forecasted orders
Control production Restrictions
Production capacities
Provide information regarding production capacities
1 year till due date:
Determine article quantities
1 year till due date:
Forecast on trucktype
1 year till due date:
Forecast truck quantities

Appendix B

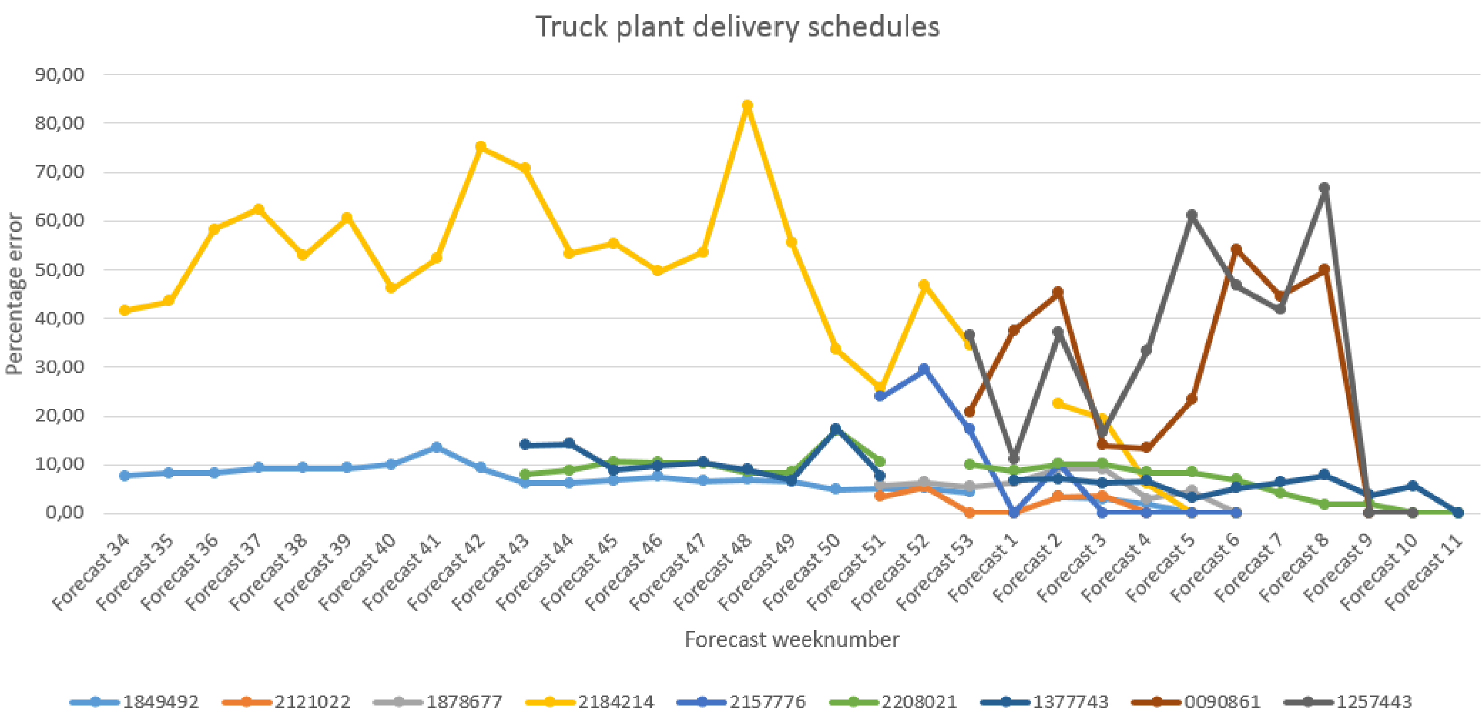
Cause-effect diagram

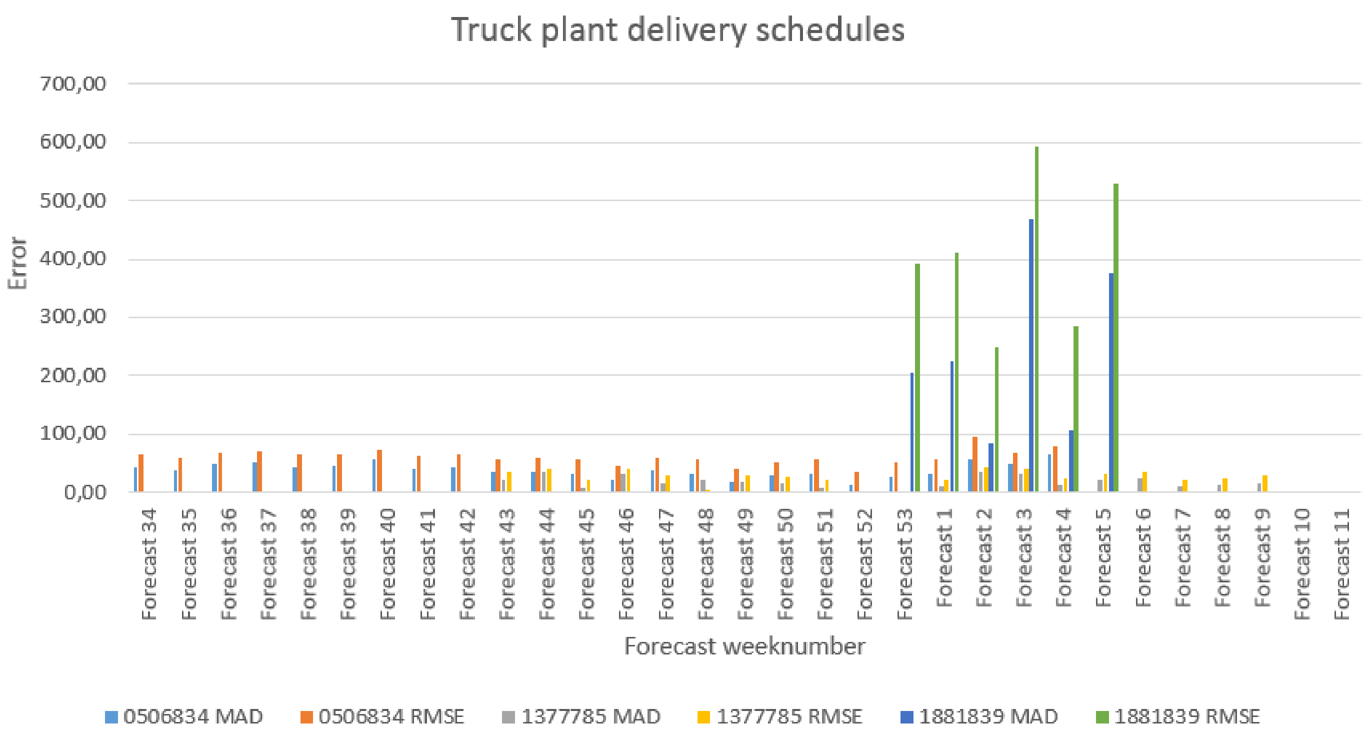

Fluctuating demand
Forecasting method is mainly based on experience from certain employees
Extra manual work
Uncertain demand process (after 6 weeks from now)
Knowledge of forecasting method is limited
High leadtimes in supply chain
Late deliveries
Changing customer specifications
High forecast error
Fluctuating forecast quantities communicated to suppliers
Weaker supplier relationships
Higher material costs
Forecasting method solely based on past data/percentages
Higher costs for emergency deliveries
Factories producing wrong quantities
Manual modifications
Too much inventory
Inventory costs
Incorrect labor capacity planning at factories
Too little inventory
Risk of production loss

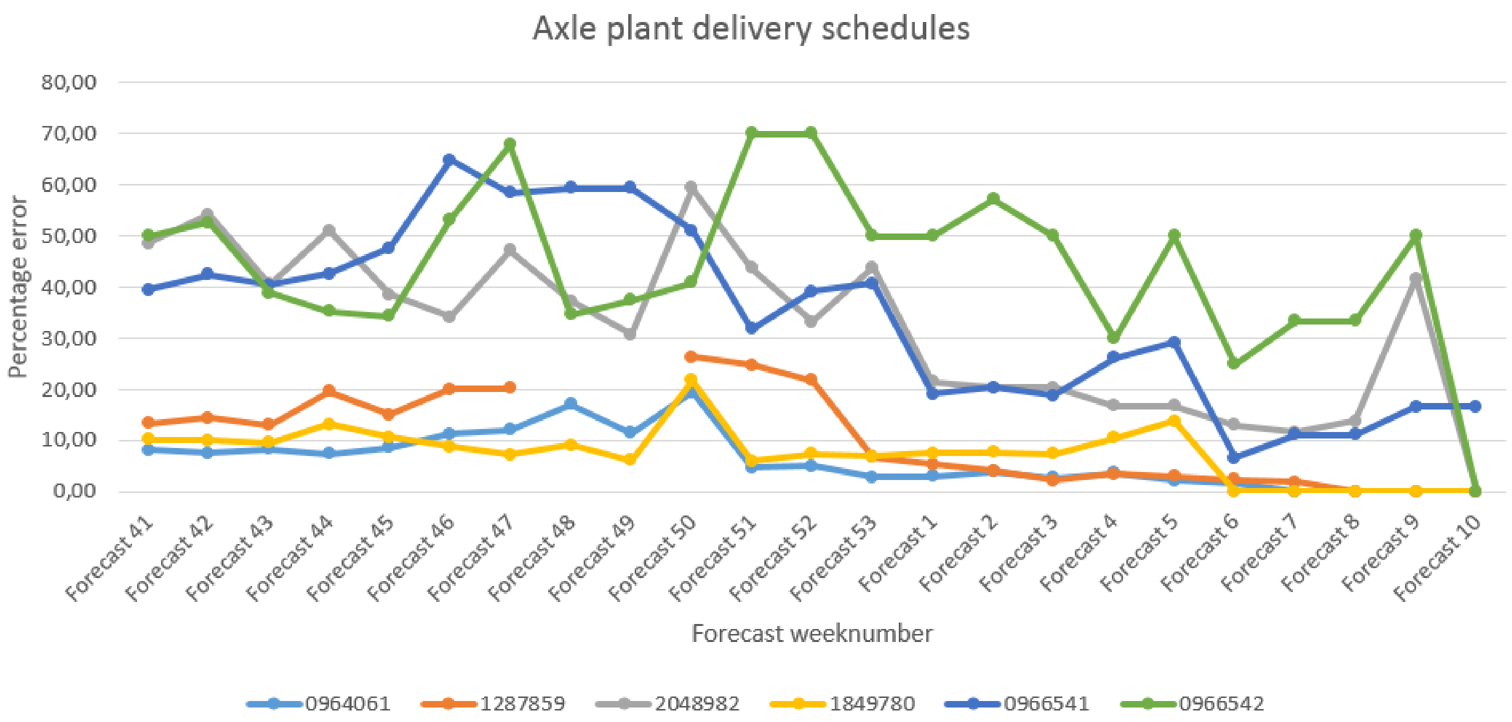
Appendix C

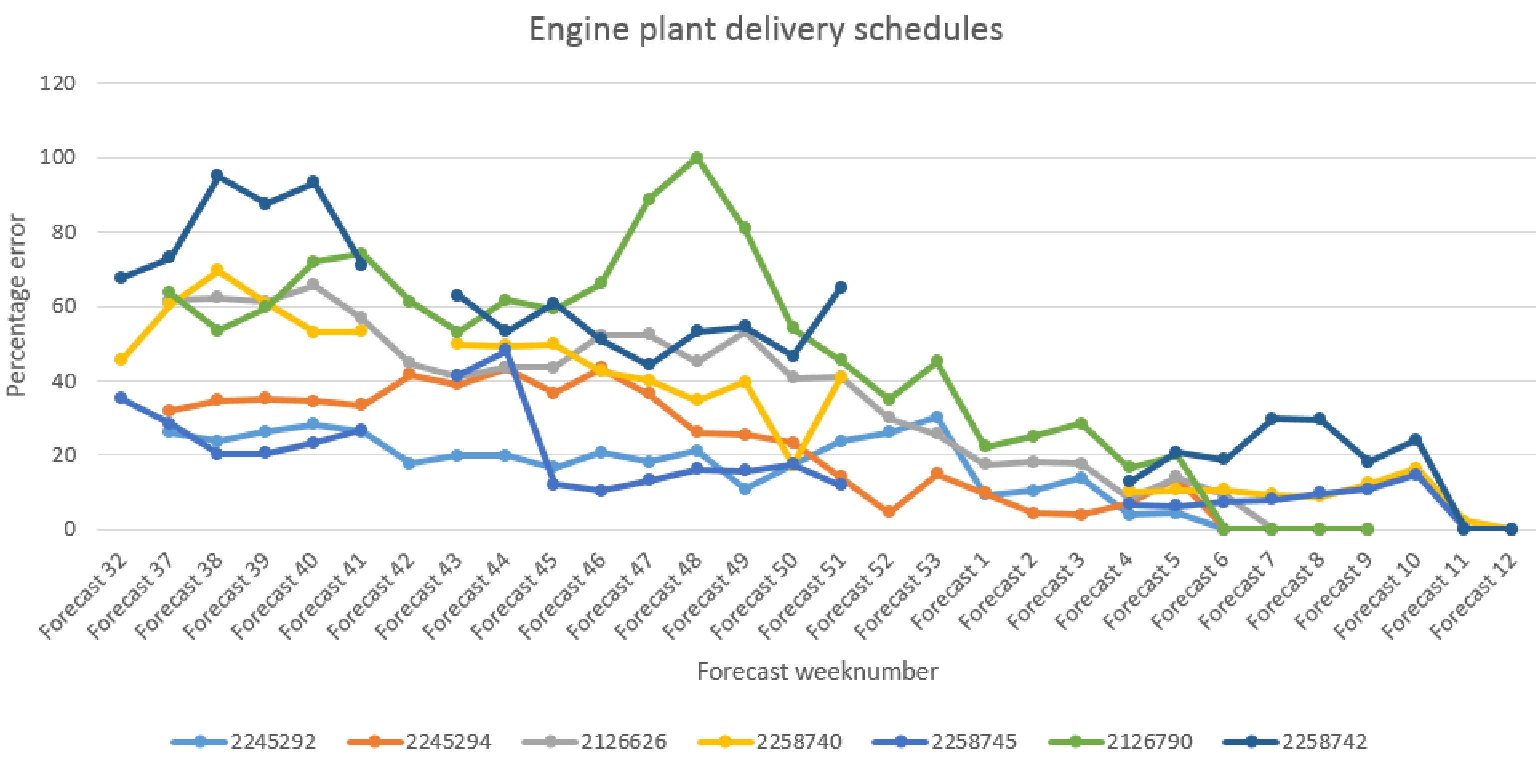
Accuracy calculation for all weeks

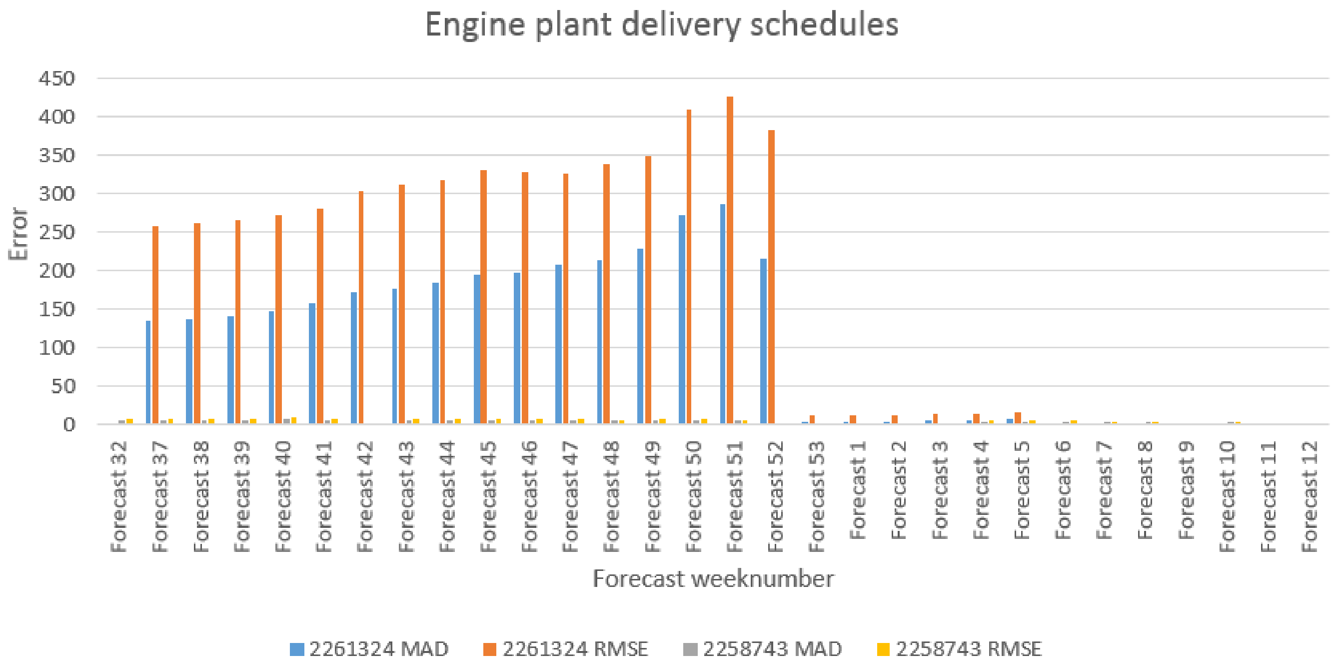
This appendix shows the complete accuracy calculation of all available weeks that contained forecasts and actual values. The first selection of graphs refers to the delivery schedule, and the last selection of graphs refers to the database data.

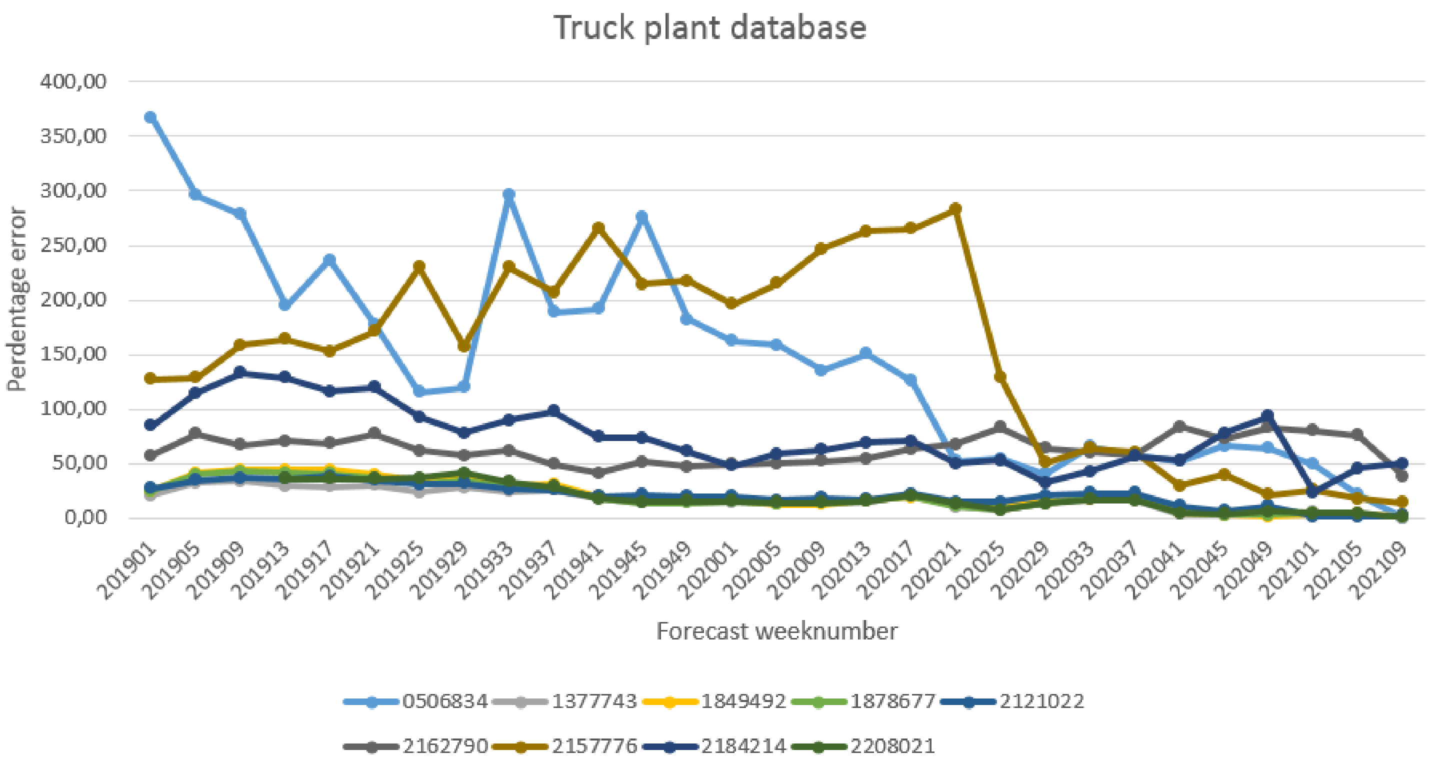

Truck plant delivery schedules
Percentage error
Forecast weeknumber
1849492
2121022
1878677
2184214
2157776
2208021
1377743
0090861
1257443

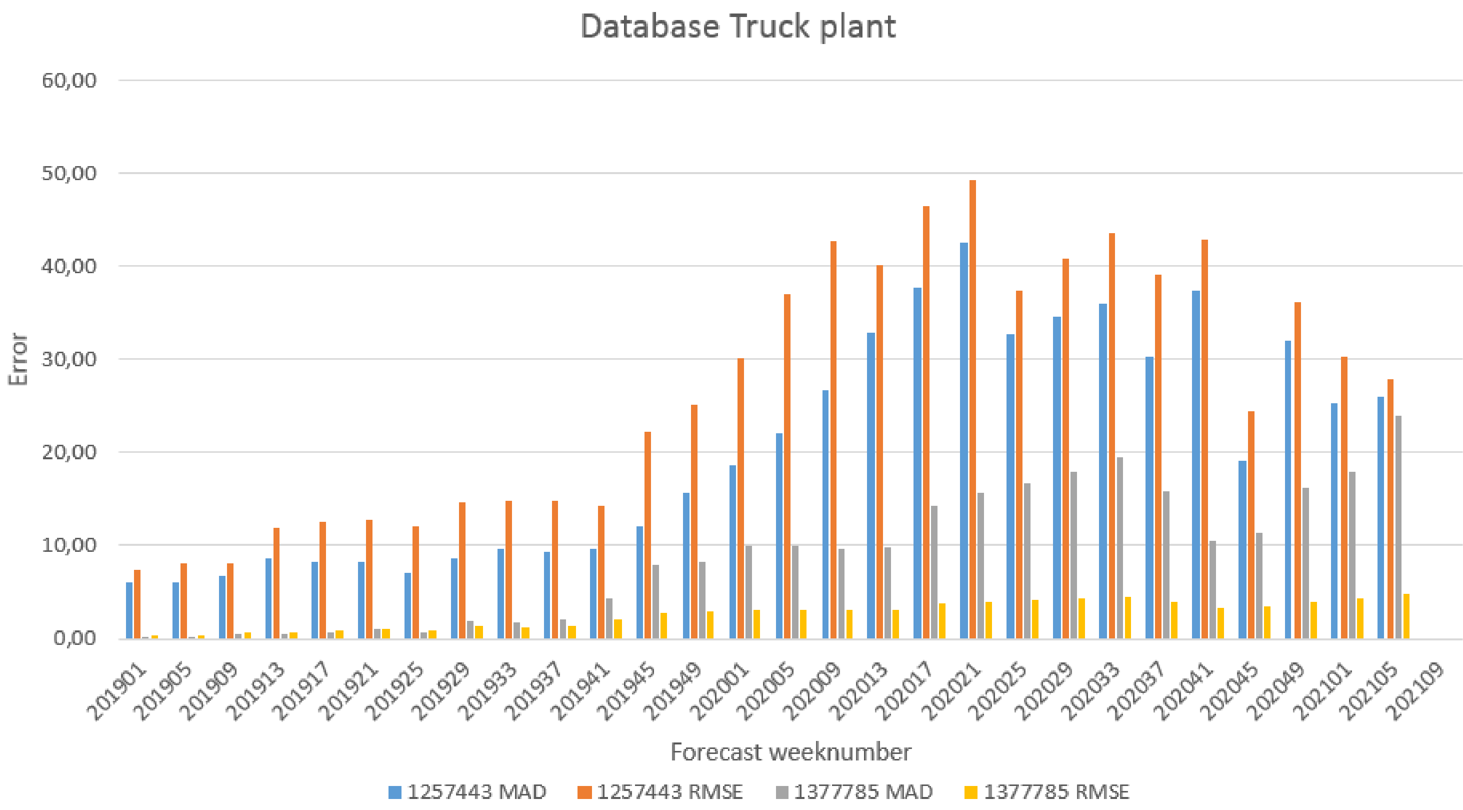

Truck plant delivery schedules
Error
Forecast weeknumber
0506834 MAD
0506834 RMSE
1377785 MAD
1377785 RMSE
1881839 MAD
1881839 RMSE

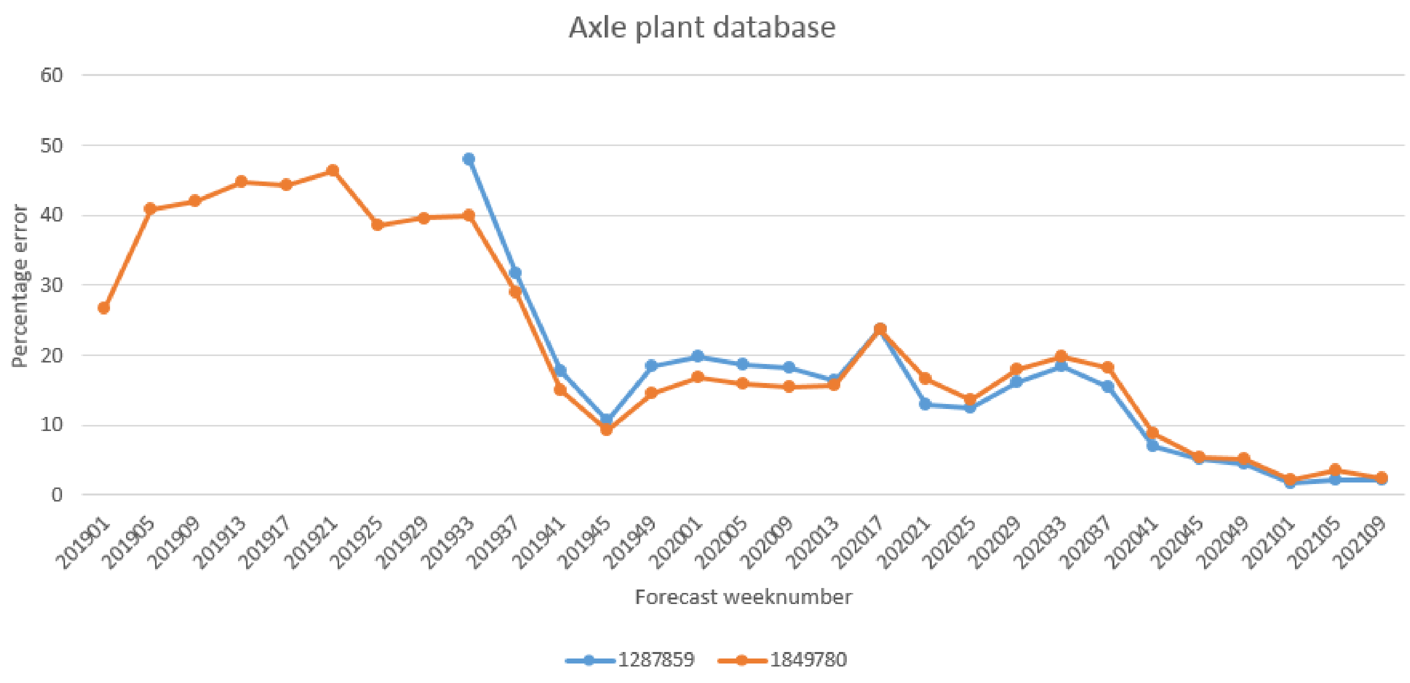

Axle plant delivery schedules
80,00
70,00
60,00
50,00
40,00
30,00
20,00
10,00
0,00
Percentage error
Forecast 41
Forecast 42
Forecast 43
Forecast 44
Forecast 45
Forecast 46
Forecast 47
Forecast 48
Forecast 49
Forecast 50
Forecast 51
Forecast 52
Forecast 53
Forecast 1
Forecast 2
Forecast 3
Forecast 4
Forecast 5
Forecast 6
Forecast 7
Forecast 8
Forecast 9
Forecast 10
Forecast weeknumber
0964061
1287859
2048982
1849780
0966541
0966542

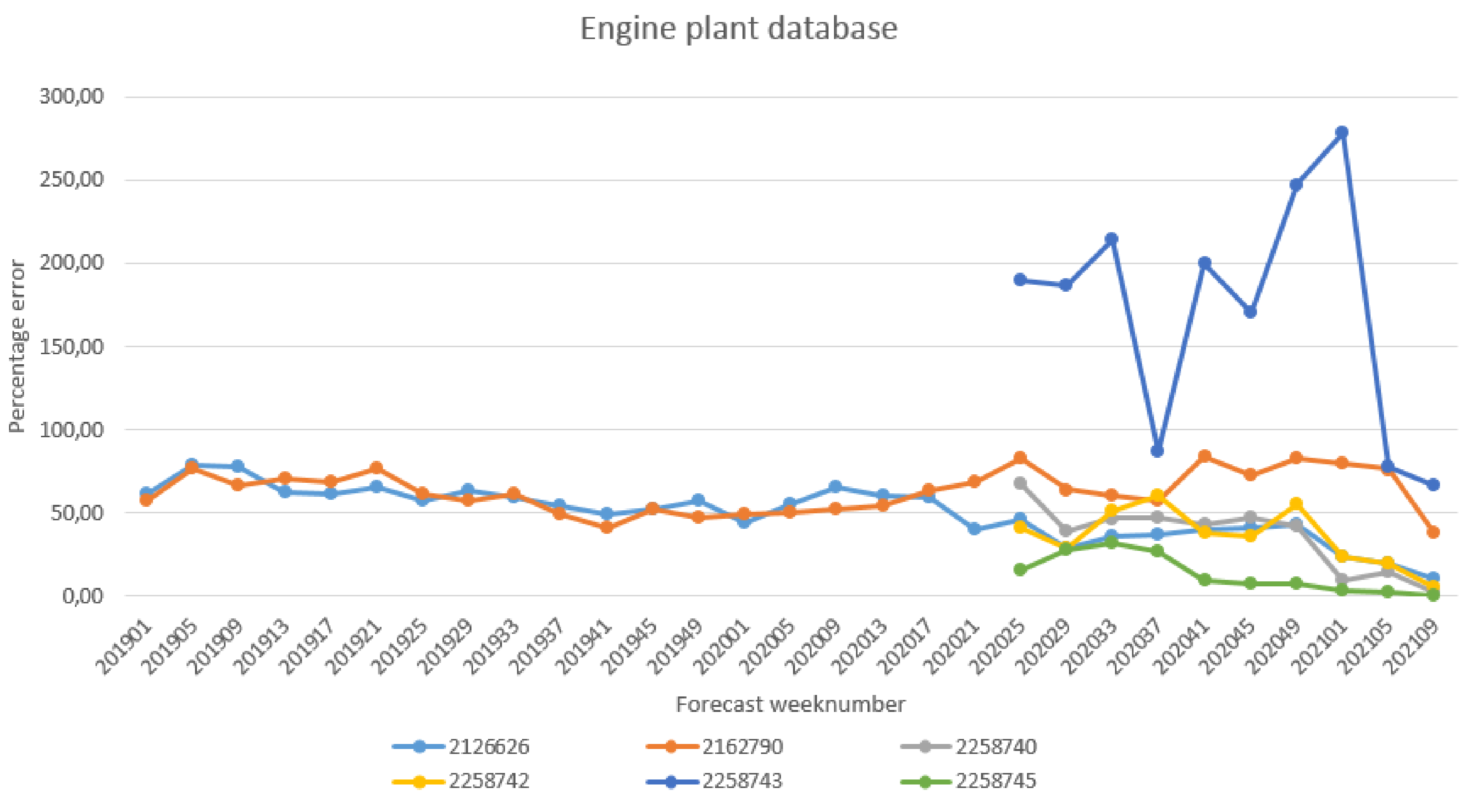

Engine plant delivery schedules
120
100
80
60
40
20
0
Percentage error
Forecast 32
Forecast 37
Forecast 38
Forecast 39
Forecast 40
Forecast 41
Forecast 42
Forecast 43
Forecast 44
Forecast 45
Forecast 46
Forecast 47
Forecast 48
Forecast 49
Forecast 50
Forecast 51
Forecast 52
Forecast 53
Forecast 1
Forecast 2
Forecast 3
Forecast 4
Forecast 5
Forecast 6
Forecast 7
Forecast 8
Forecast 9
Forecast 10
Forecast 11
Forecast 12
Forecast weeknumber
2245292
2245294
2126626
2258740
2258745
2126790
2258742


Engine plant delivery schedules
Error
450
400
350
300
250
200
150
100
50
0
Forecast 32
Forecast 37
Forecast 38
Forecast 39
Forecast 40
Forecast 41
Forecast 42
Forecast 43
Forecast 44
Forecast 45
Forecast 46
Forecast 47
Forecast 48
Forecast 49
Forecast 50
Forecast 51
Forecast 52
Forecast 53
Forecast 1
Forecast 2
Forecast 3
Forecast 4
Forecast 5
Forecast 6
Forecast 7
Forecast 8
Forecast 9
Forecast 10
Forecast 11
Forecast 12
Forecast weeknumber
2261324 MAD
2261324 RMSE
2258743 MAD
2258743 RMSE


Truck plant database
Perdentage error
400,00
350,00
300,00
250,00
200,00
150,00
100,00
50,00
0,00
201901
201905
201909
201913
201917
201921
201925
201929
201933
201937
201941
201945
201949
202001
202005
202009
202013
202017
202021
202025
202029
202033
202037
202041
202045
202049
202101
202105
202109
Forecast weeknumber
0506834
1377743
1849492
1878677
2121022
2162790
2157776
2184214
2208021

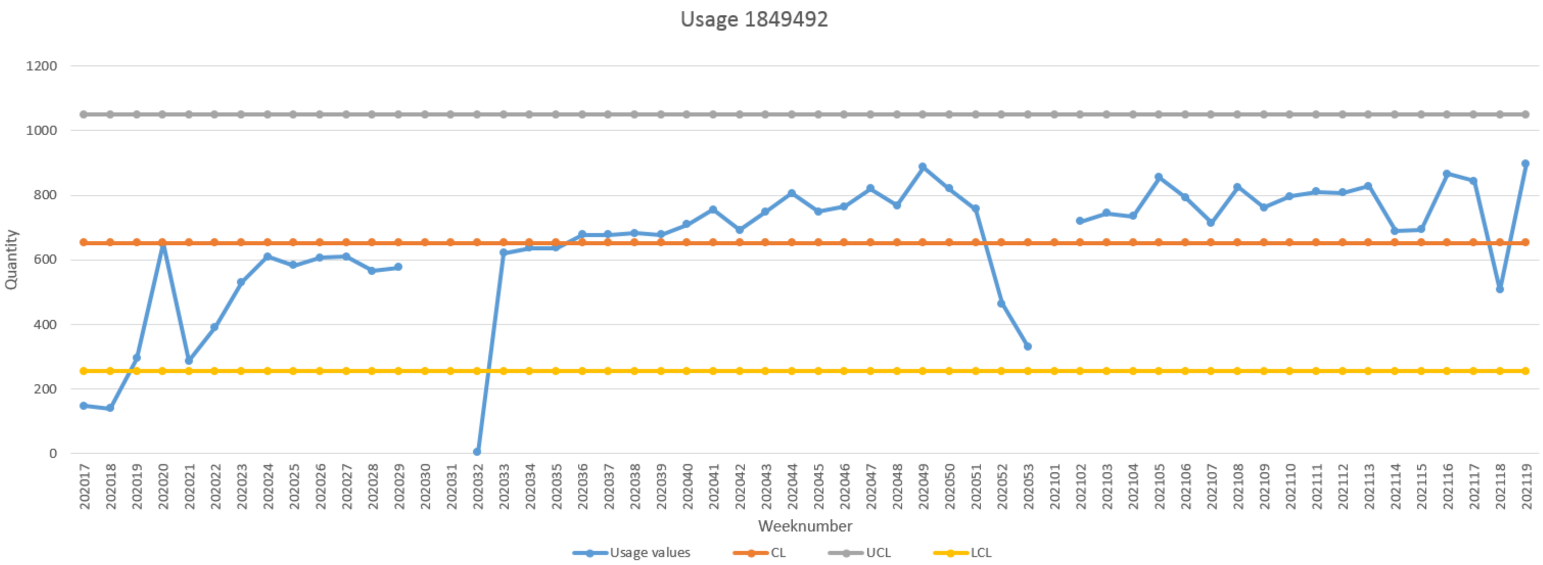

Database Truck plant
Error
Forecast weeknumber
1257443 MAD
1257443 RMSE
1377785 MAD
1377785 RMSE

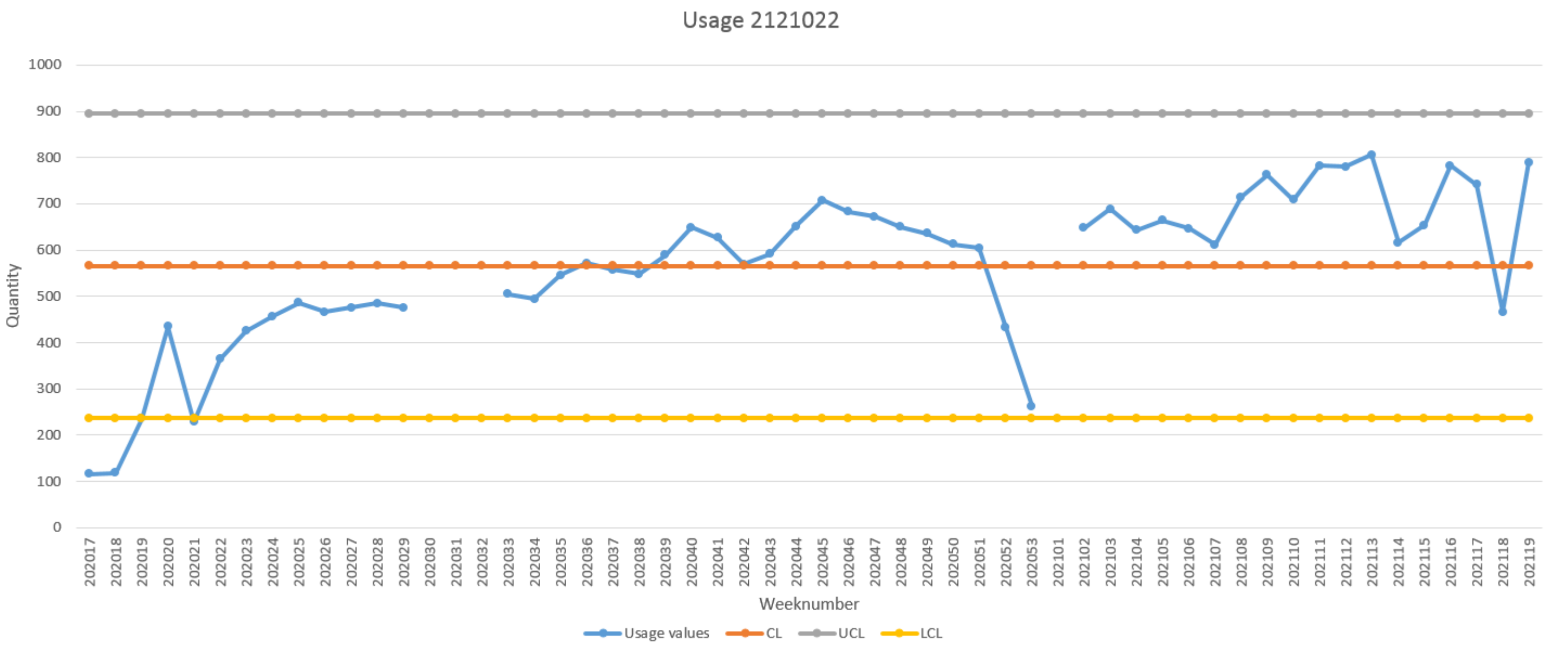

Axle plant database
Percentage error
Forecast weeknumber
1287859
1849780

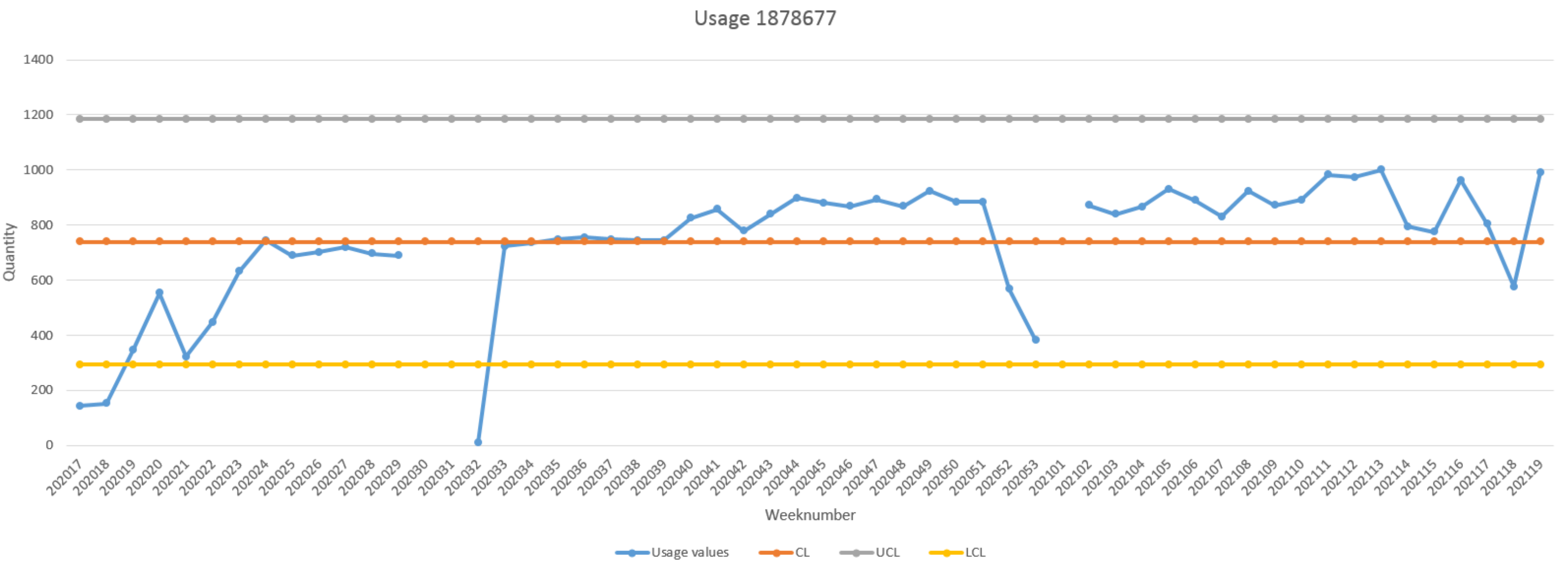

Engine plant database
300,00
250,00
200,00
150,00
100,00
50,00
0,00
Percentage error
201901
201905
201909
201913
201917
201921
201925
201929
201933
201937
201941
201945
201949
202001
202005
202009
202013
202017
202021
202025
202029
202033
202037
202041
202045
202049
202101
202105
202109
Forecast weeknumber
2126626
2162790
2258740
2258742
2258743
2258745

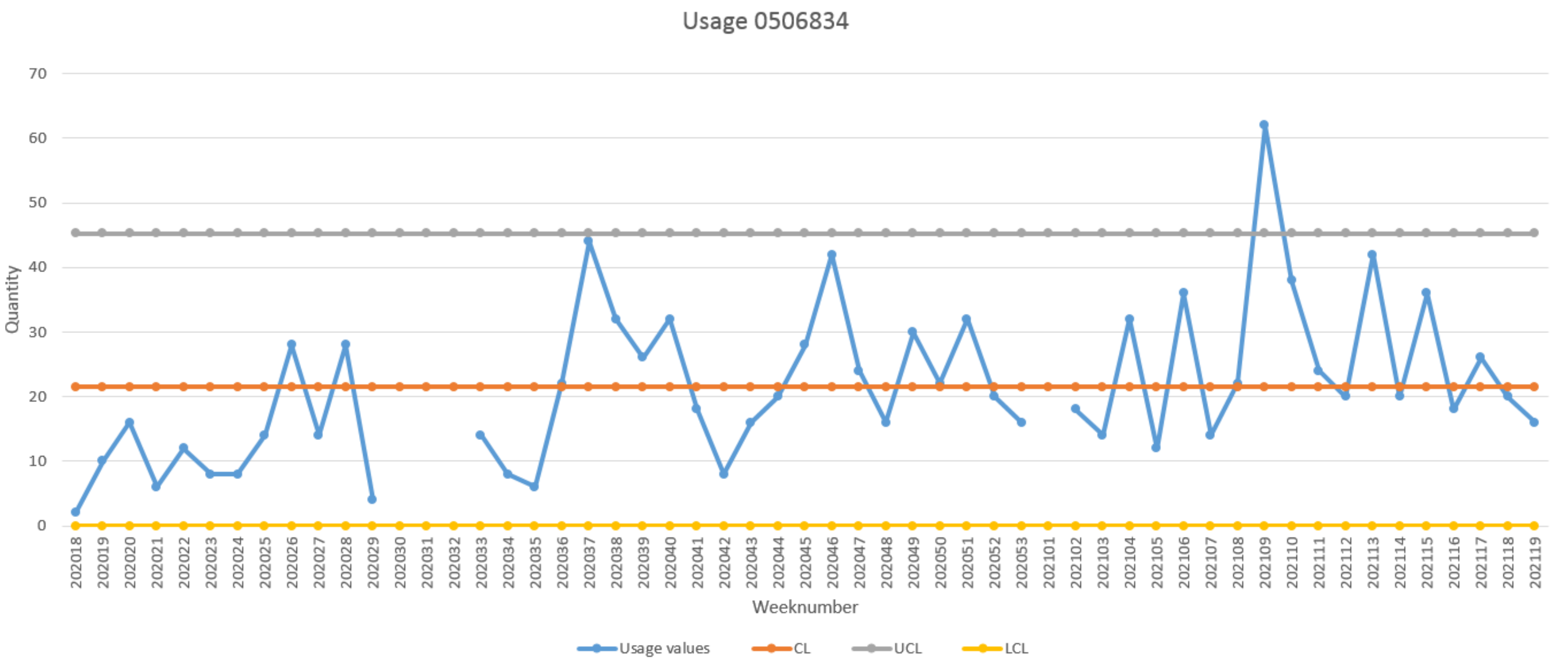
Appendix D

Control charts of usage data

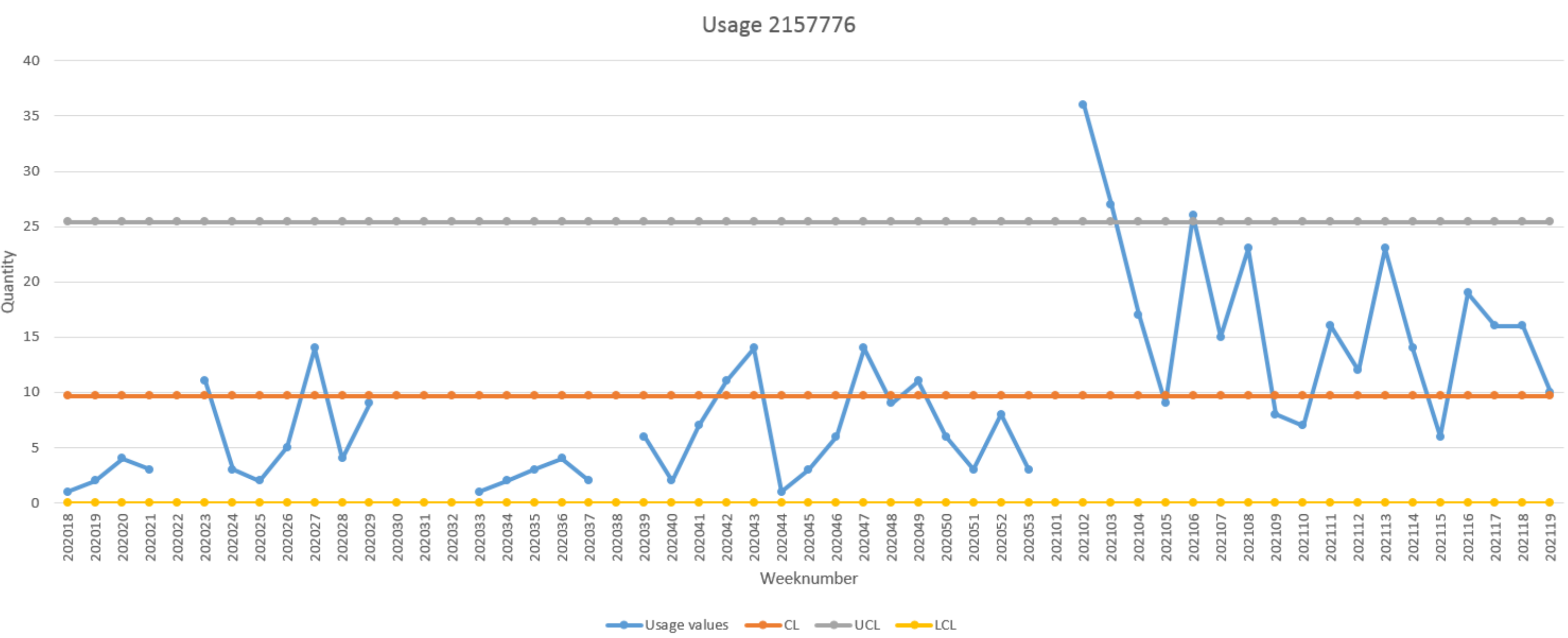



Usage 2121022
Quantity
Weeknumber
Usage values
CL
UCL
LCL

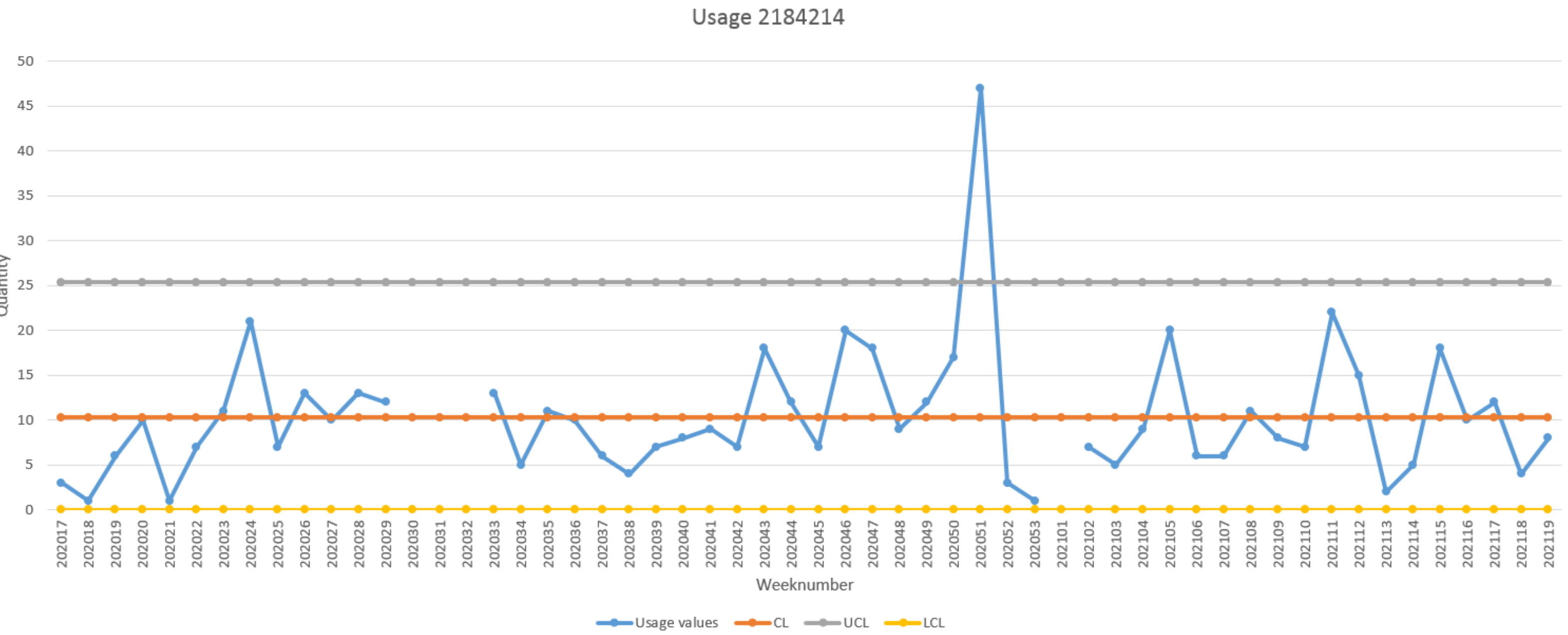

Usage 1878677
Quantity
Weeknumber
Usage values
CL
UCL
LCL

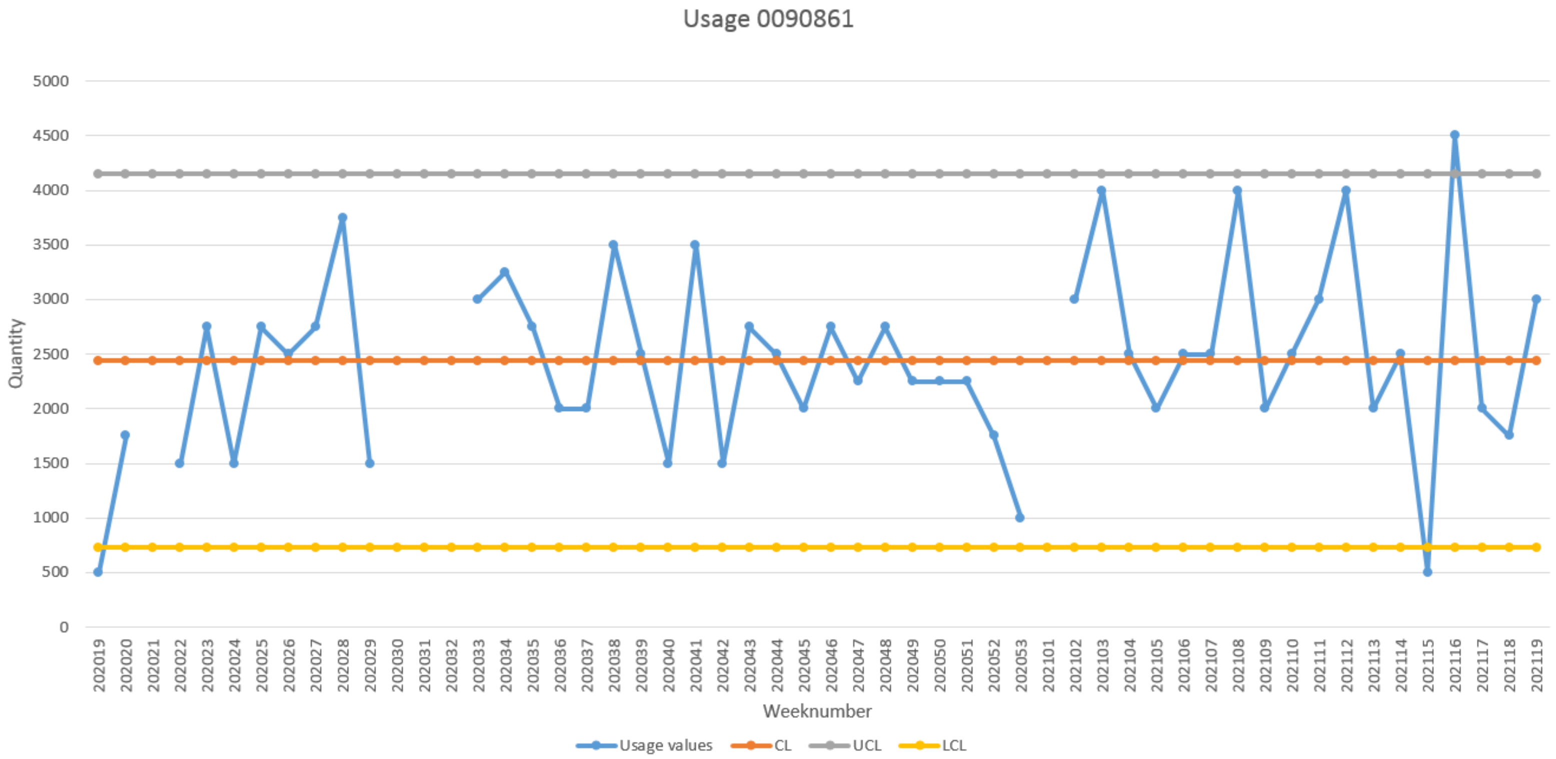


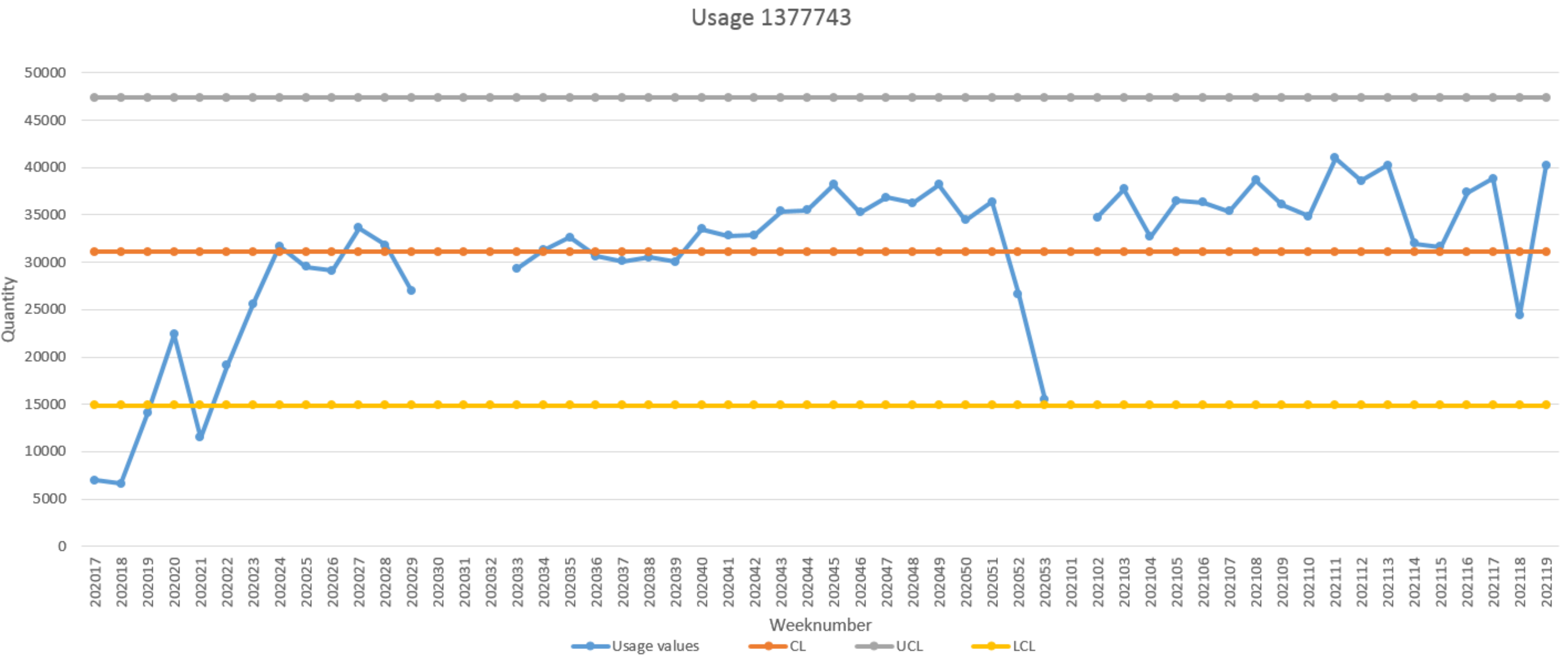
Usage 0506834
Quantity
Weeknumber
Usage values
CL
UCL
LCL

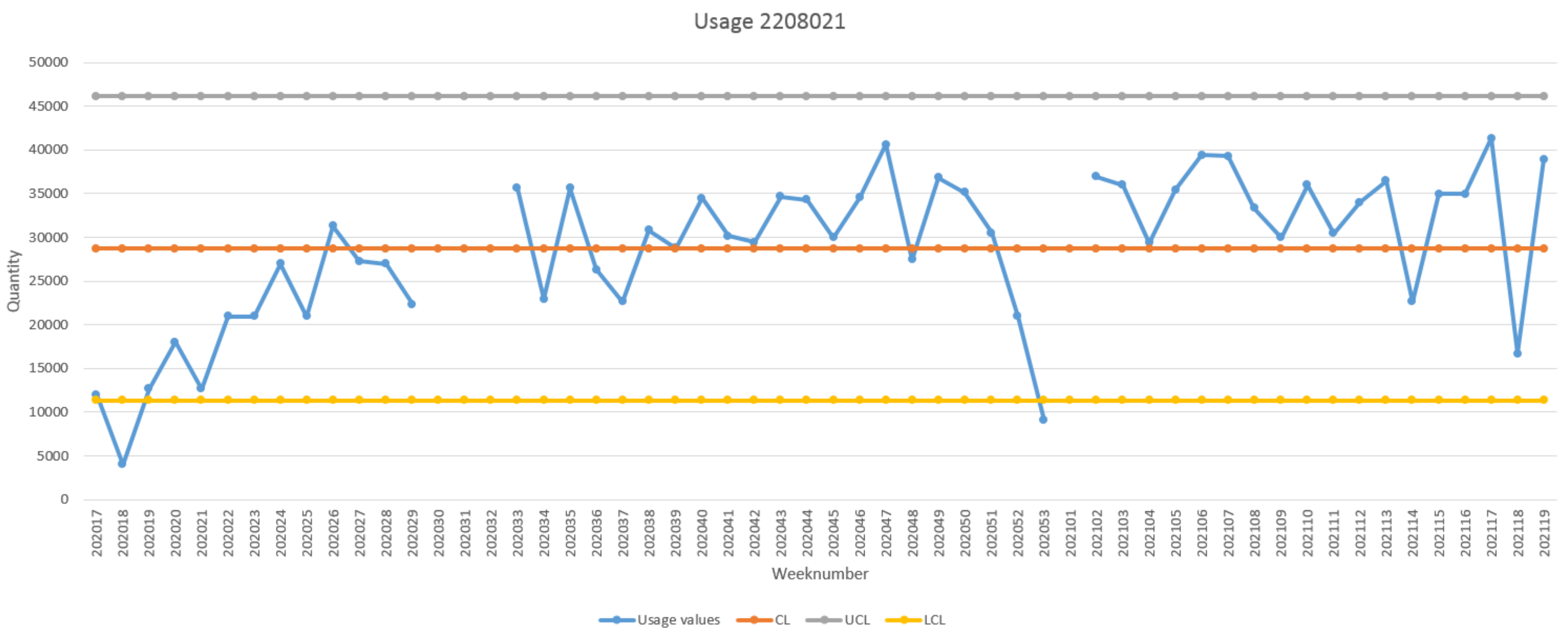


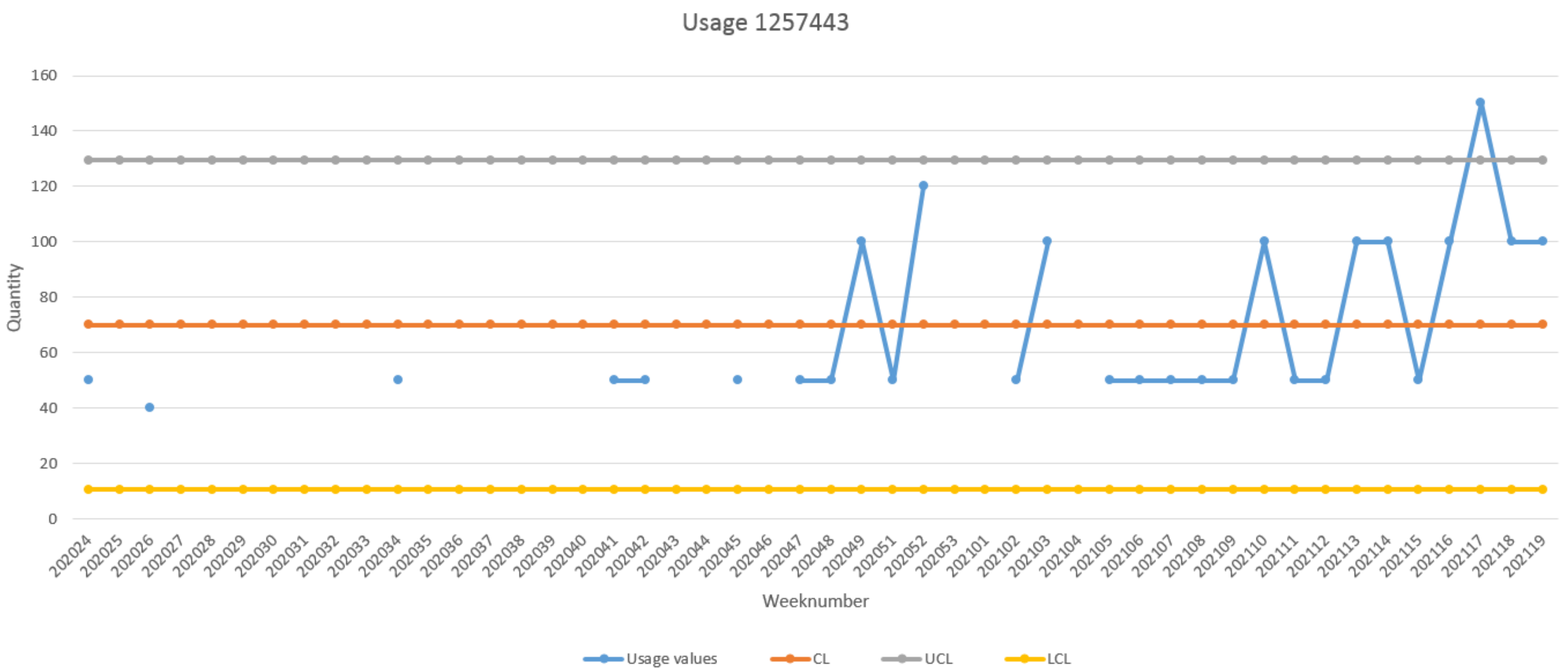
Usage 2157776
Quantity
Weeknumber
Usage values
CL
UCL
LCL

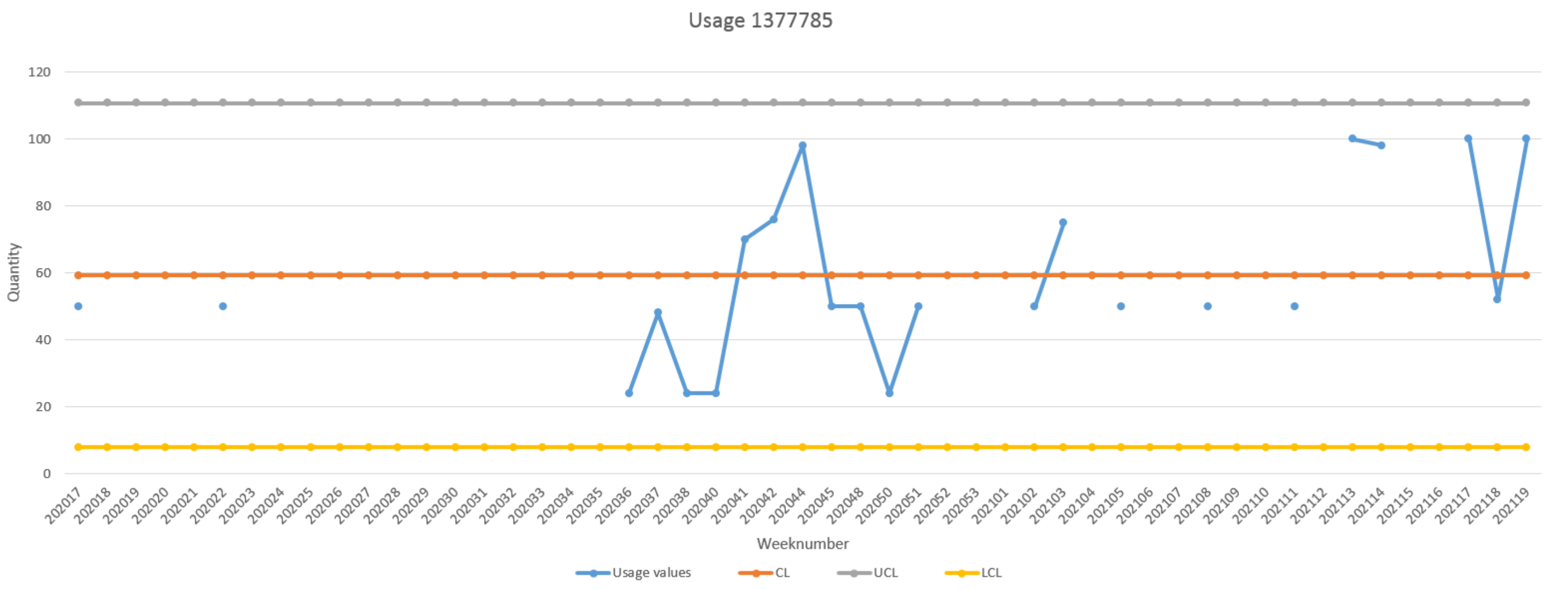

Usage 2184214
Quantity
Weeknumber
Usage values
CL
UCL
LCL

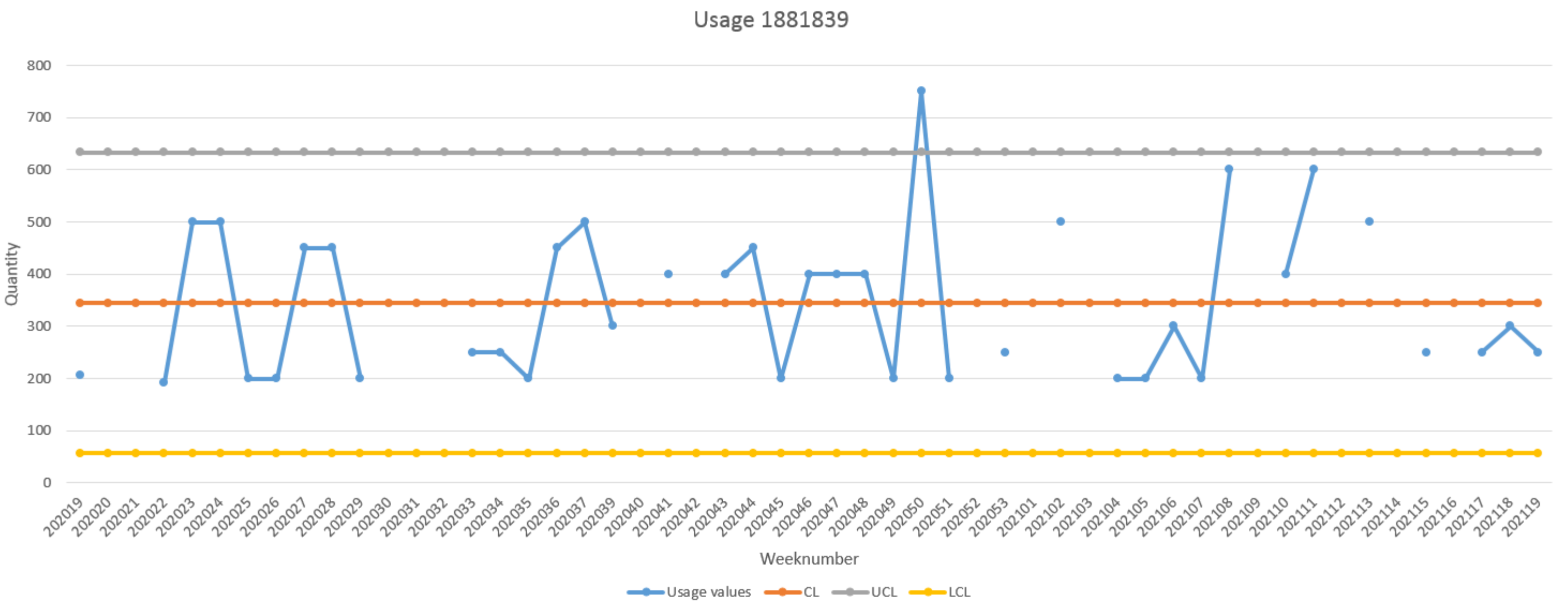

Usage 0090861
Quantity
Weeknumber
Usage values
CL
UCL
LCL

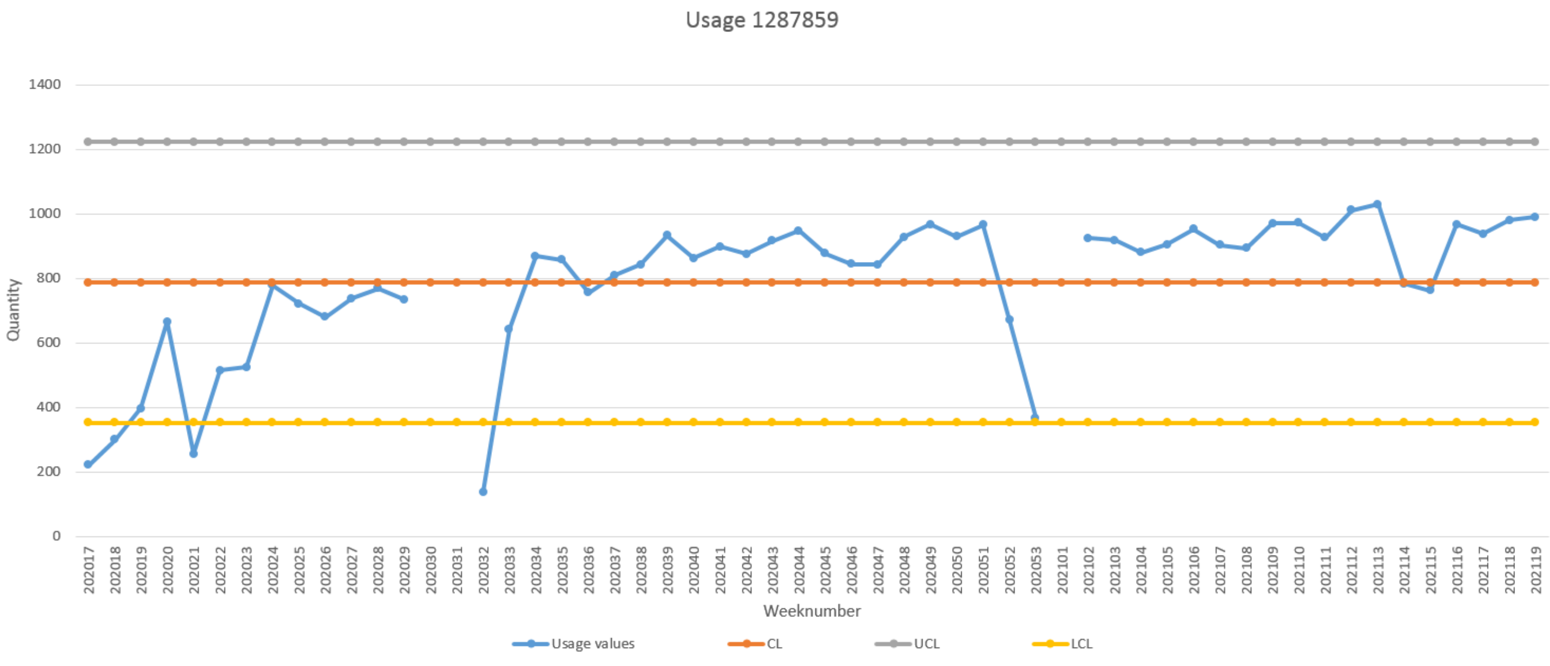

Usage 1377743
Quantity
Weeknumber
Usage values
CL
UCL
LCL

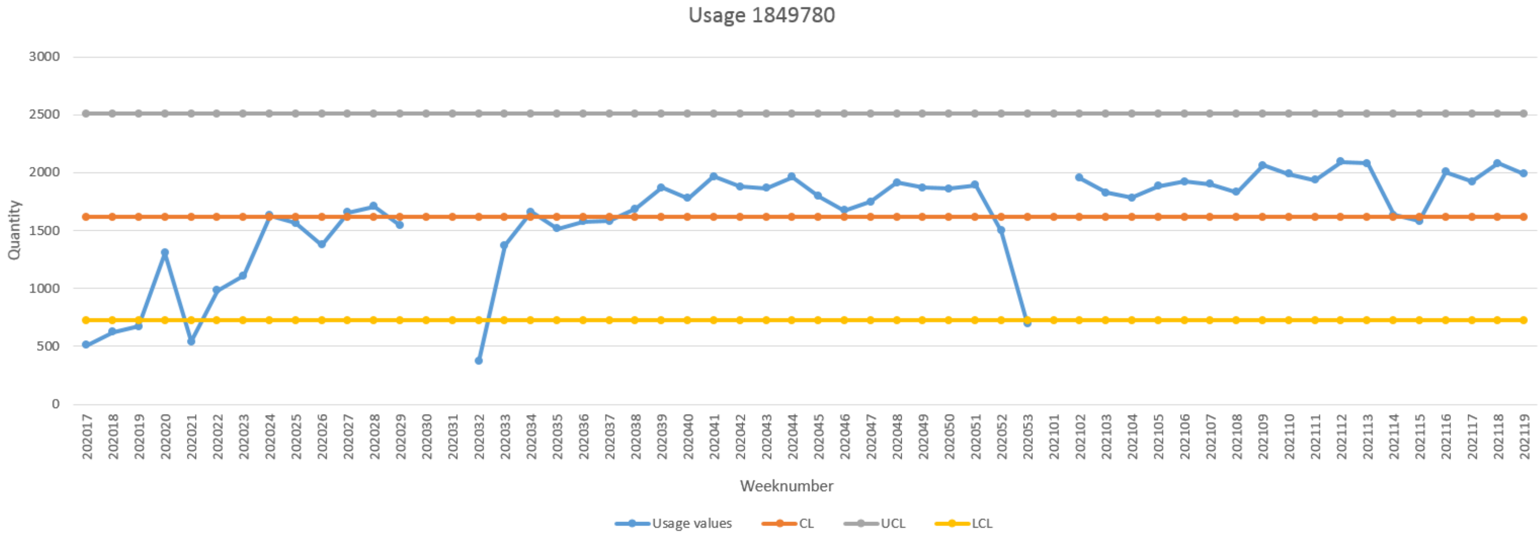

Usage 2208021
Quantity
Weeknumber
Usage values
CL
UCL
LCL

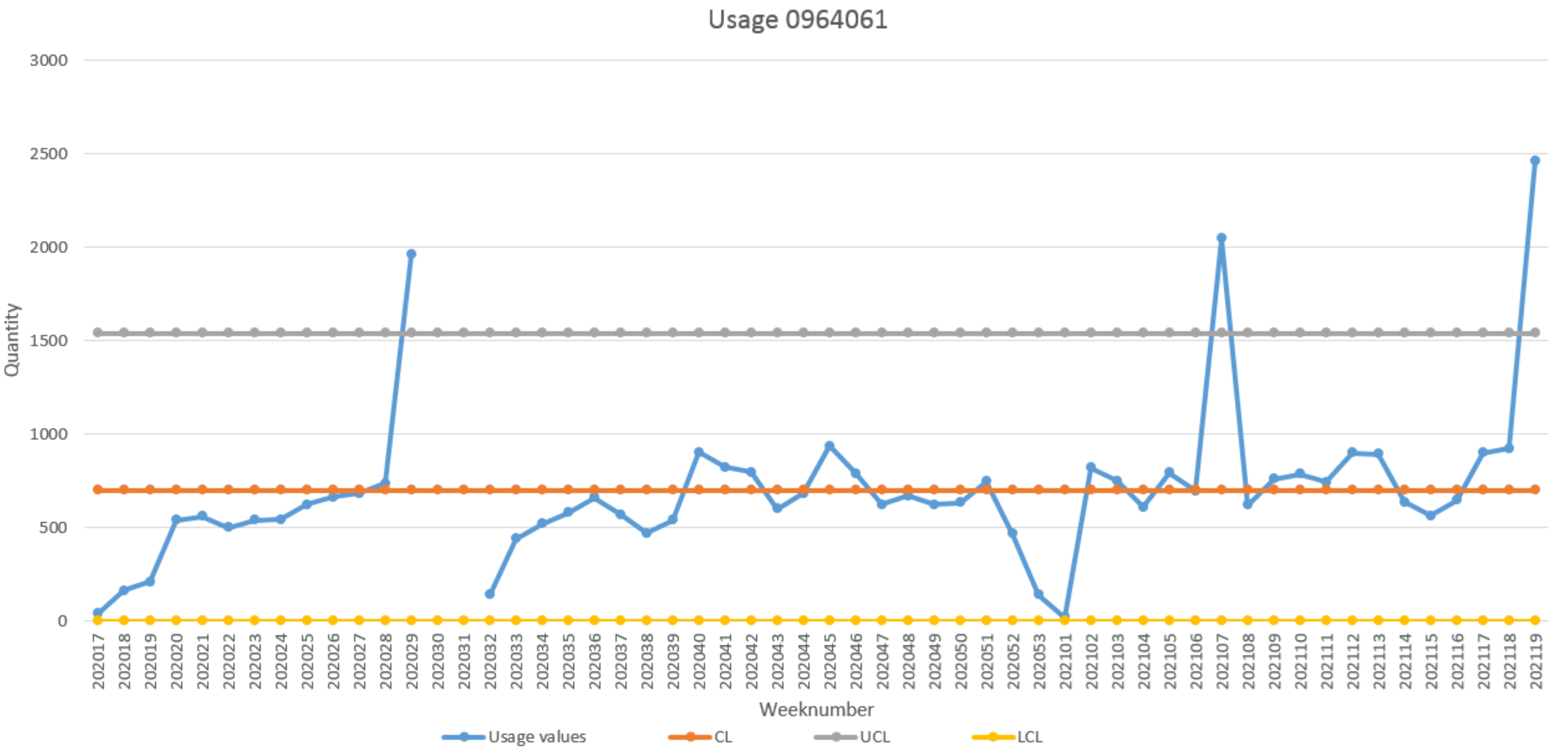

Usage 1257443
Quantity
Weeknumber
Usage values
CL
UCL
LCL


Usage 1377785
Quantity
Weeknumber
Usage values
CL
UCL
LCL


Usage 1881839
Quantity
Weeknumber
Usage values
CL
UCL
LCL


Usage 1287859
Quantity
Weeknumber
Usage values
CL
UCL
LCL


Usage 1849780
3000
2500
2000
1500
1000
500
0
Quantity
Weeknumber
Usage values
CL
UCL
LCL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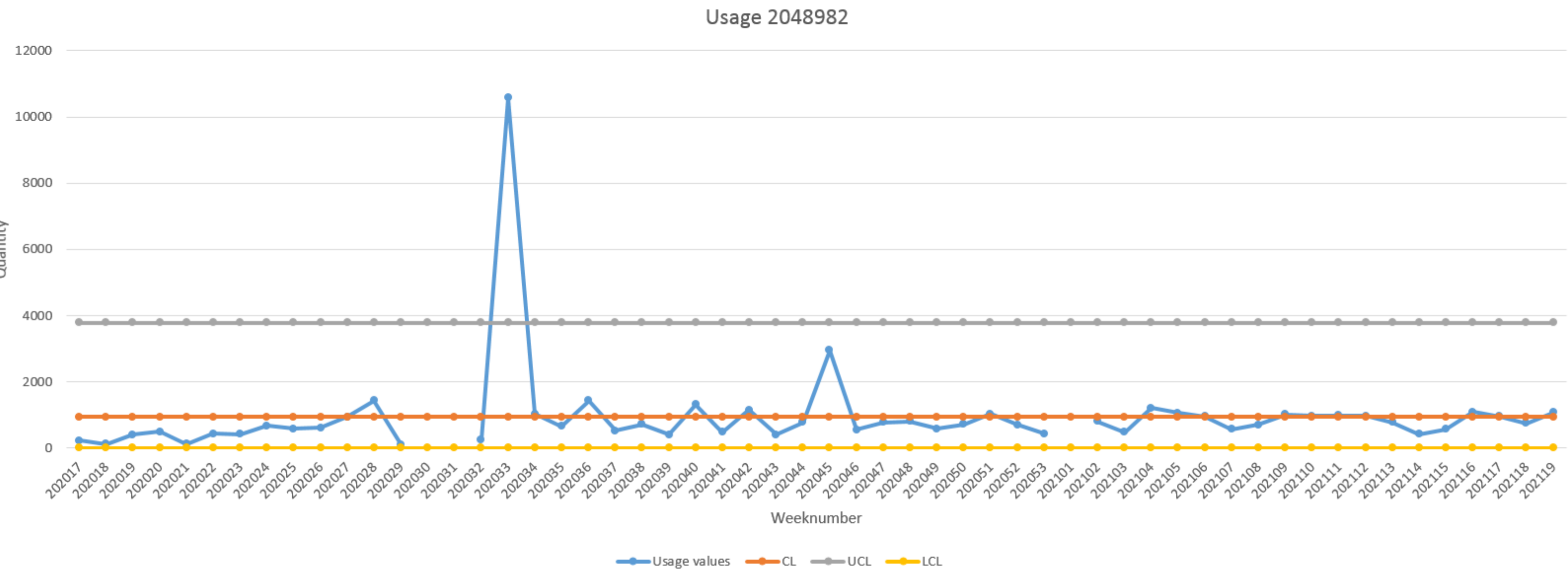
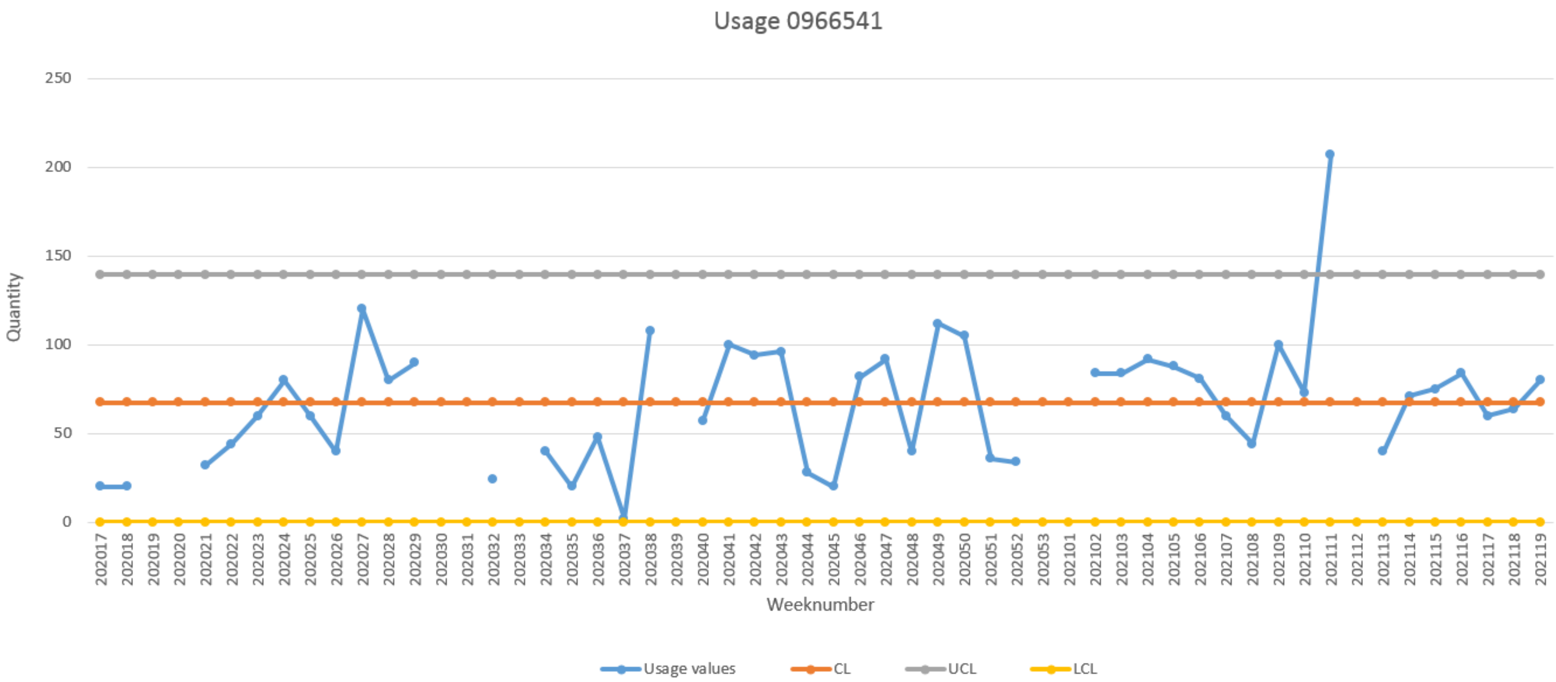
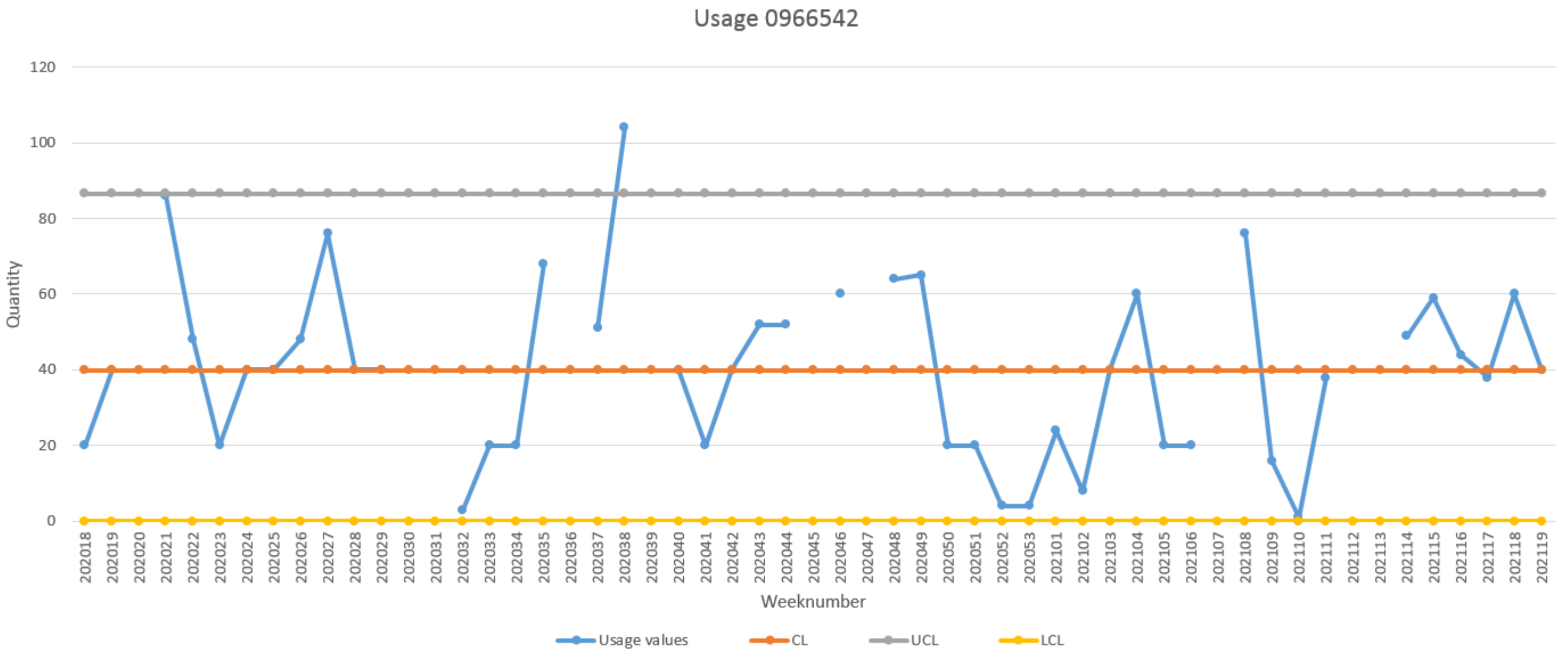
2500
2000
1500
1000
500
0
Quantity
Weeknumber
Usage values
CL
UCL
LCL


Usage 2048982
Quantity
Weeknumber
Usage values
CL
UCL
LCL


Usage 0966541
Quantity
Weeknumber
Usage values
CL
UCL
LCL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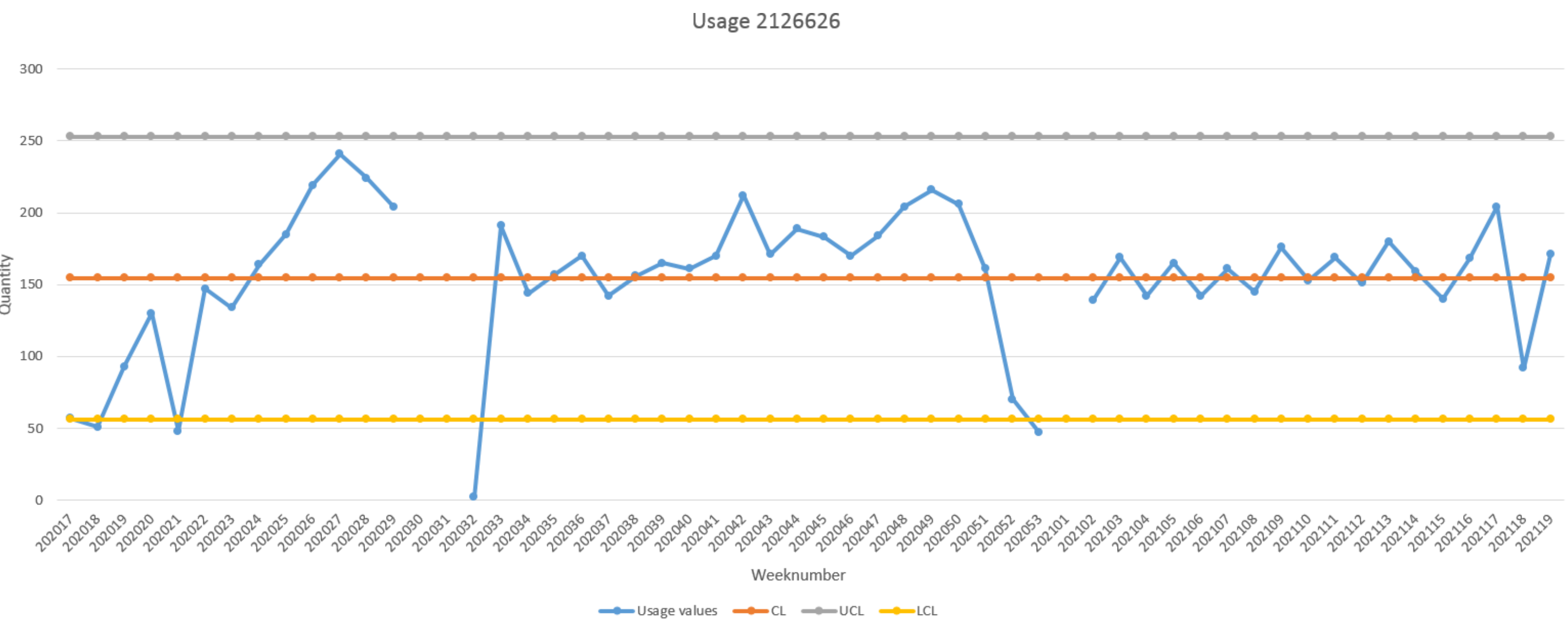
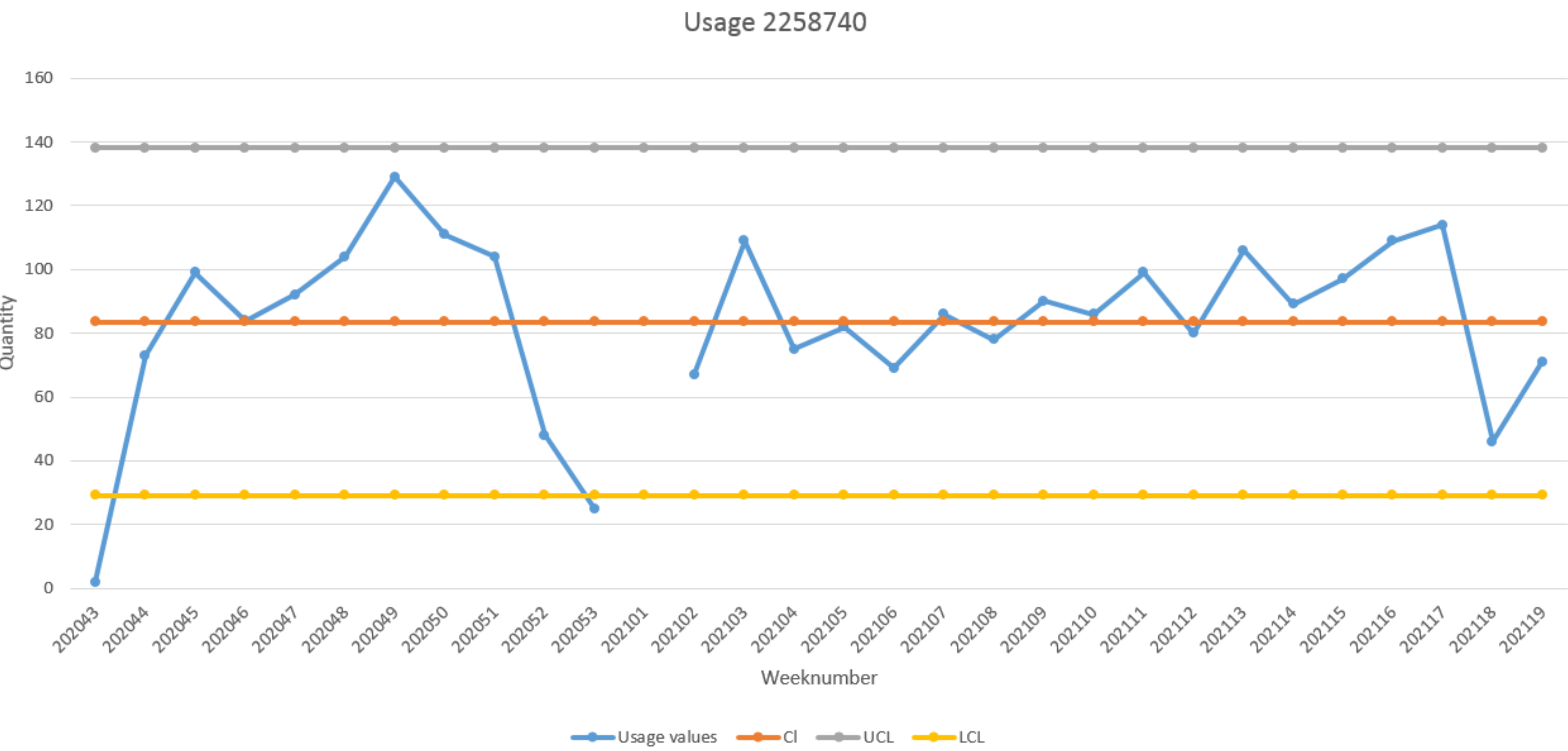
Quantity
Weeknumber
Usage values
CL
UCL
LCL


Usage 2126626
Quantity
Weeknumber
Usage values
CL
UCL
LCL


Usage 2258740
160
140
120
100
80
60
40
20
0
Quantity
202043
202044
202045
202046
202047
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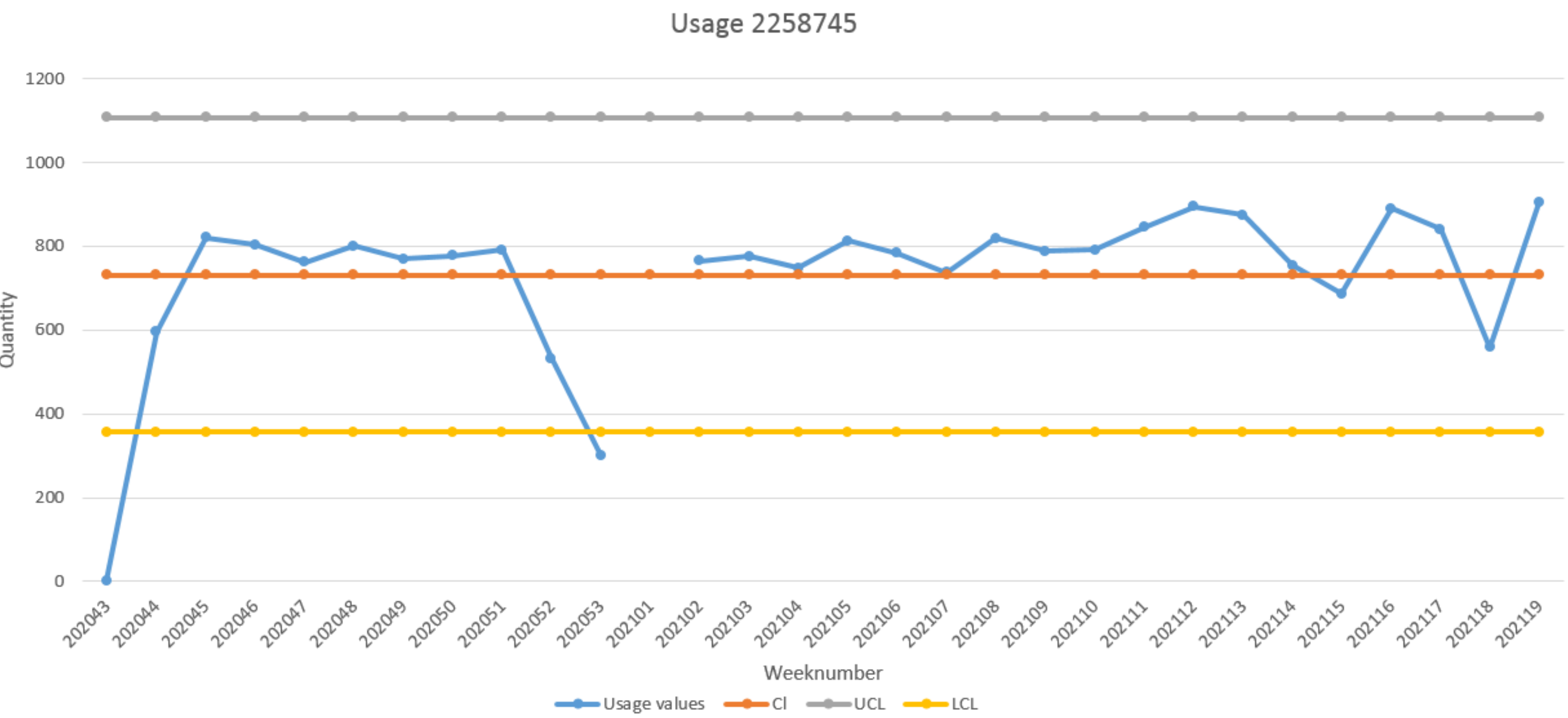
202049
202050
202051
202052
202053
202101
202102
202103
202104
202105
202106
202107
202108
202109
202110
202111
202112
202113
202114
202115
202116
202117
202118
202119
Weeknumber
Usage values
Cl
UCL
LCL


Usage 2258745
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1000
800
600
400
200
0
Quantity
202043
202044
202045
202046
202047
202048
202049
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202052
202053
202101
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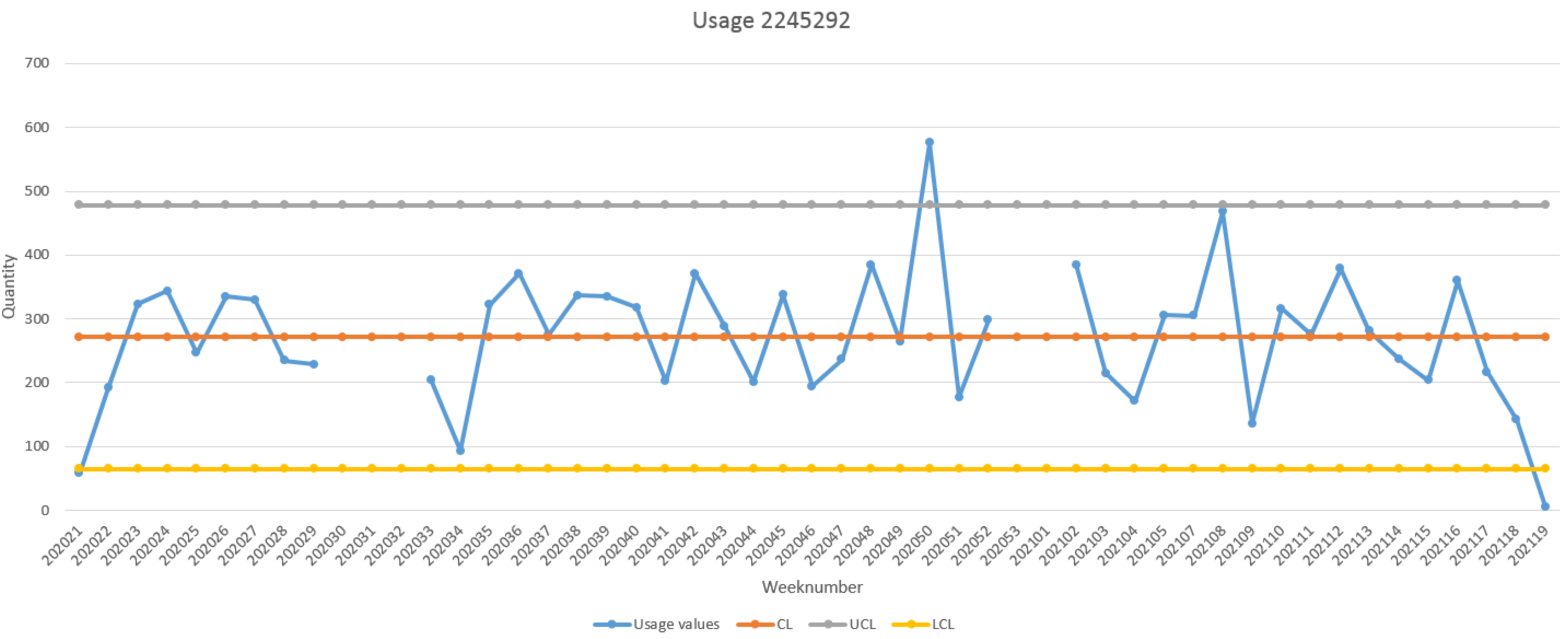
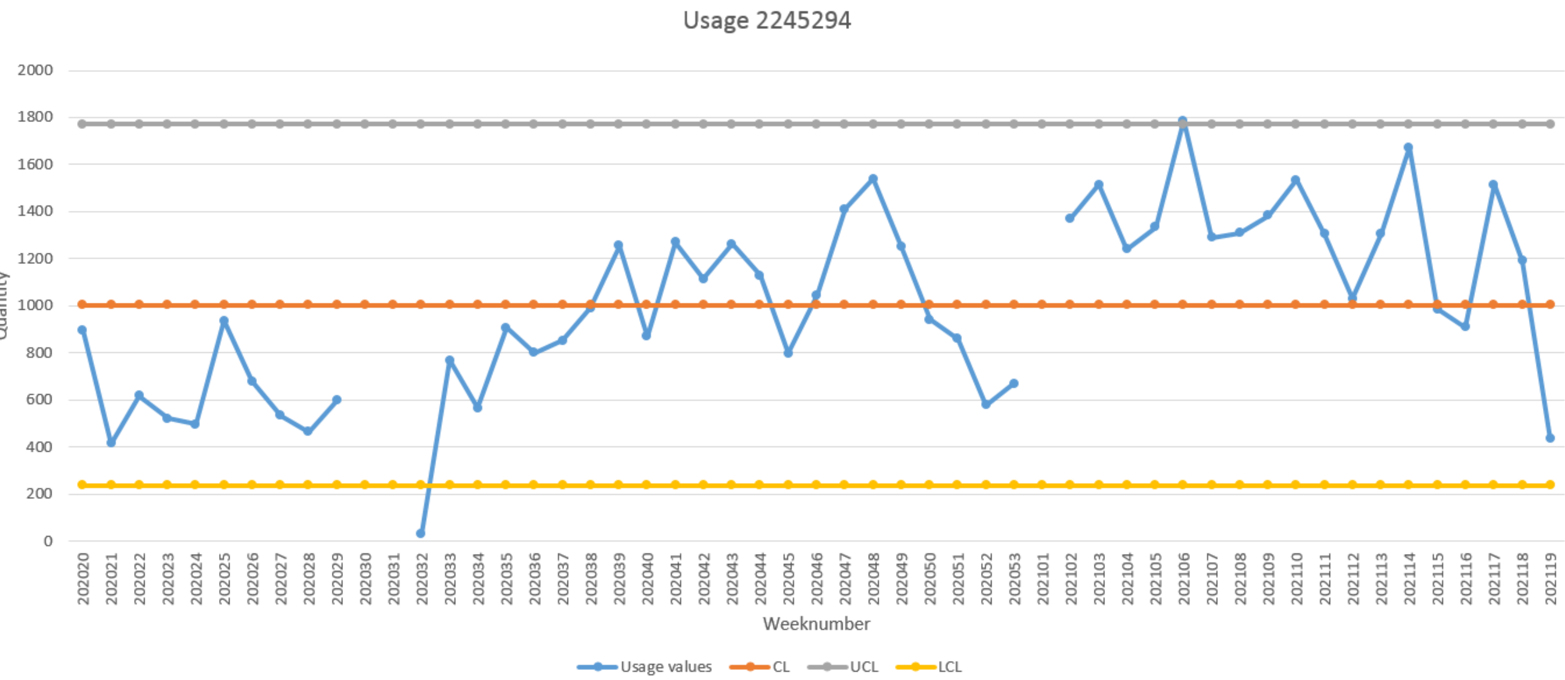
202104
202105
202106
202107
202108
202109
202110
202111
202112
202113
202114
202115
202116
202117
202118
202119
Weeknumber
Usage values
Cl
UCL
LCL


Usage 2245292
Quantity
Weeknumber
Usage values
CL
UCL
LCL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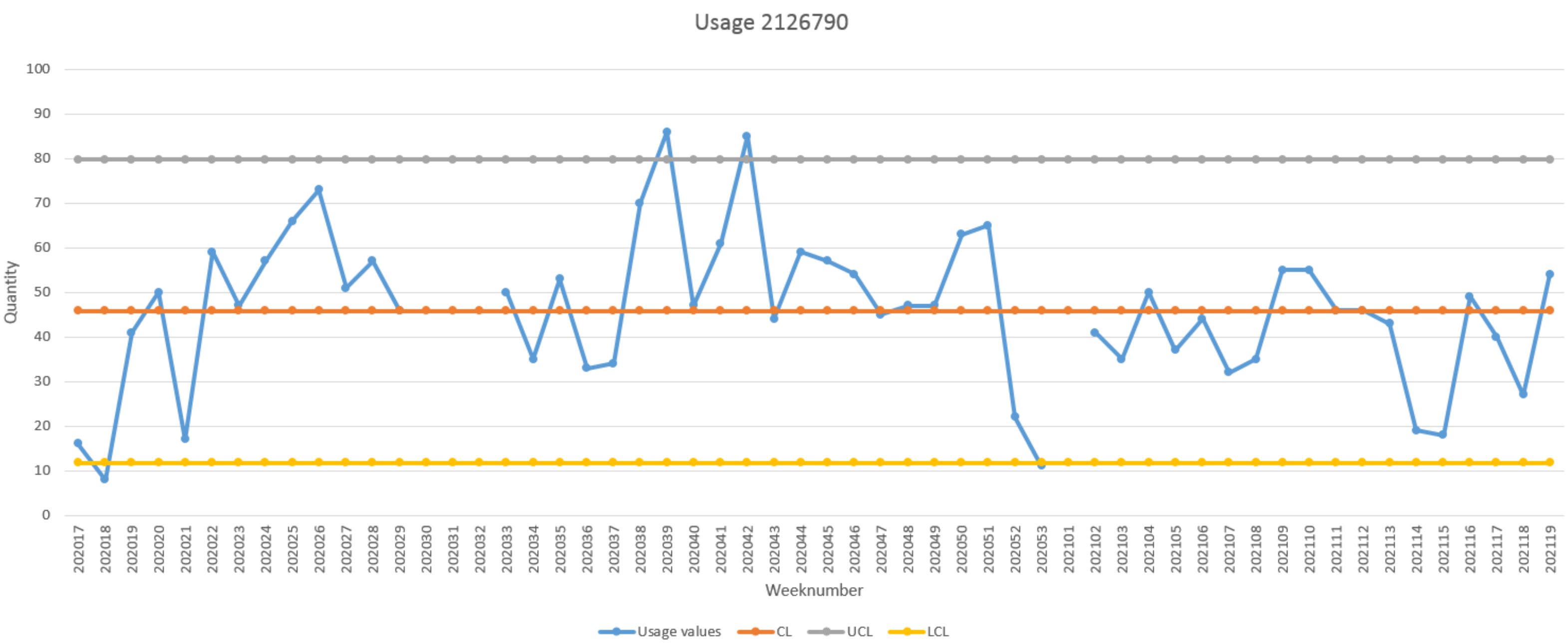
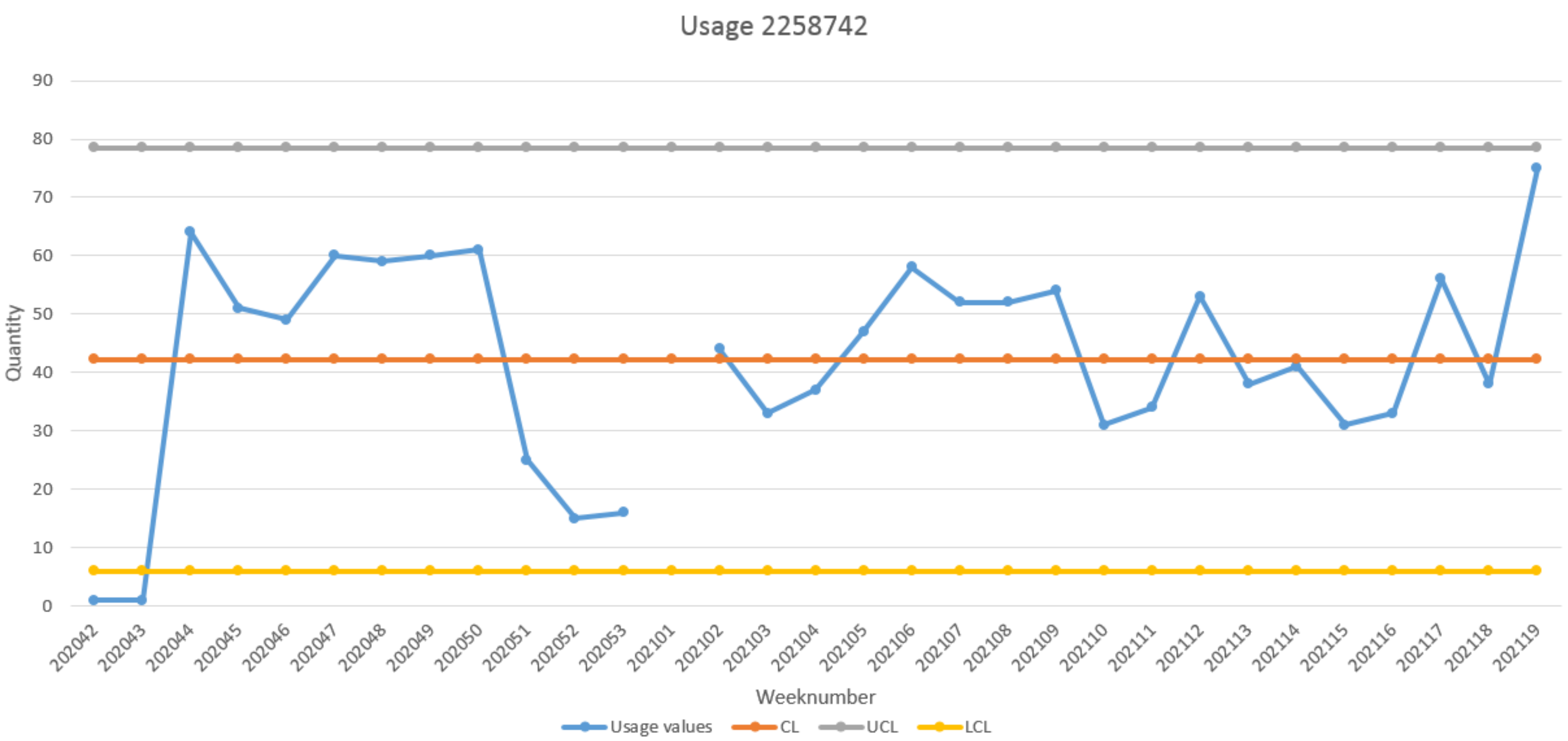
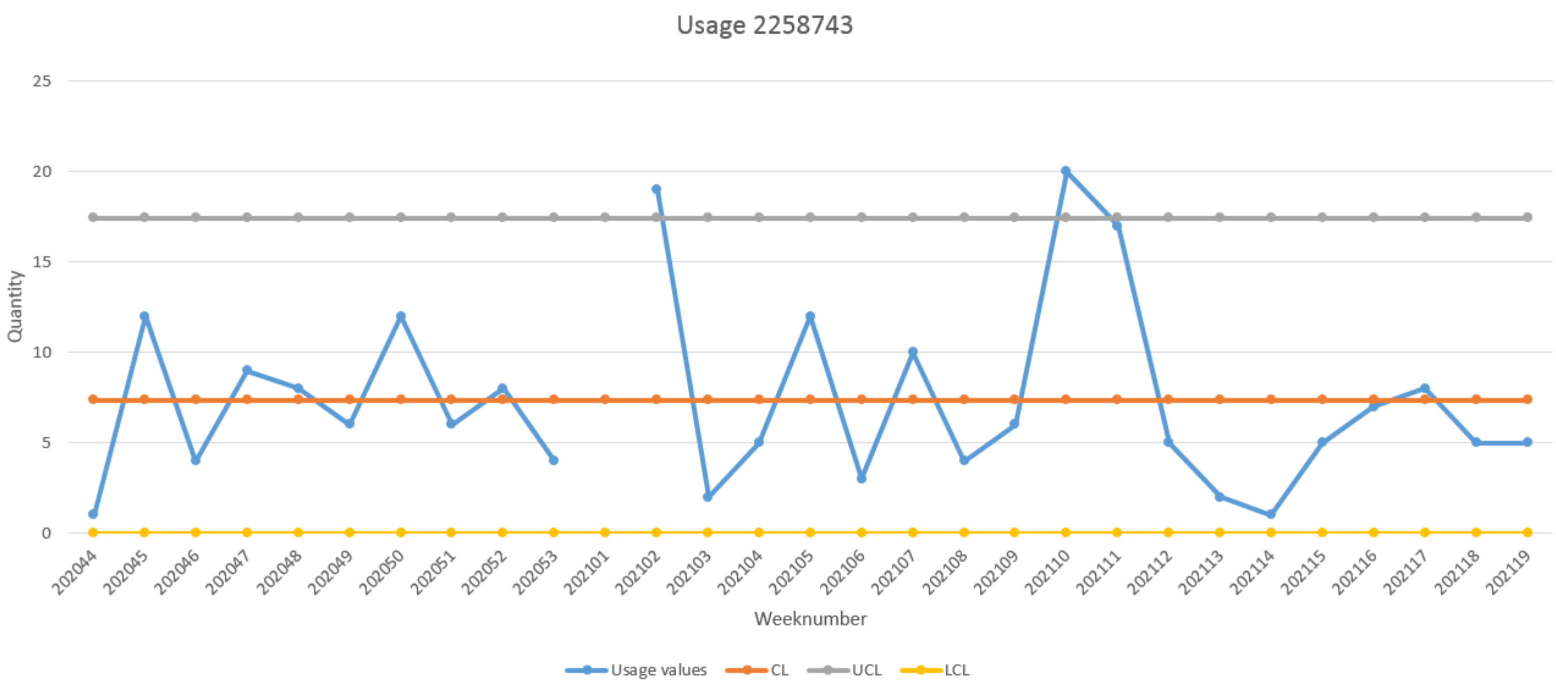
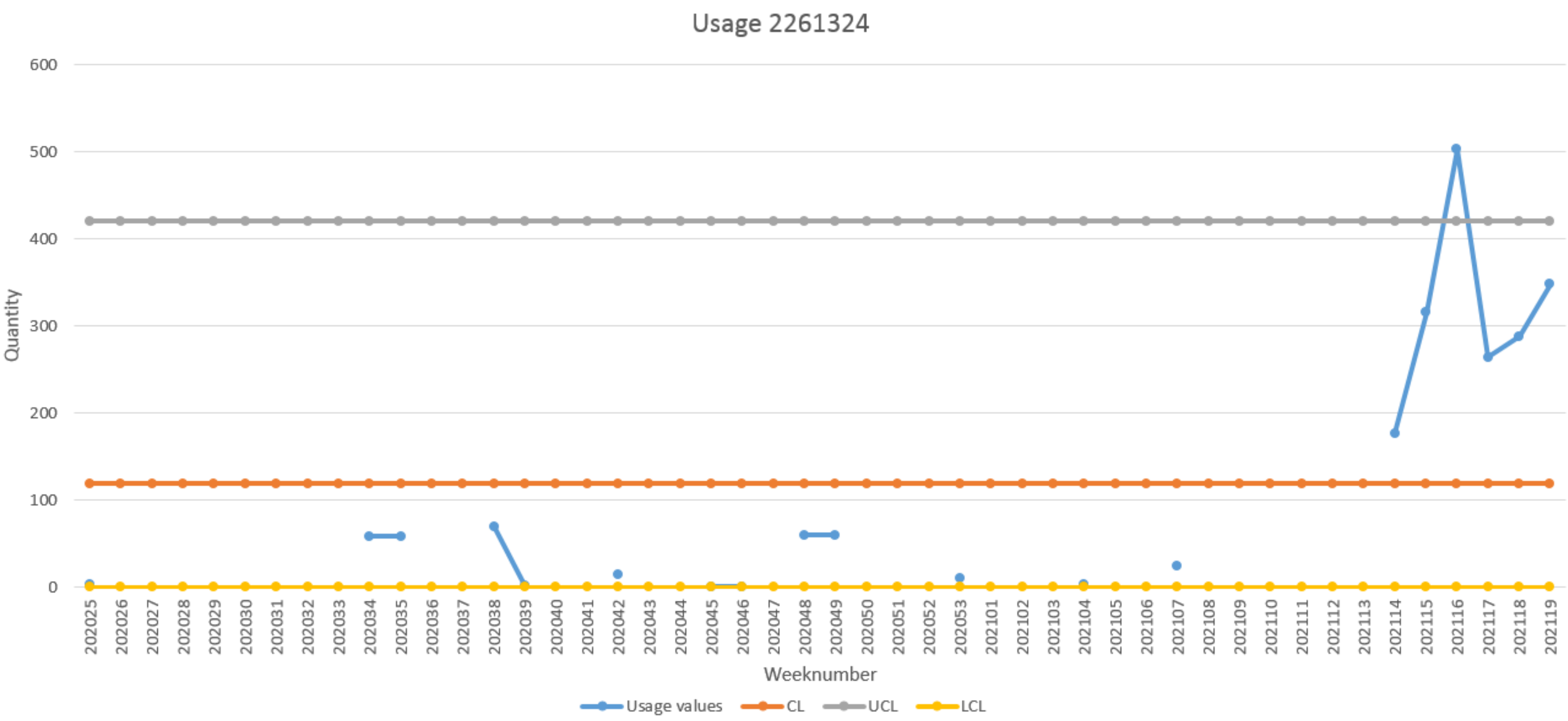
Weeknumber
Usage values
CL
UCL
LCL


Usage 2126790
Quantity
Weeknumber
Usage values
CL
UCL
LCL


Usage 2258742
Quantity
Weeknumber
Usage values
CL
UCL
LCL


Usage 2258743
Quantity
Weeknumber
Usage values
CL
UCL
LCL

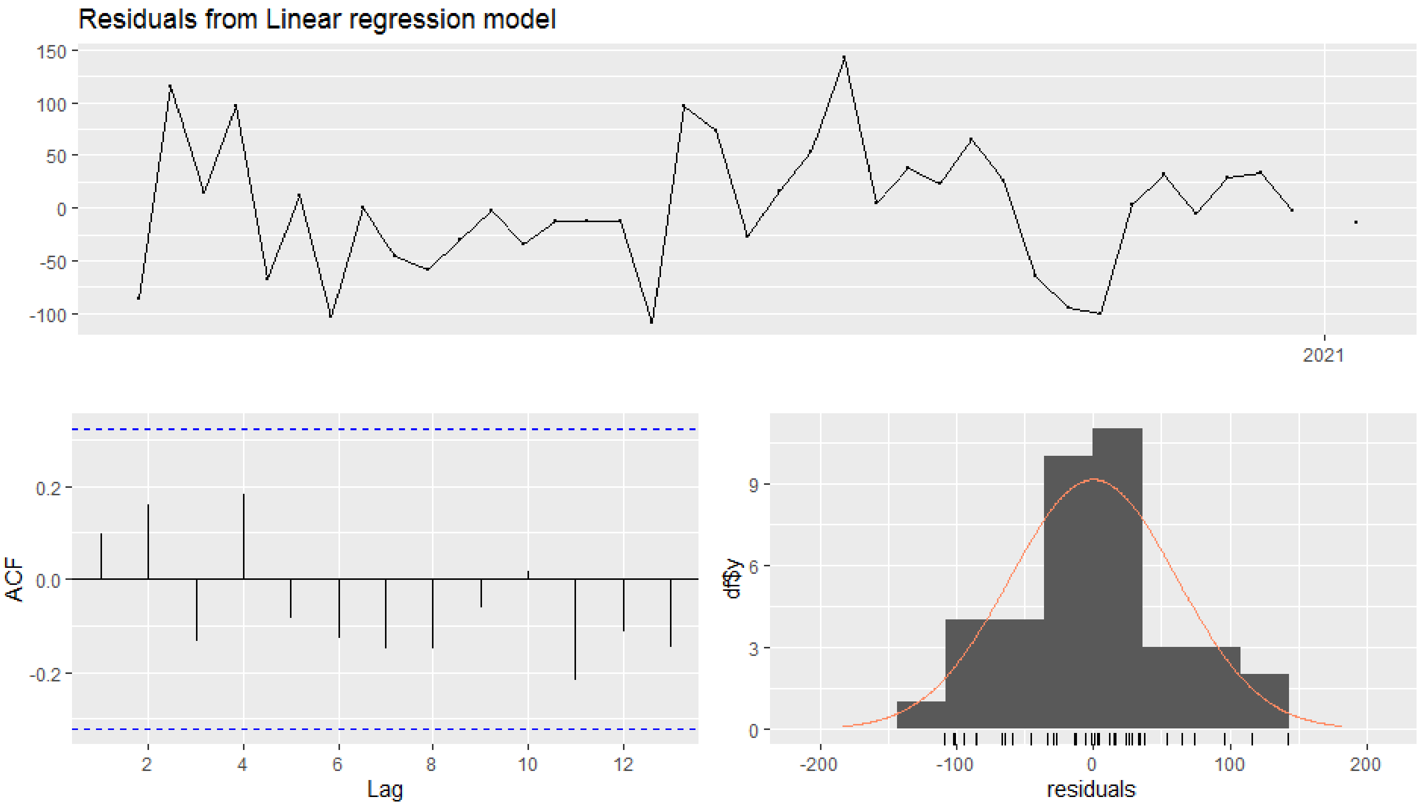

Usage 2261324
Quantity
Weeknumber
Usage values
CL
UCL
LCL

Appendix E

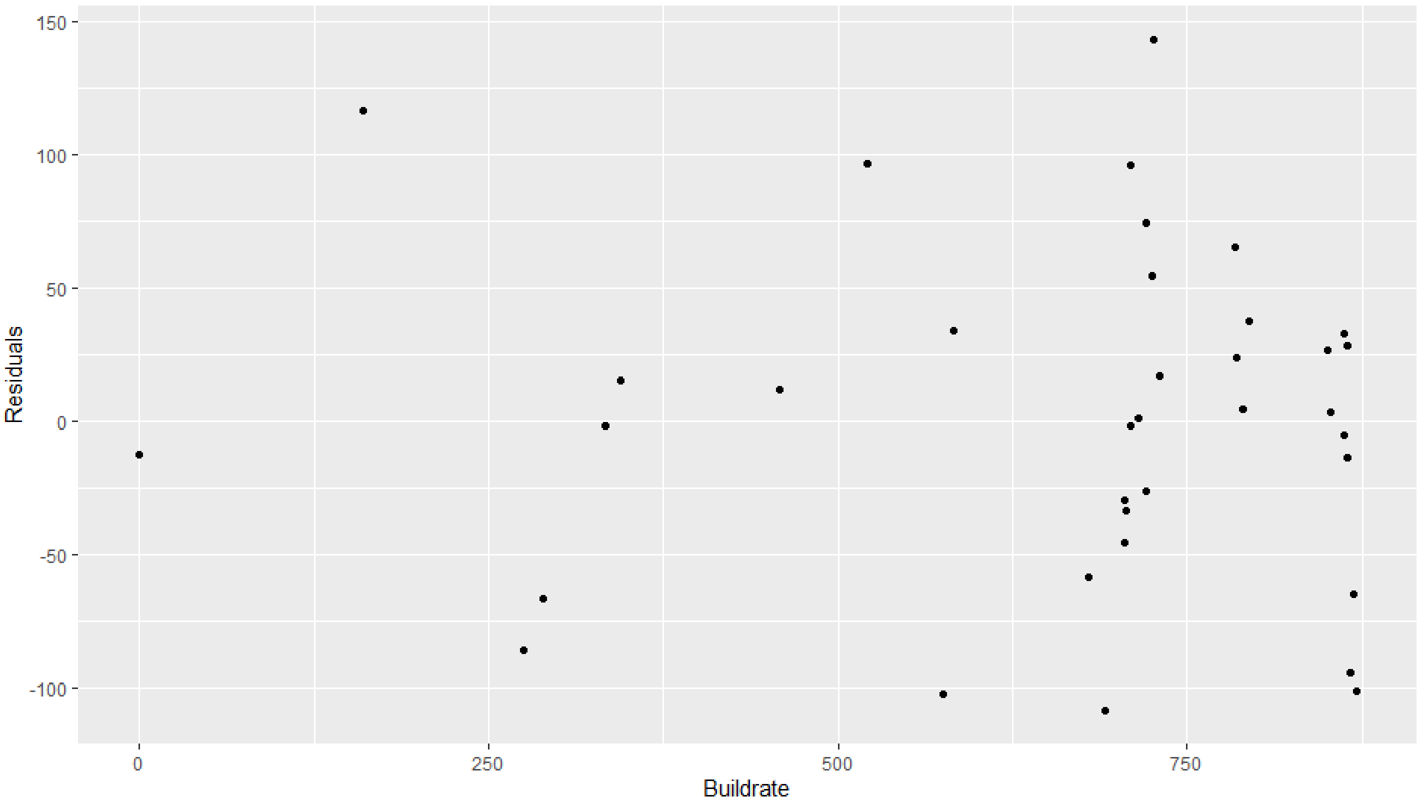
Assumptions testing of linear regression

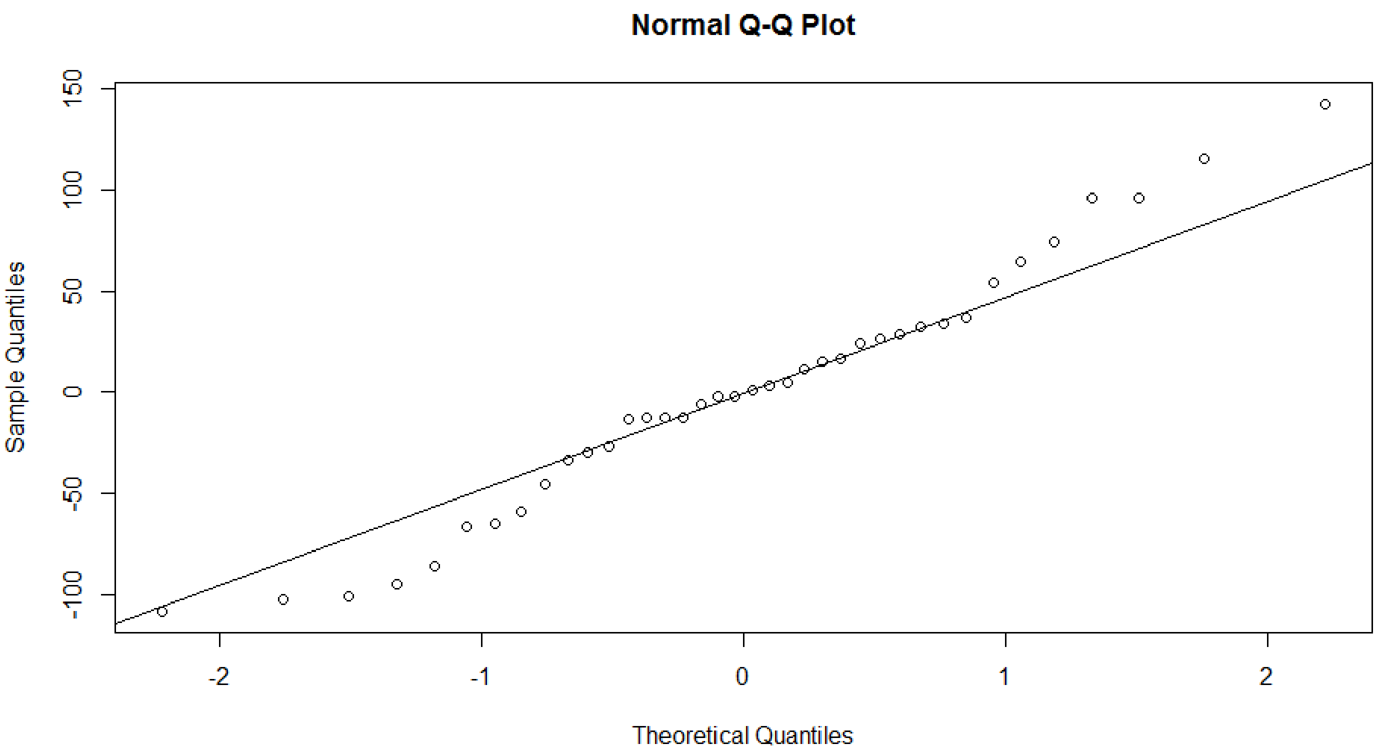
Article	p-value (Breusch-Pagan test)	p-value (Breusch-Godfrey test)
1287859	0.9643	0.5677
1377743	0.8674	0.6188
1849492	0.9176	0.7955
1849780	0.7573	0.2019
1878677	0.1906	0.7901
2121022	0.5051	0.1079
2208021	0.07081	0.258

Article 1287859

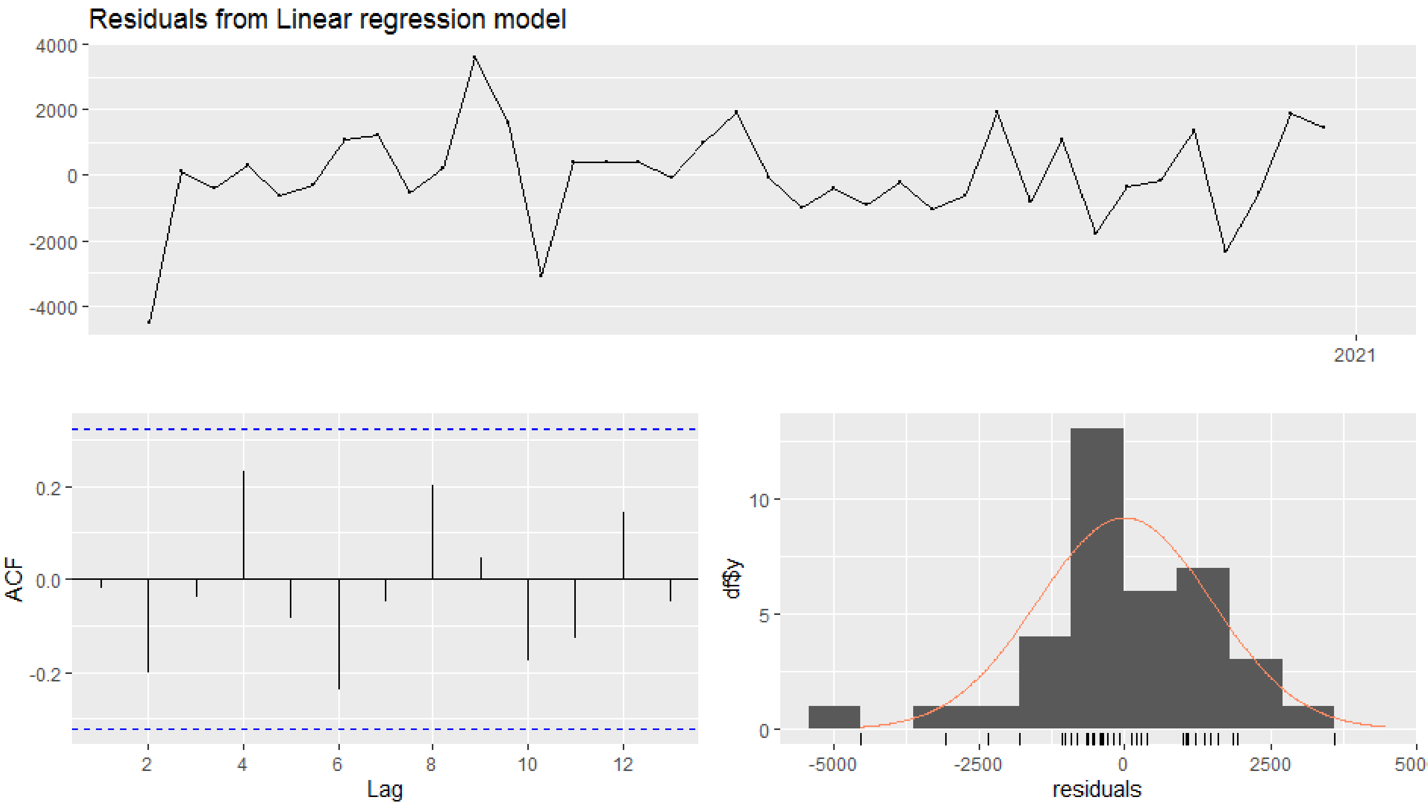


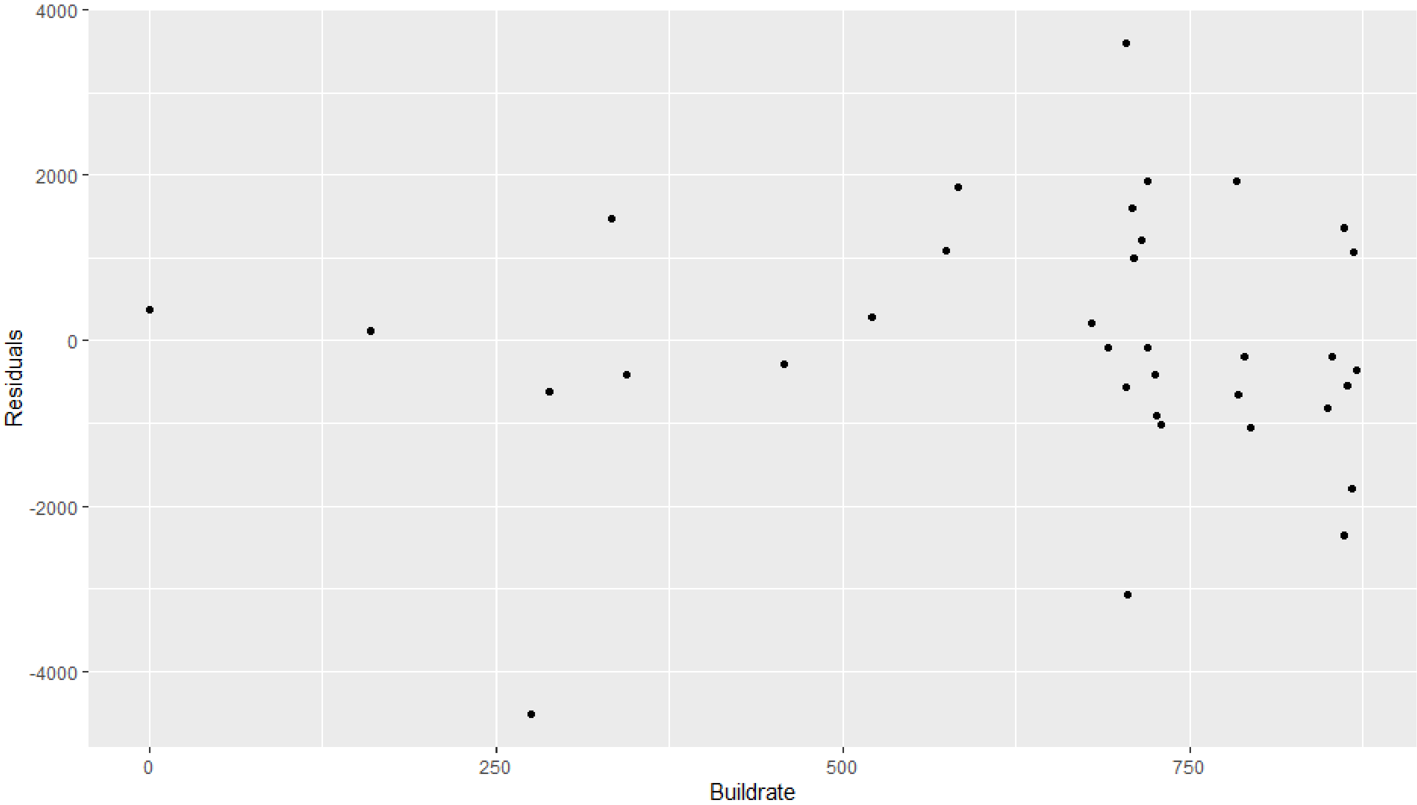
Residuals from Linear regression model
150
100
50
0
-50
-100
2021
ACF
0.2
0.0
-0.2
2
4
6
8
10
12
Lag
df$y
9
6
3
0
-200
-100
0
100
200
residuals

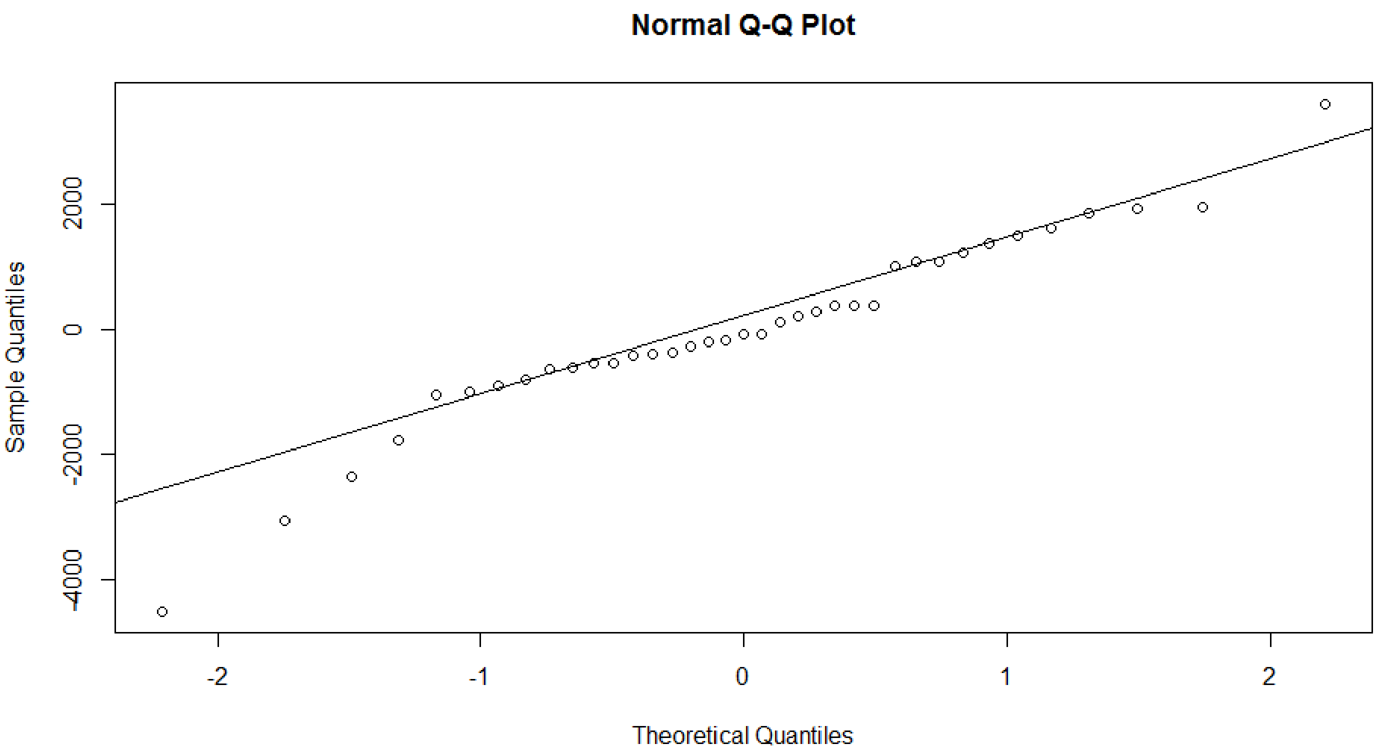

150
100
50
0
-50
-100
Residuals
0
250
500
750
Buildrate


Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles
150
100
50
0
-50
-100
-2
-1
0
1
2

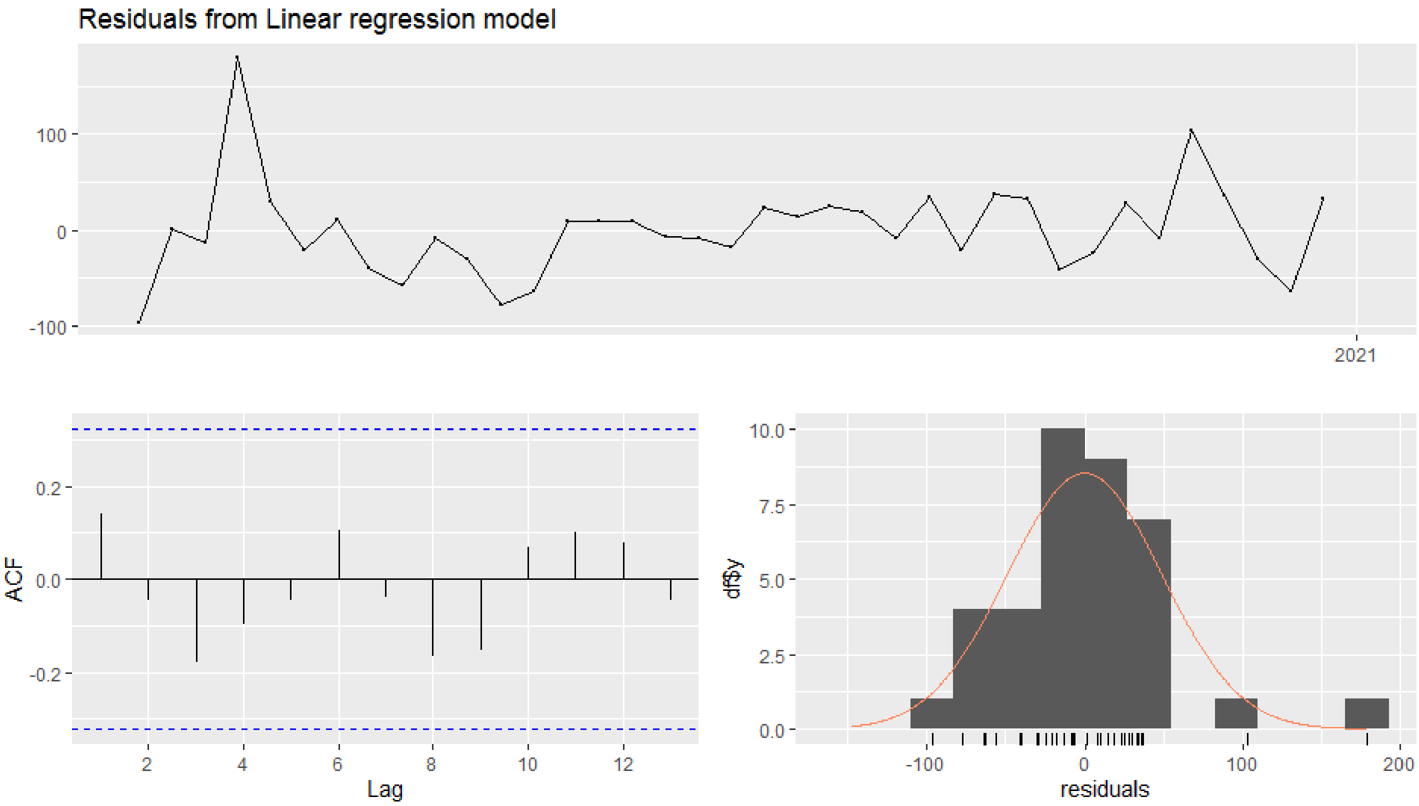
Article 1377743

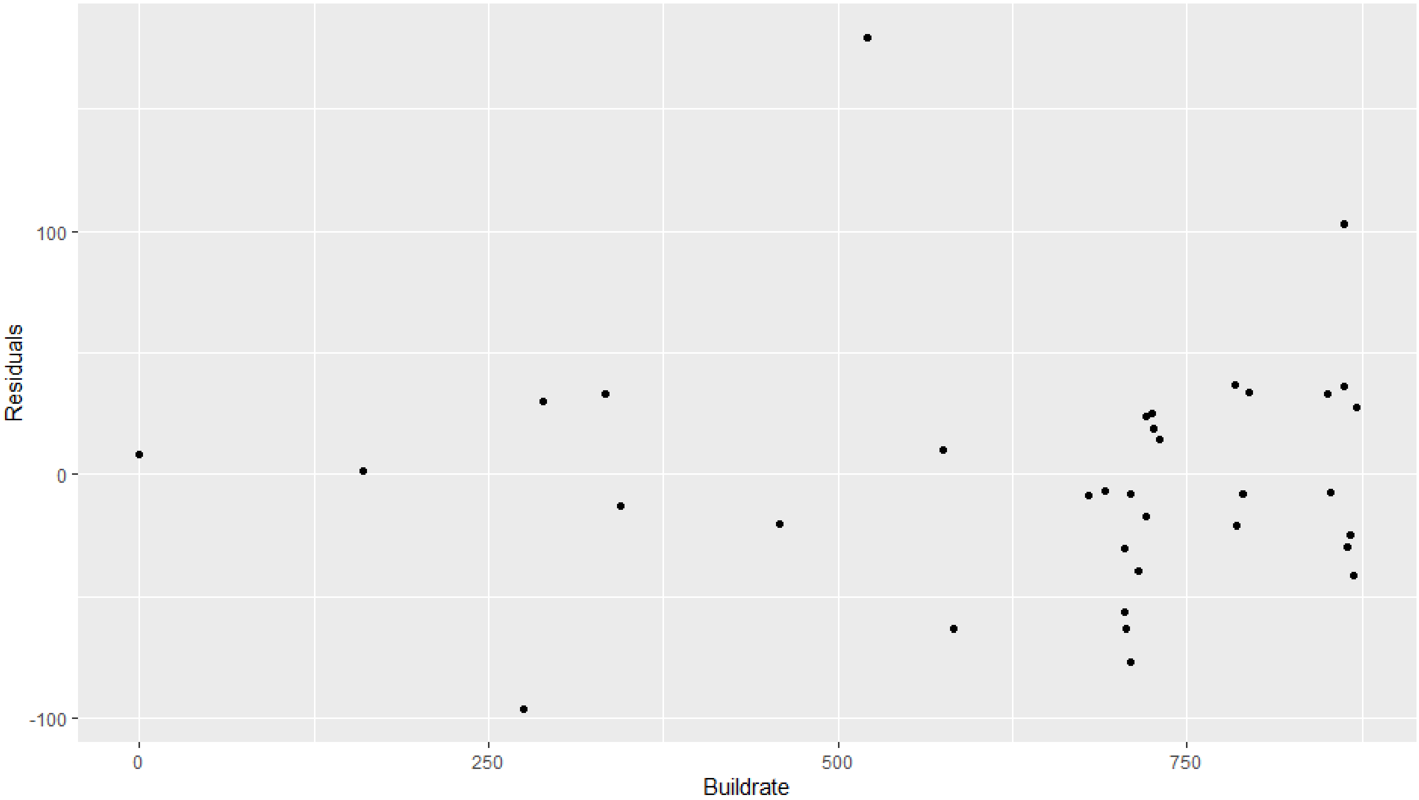


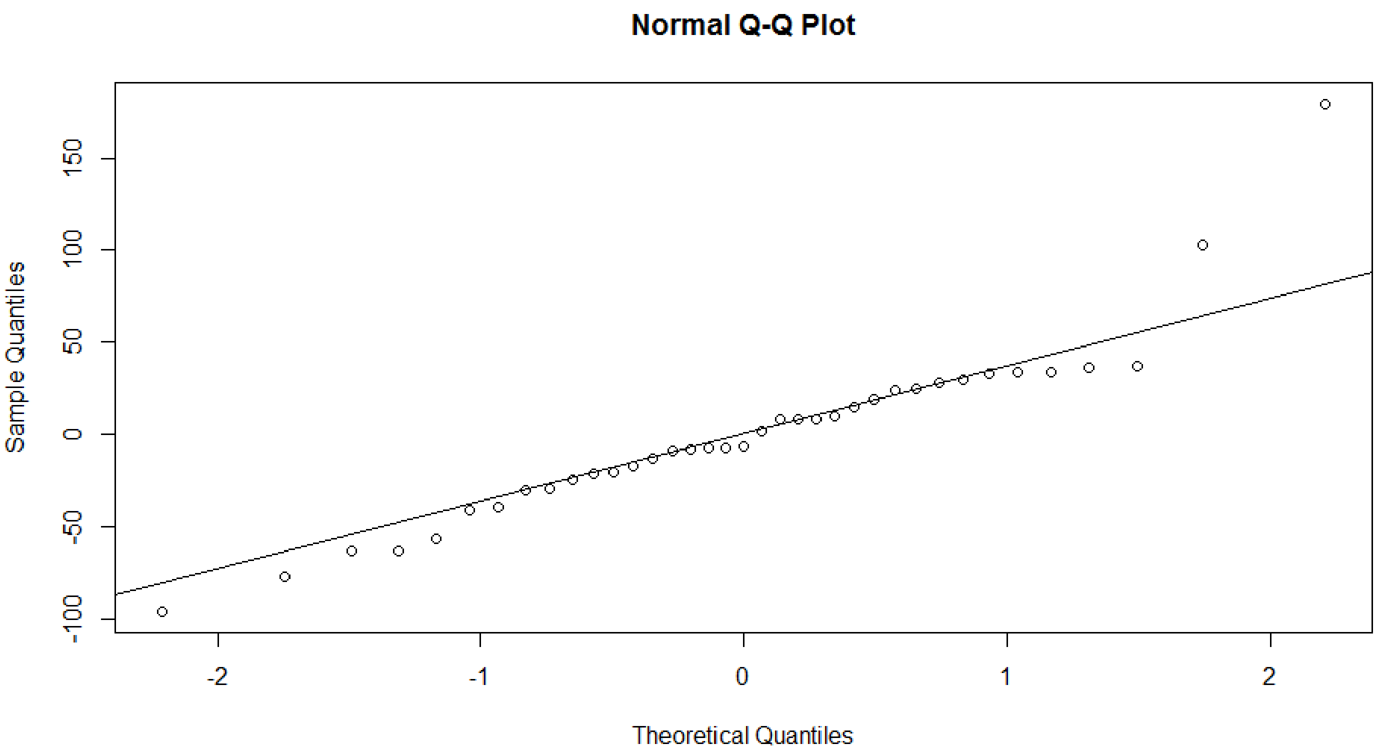

4000
2000
0
-2000
-4000
Residuals
0
250
500
750
Buildrate


Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles
2000
0
-2000
-4000
-2
-1
0
1
2

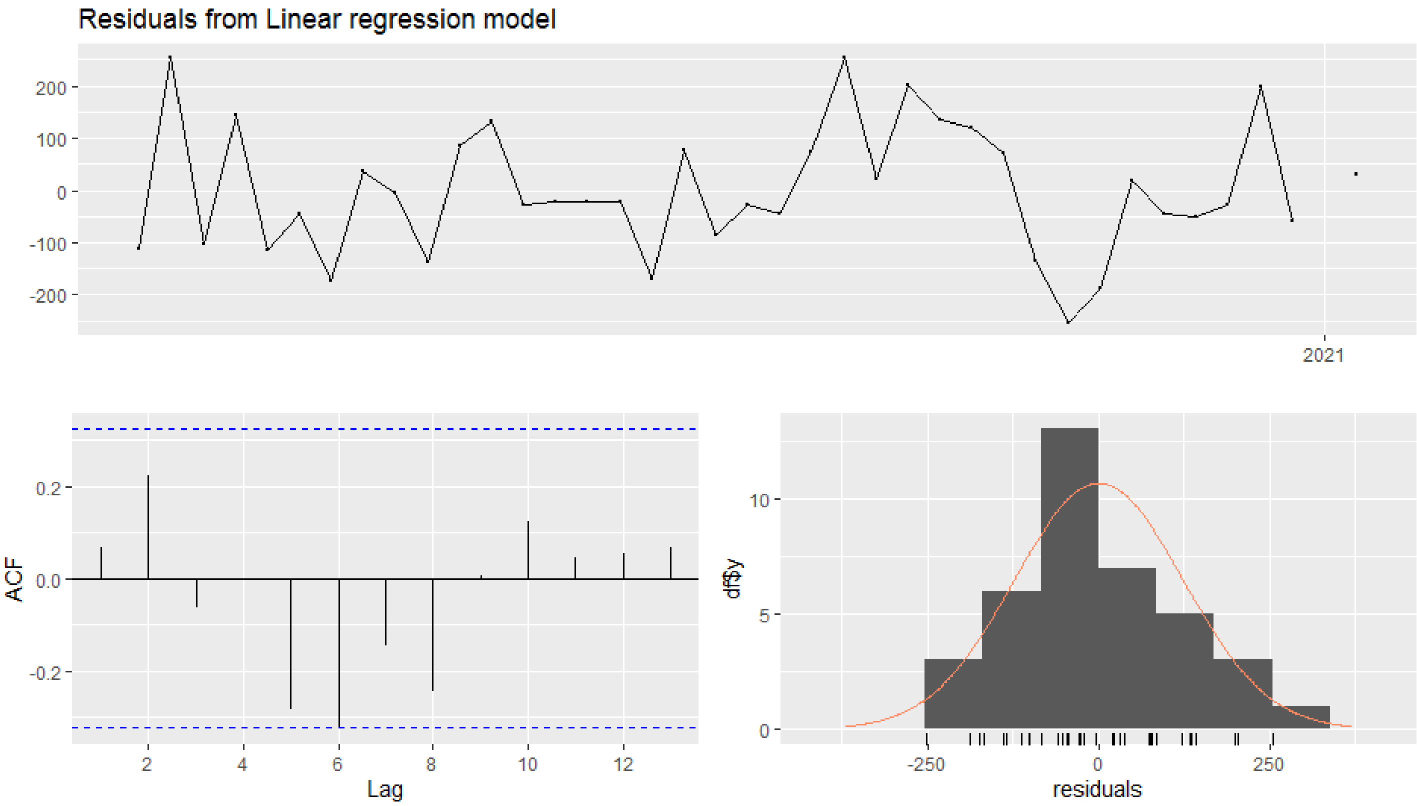
Article 1849492

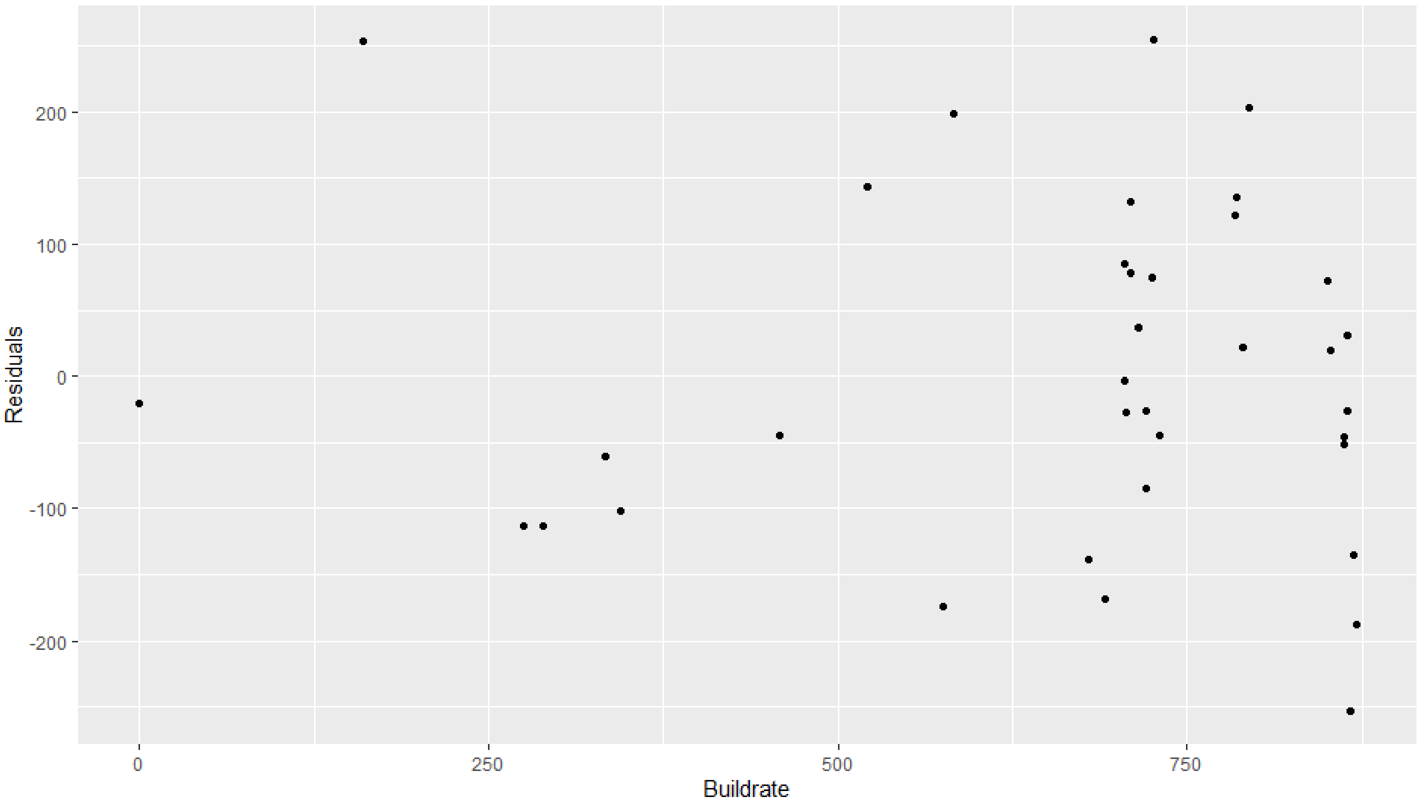


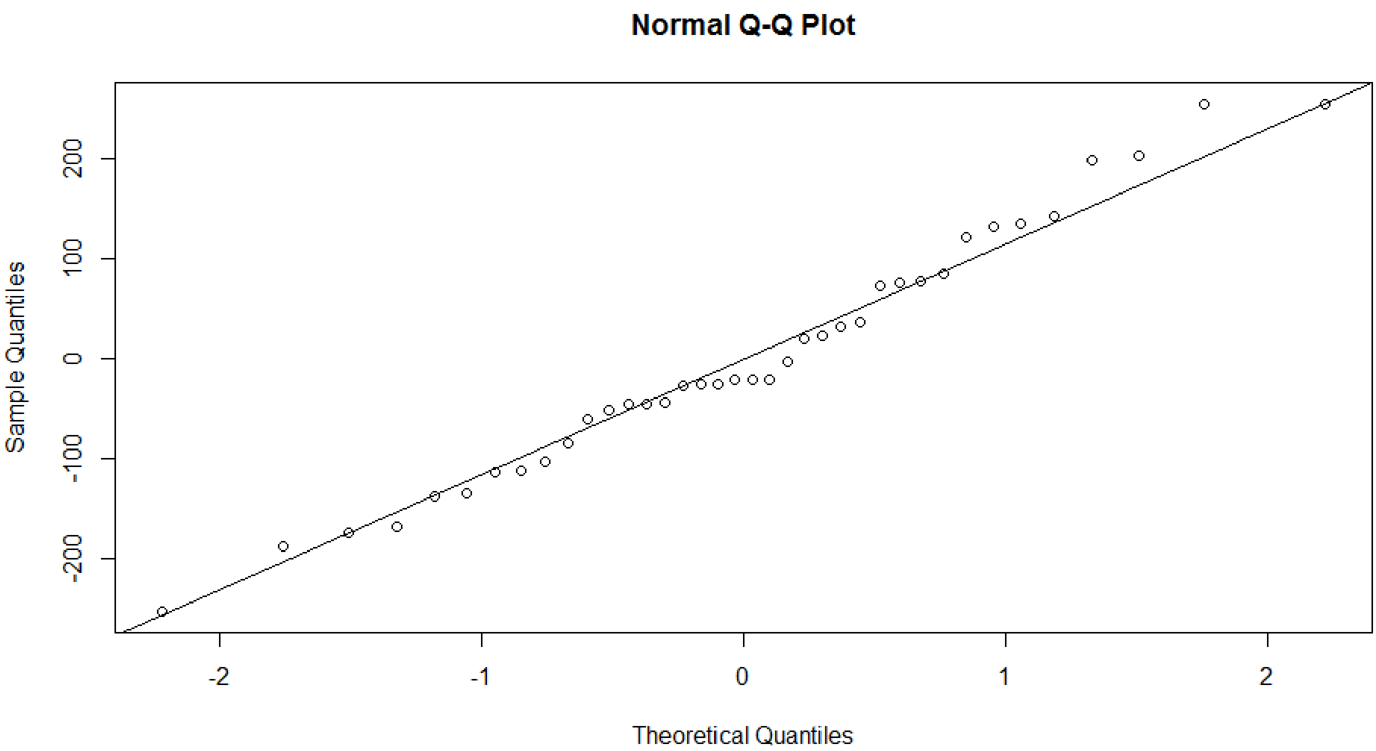

100
0
-100
Residuals
0
250
500
750
Buildrate


Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles
-100
-50
0
50
100
150
-2
-1
0
1
2

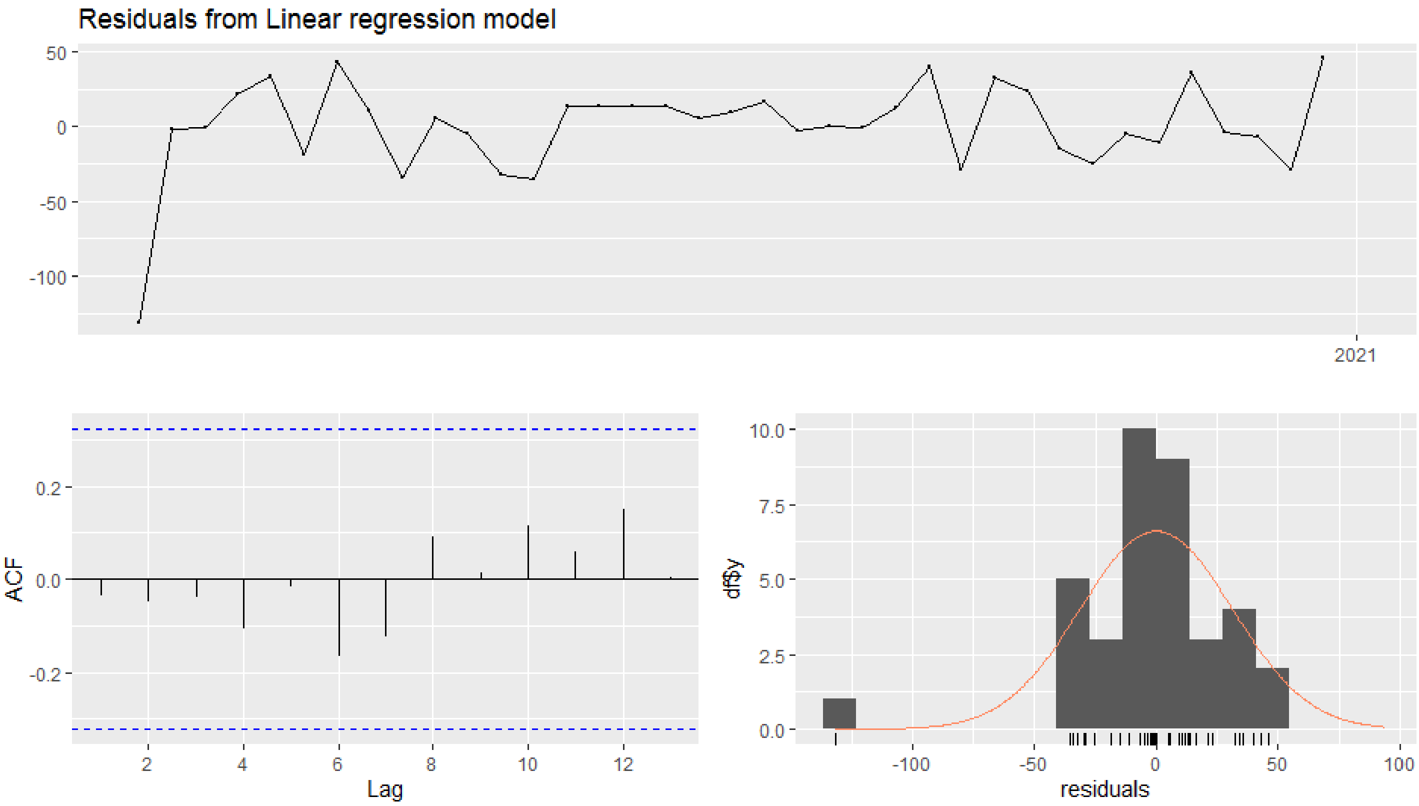
Article 1849780

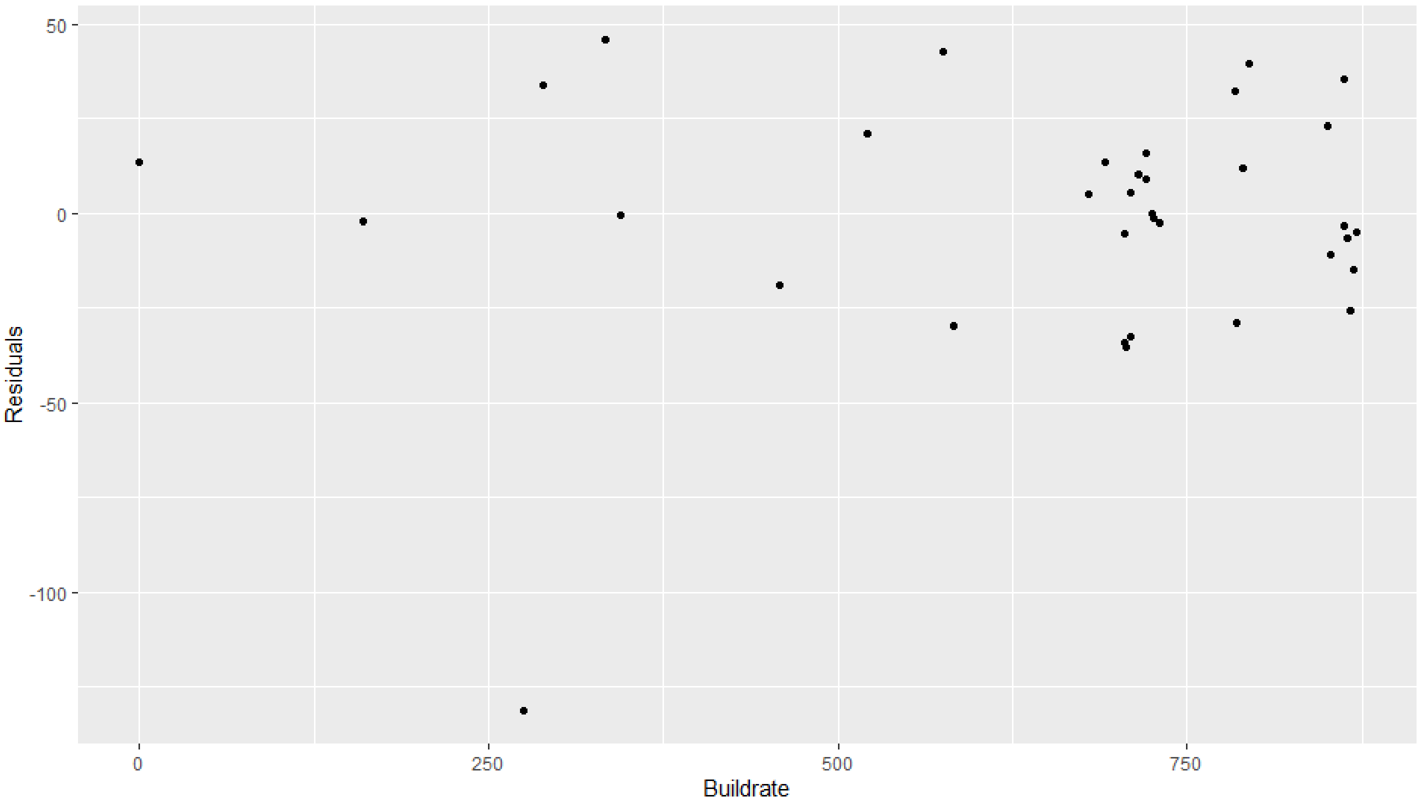


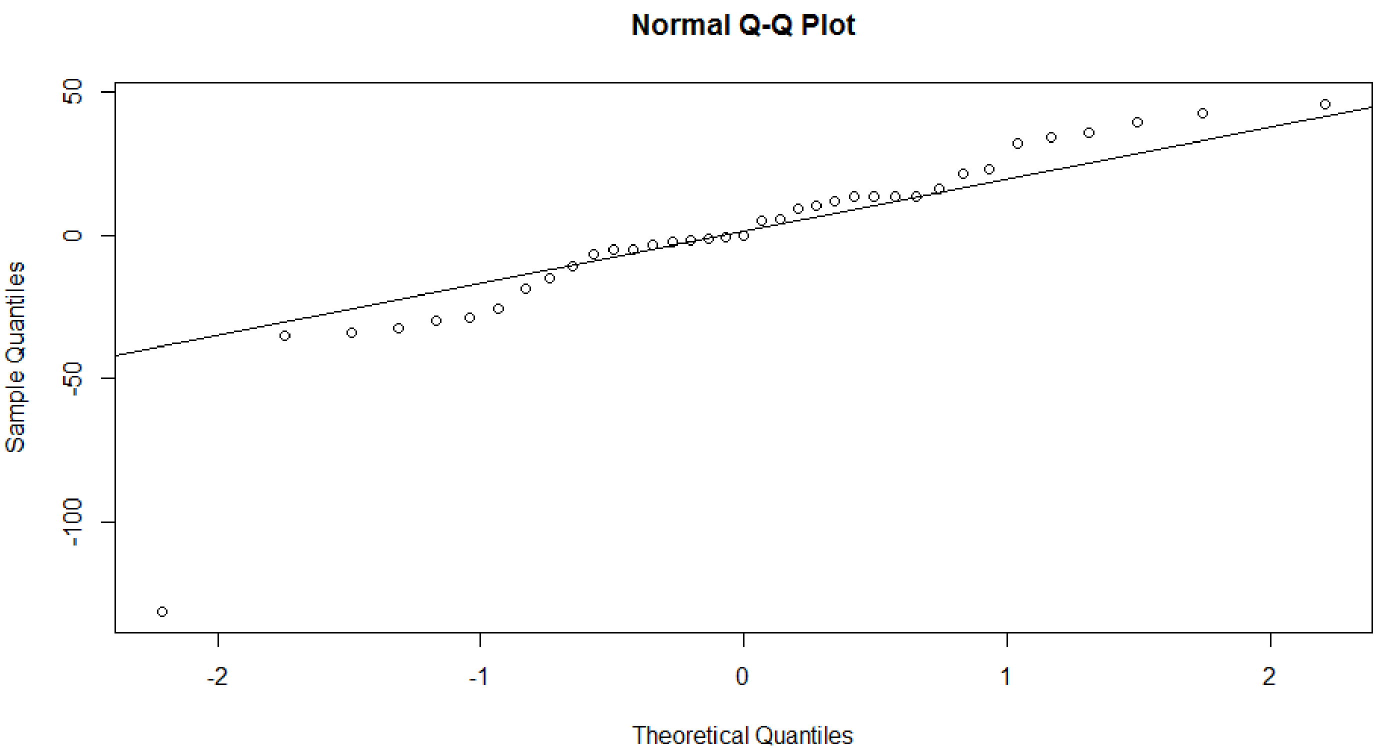

Residuals
200
100
0
-100
-200
0
250
500
750
Buildrate


Normal Q-Q Plot
Sample Quantiles
-200
-100
0
100
200
-2
-1
0
1
2
Theoretical Quantiles

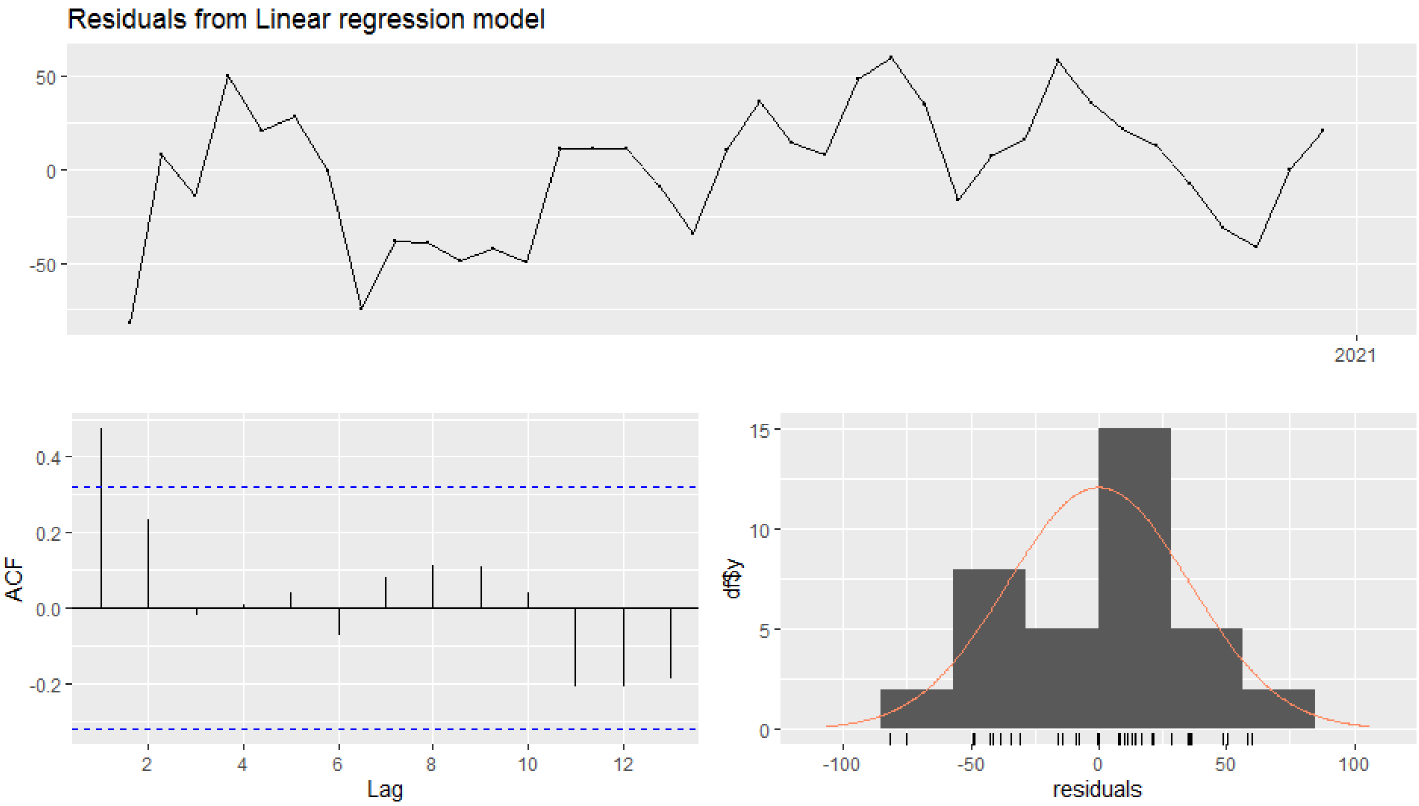
Article 1878677

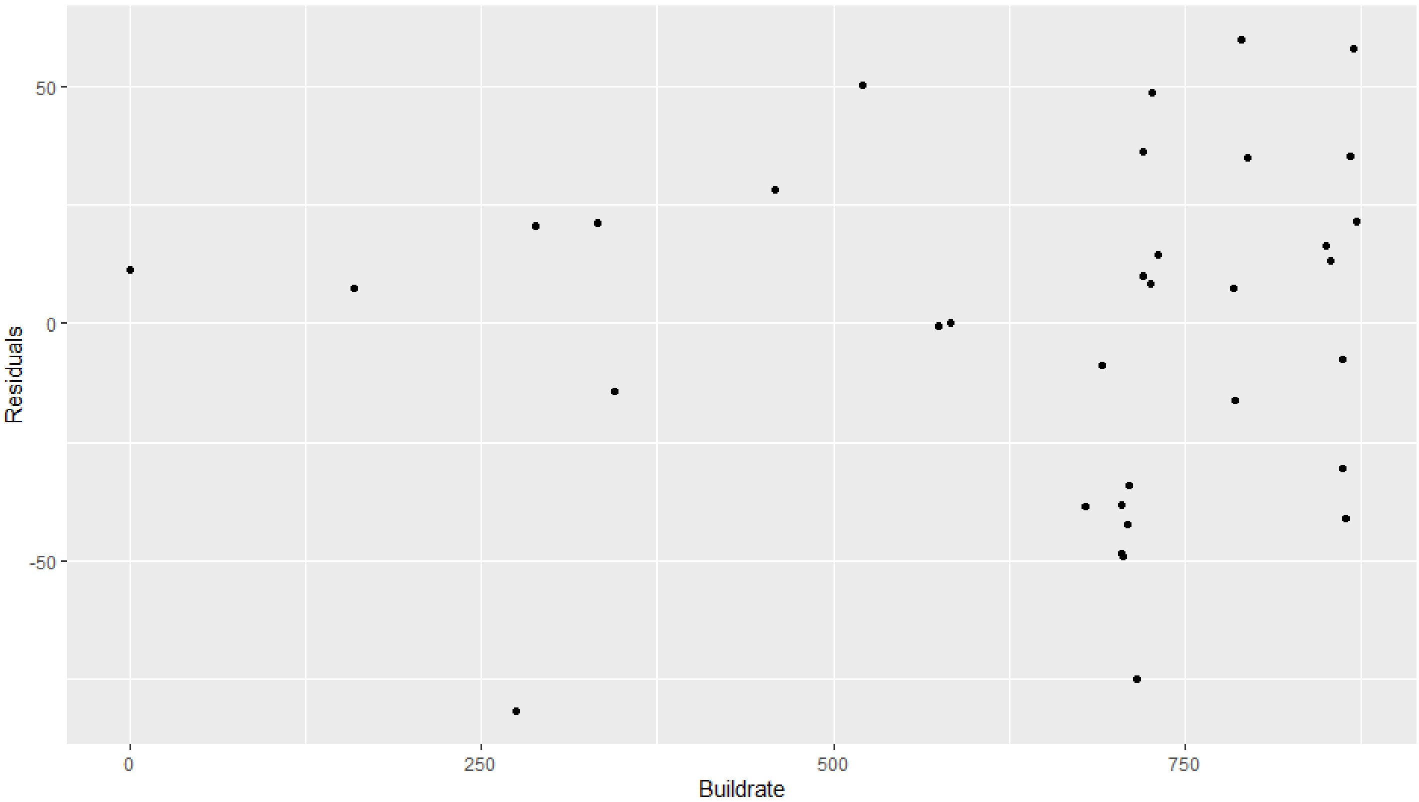


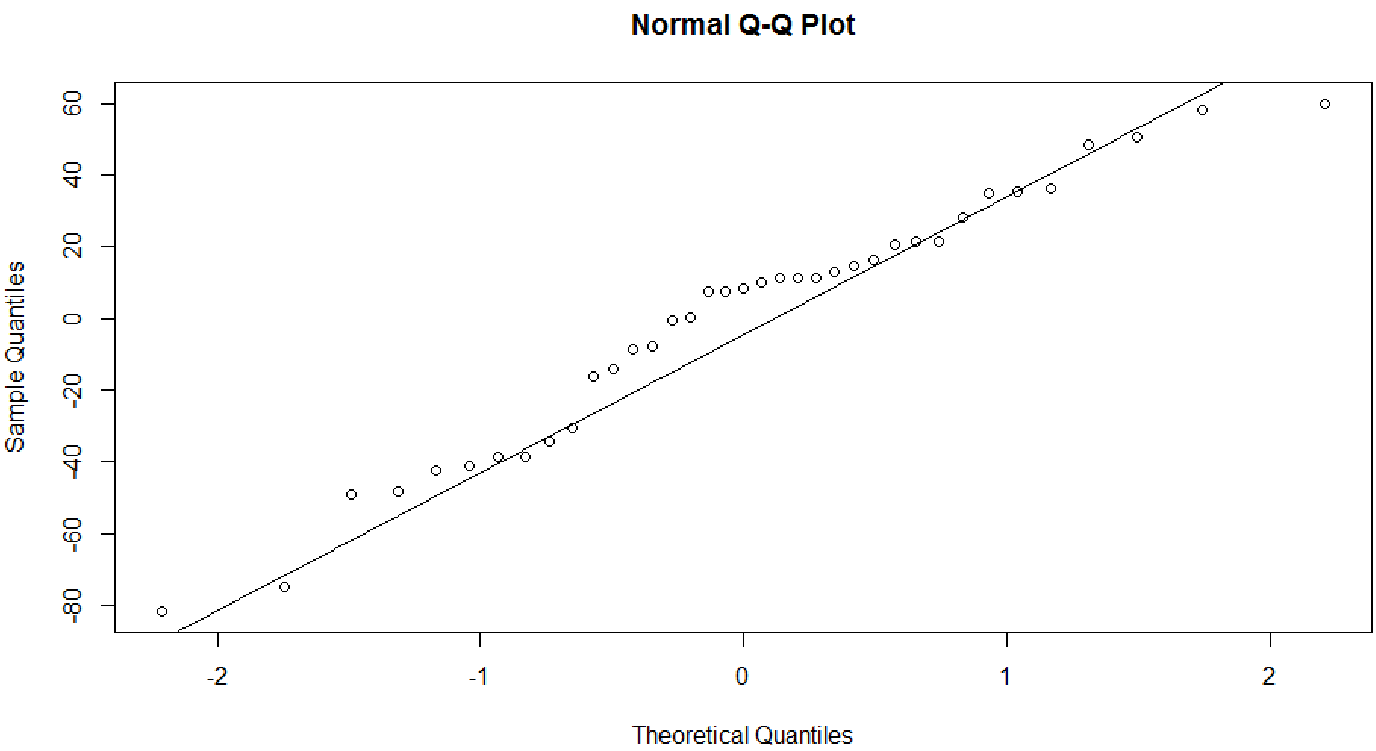

50
0
-50
-100
Residuals
0
250
500
750
Buildrate


Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles
50
0
-50
-100
-2
-1
0
1
2

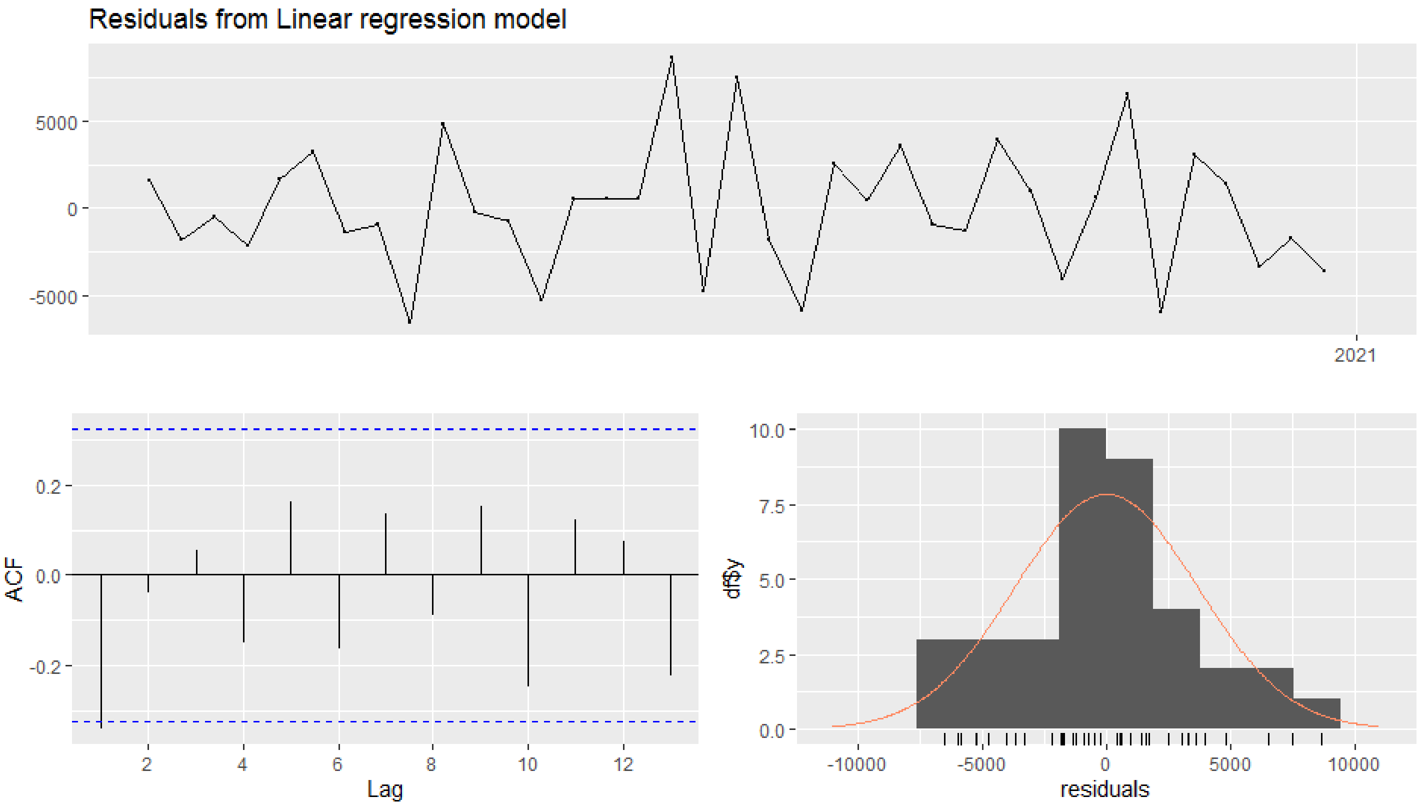
Article 2121022

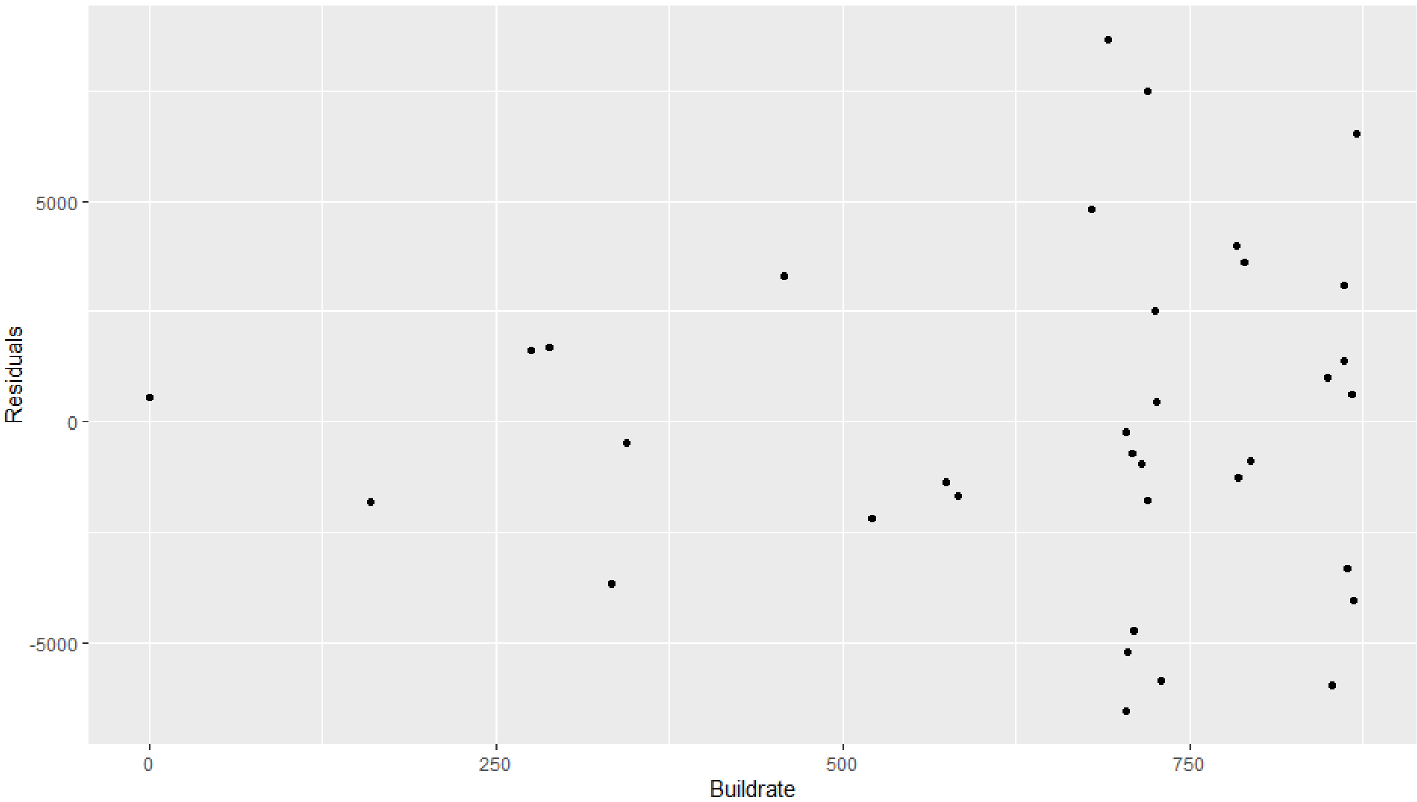


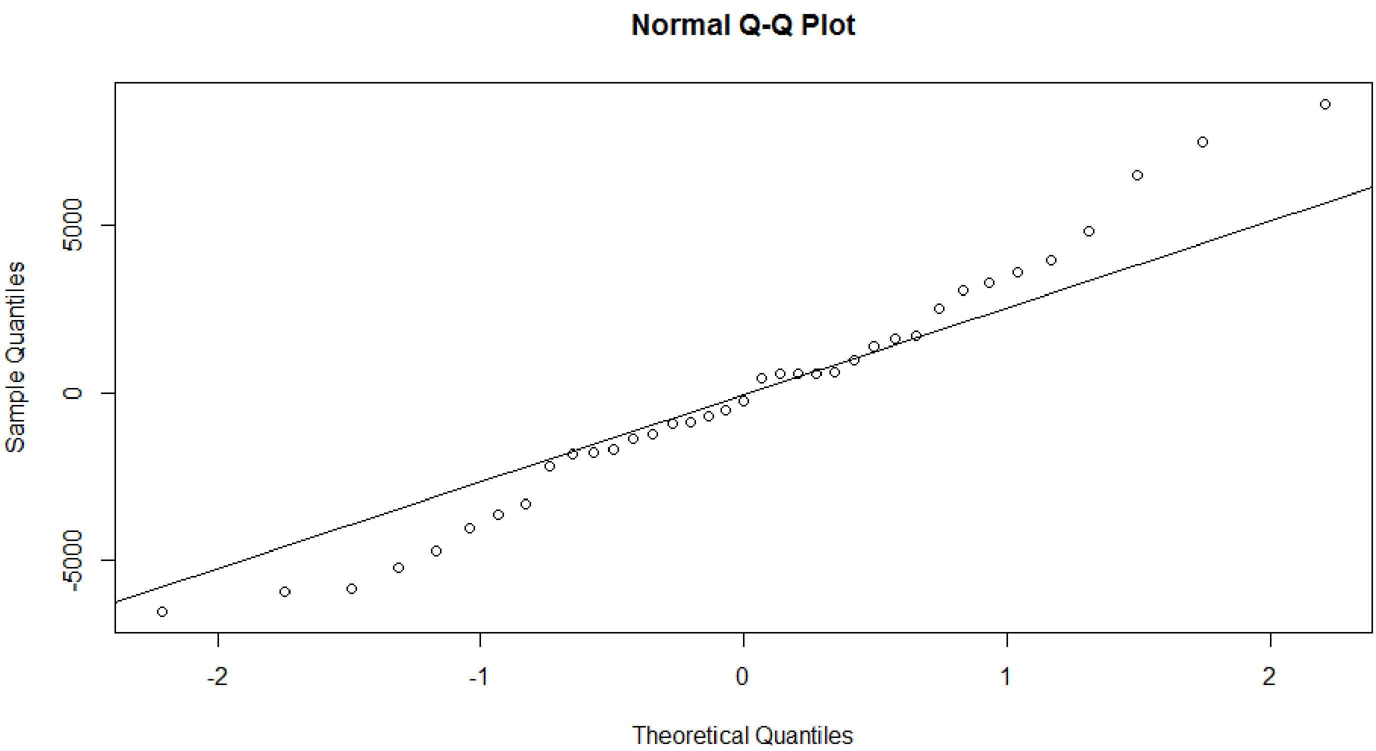

50
0
-50
Residuals
0
250
500
750
Buildrate


Normal Q-Q Plot
Sample Quantiles
60
40
20
0
-20
-40
-60
-80
-2
-1
0
1
2
Theoretical Quantiles

Article 2208021




Residuals
5000
0
-5000
0
250
500
750
Buildrate


Normal Q-Q Plot
Sample Quantiles
-5000
0
5000
-2
-1
0
1
2
Theoretical Quantiles

Appendix F

Parameter values for level forecasts

This appendix shows the smoothing constants for the exponential smoothing methods and the ARIMA parameters per article number.

Fastmovers YL98

	2126626	**2258740**	**2245745**
SES	$\alpha = 0.4$	$\alpha = 0.0001$	$\alpha = 0.0001$
ETS	$\alpha = 0.4$	$\alpha = 0.0001$	$\alpha = 0.0001$
Holt	$\alpha = 0.3$ $\beta = 0.2$	$\alpha = 0.0001$ $\beta = 0.0001$	$\alpha = 0.0002$ $\beta = 0.0001$
ARIMA	(0,0,0)	(0,0,0)	(0,0,0)

Slowmovers YL98

	0506834	**2157776**	**2184214**	**2126790**	**2258742**	**2258743**
SES	$\alpha = 0.005$	$\alpha = 0.1$	$\alpha = 0.001$	$\alpha = 0.7$	$\alpha = 0.5$	$\alpha = 0.001$
ETS	$\alpha = 0.005$ $\beta = 0.005$	$\alpha = 0.1$ $\beta = 0.01$	$\alpha = 0.005$	$\alpha = 0.35$	$\alpha = 0.5$	$\alpha = 0.0001$
Holt	$\alpha = 0.001$ $\beta = 0.001$	$\alpha = 0.1$ $\beta = 0.1$	$\alpha = 0.005$ $\beta = 0.001$	$\alpha = 0.001$ $\beta = 0.001$	$\alpha = 0.6$ $\beta = 0.0005$	$\alpha = 0.0001$ $\beta = 0.0001$
ARIMA	(0,0,1)	(0,0,2)	(0,0,2)	(1,0,1)	(0,0,0)	(0,0,1)

YL99

	0964061	**2048982**	**2245292**	**2245294**	**0966541**	**0966542**	**2261324**
SES	$\alpha = 0.4$	$\alpha = 0.25$	$\alpha = 0.75$	$\alpha = 0.4$	$\alpha = 0.3$	$\alpha = 0.5$	$\alpha = 0.05$
ETS	$\alpha = 0.35$	$\alpha = 0.3$	$\alpha = 0.6$	$\alpha = 0.4$	$\alpha = 0.4$	$\alpha = 0.4$	$\alpha = 0.1$
Holt	$\alpha = 0.01$ $\beta = 0.001$	$\alpha = 0.01$ $\beta = 0.001$	$\alpha = 0.5$ $\beta = 0.001$	$\alpha = 0.001$ $\beta = 0.001$	$\alpha = 0.01$ $\beta = 0.001$	$\alpha = 0.01$ $\beta = 0.001$	$\alpha = 0.01$ $\beta = 0.001$
ARIMA	(0,1,0)	(1,1,2)	(2,1,2)	(1,1,1)	(0,1,1)	(1,0,1)	(0,1,1)

Steering code 3

	0090861	**1377785**	**1257443**	**1881839**
SES	$\alpha = 0.18$	$\alpha = 0.9$	$\alpha = 0.9$	$\alpha = 0.01$
ETS	$\alpha = 0.18$	$\alpha = 0.9$	$\alpha = 0.9$	$\alpha = 0.1$
Holt	$\alpha = 0.5$ $\beta = 0.02$	$\alpha = 0.9$ $\beta = 0.001$	$\alpha = 0.5$ $\beta = 0.001$	$\alpha = 0.01$ $\beta = 0.001$
ARIMA	(1,1,0)	(1,1,0)	(1,1,0)	(0,0,1)