YES, WE WANT TO FORECAST! BUT HOW?

Forecasting the demand for truck drivers to optimize the business and its supply chain.

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PREFACE

This thesis is the final part of my Master Business Administration, with specialisation Digital Business. The thesis was commissioned by and done in collaboration with Bricklog BV. I want to thank everyone at Bricklog for this opportunity. In particular, I would like to thank Bart van Meulenbroek and Marjolijn Benneker for this opportunity.

During this thesis I have been able to develop myself, on a personal and professional level. In particular, I was able to strengthen my programming skills, knowledge of machine learning and logistics. I could not have done this without the help and trust of my first supervisor, dr. Matthias de Visser. I would therefore like to thank him. I really appreciated he gave me autonomy and the possibility to think out-of-the-box. Furthermore, the feedback and conversations helped me writing my thesis.

Also, I want to thank my family and friends. First of all, I would like to express my gratitude to my mother, my father, my sister and my boyfriend. They have really helped and supported me. Next, I want to thank my fellow students. Our discussions about academic, business and personal topics helped me a lot.

Finally, I would like to thank the University of Twente in general. During my studies at this university I discovered my passion for Business Administration and especially Digital Business. This thesis is a nice ending to a very educational and beautiful time.

Kirsten van Veen
Rijsenhout, August 2020

EXECUTIVE SUMMARY

This study was commissioned by and executed in collaboration with Bricklog BV. Bricklog BV is a company founded in 2015 by professionals who have years of experience in logistics companies and have had management positions in these companies. They started Bricklog to help smaller logistics companies with various business topics and problems. This study was carried out for Bricklog but also for all logistics companies. This report can be used for gaining information about forecasting in logistics processes. There is investigated how the demand for truck drivers can be predicted by testing the usability of various artifacts. Forecasting promises to deliver many benefits for businesses in the supply chain. These benefits are cost reduction, more on-time deliveries, reduction of the inventory, higher satisfaction among customers and better supply chain relationships for logistics companies. Besides, this research can help companies in the logistics industry with determining how many truck drivers they need in the future. This will most likely lead to cost savings. In order to determine how many truck drivers will be needed in the future planning, in this study three different dependent variables are predicted. At first, the Ratio Drivers/Pallets is predicted. In order to be able to predict the demand for truck drivers, the number of truck drivers needed is compared to the number of pallets to be transported in a day. Second, the variable Driving Hours per Pallet is predicted. This variable shows how much time it took to logistics one pallet. The third variable that is predicted in this research is Driving Hours. This is simply the total time of deployment of all truck drivers working that day. Next, there is investigated what influence external variables such as weather and traffic jam have on the forecasts. There is investigated whether these external variables can provide a better prediction or whether these variables deteriorate forecasting. It seems that the demand for truck drivers in relation to external variables has hardly been investigated in previous studies. However, it is suspected by experts of Bricklog that these external variables have an effect. There are also reports from the industry that these variables have an effect (TTM, 2019).

The approach of this research is a design research approach. Design research ensures that various artifacts are tested for usability to solve a real-world problem. In the study, both relatively new and relatively older forecasting techniques are used. A technique that is relatively new and little researched is the Support Vector Machine. The application of the SVM algorithm for data classification in the logistic domain seems promising. The artifacts have been assessed through performance measures. The used performance measures are accuracy, recall and precision. A second artifact was then developed. Linear Regression and Support Vector Regression were tested as forecasting techniques. Because these techniques are regression techniques, other performance

measures have been used for evaluation. The performance measures used are RMSE, MAE, MAPE, Aggregate forecast accuracy and R-squared.

The research showed that the first artifact, Support Vector machine, ultimately did not function sufficiently in the context of the research. The three dependent variables were not accurately predicted with the predictor variables used. On the contrary, the second artifact performed well. This second artifact consisted of the techniques Linear Regression and Support Vector Regression. Using Linear Regression made that the forecast was done accurately. Also, Support Vector Regression seems to perform well. This technique performed for a few forecasts even better than Linear Regression, but in general Linear Regression outperformed Support Vector Regression. Also, the three dependent variables could not be predicted equally well. I recommend fellow forecasters not to use the dependent variable, Driving Hours per Pallet. In contrast, dependent variables that were predicted accurately are the variable Ratio Drivers/Pallets and the variable Driving Hours. The dependent variable Driving Hours variable was best predicted. Additionally, this variable is also the simplest to predict, which is probably beneficial. This variable is best predicted with two lagged dependent variables as predictors. In this study, these are lagged dependent variables with t-1 and t-7.

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CHAPTER 1: INTRODUCTION

This research was commissioned by Bricklog. Bricklog is located in Apeldoorn and founded in 2015 by professionals with management positions at logistics companies. The founders have many years of experience in logistics and technology. The target group for their business is Small Medium Enterprises (hereinafter abbreviated as SME). Bricklog currently offers various services in the field of knowledge and network, projects and professionals and innovation and technology. Bricklog tries to adapt these services into what the logistics industry needs. For example, during the execution of this investigation, COVID-19 broke out, whereby Bricklog noted that the future for many companies (including their own) became uncertain. That is why employees of Bricklog quickly developed a *scenario planner* for these companies so that they would be able to map out different scenarios. Also, Bricklog wants to investigate another way of reducing the uncertainty of the future, which is forecasting. In the future, Bricklog wants to offer a new service, forecasting of logistics processes. Bricklog employees were already looking at the potential of forecasting (a subset of machine learning) before the outbreak of COVID-19. After the outbreak, they started to see the importance of forecasting even more. The challenge that Bricklog is facing today is to realize customer specific forecasting. The employees of Bricklog would like to know which forecasting technique to choose and which data they can use best. For this reason, this thesis is conducted in order to look for these answers. Also, this research could help other logistics companies to create accurate forecasts for logistics.

1.1 FORECASTING THE DEMAND FOR TRUCK DRIVERS AS A SERVICE

In the future, Bricklog wants to offer forecasts of several logistics processes. To try out forecasting, they want to start with one of the essential components of logistics, a forecast of the demand for truck drivers. Truck drivers form a large part of the workforce of logistics companies and are therefore essential. Bricklog kept an eye on the trends of forecasting and noticed that the demand for truck drivers depend not only on the customers of the logistics companies but also on external variables. For example, their customer Picnic, has found that weather variables influence the logistics process (TTM, 2019). Also, experts at Bricklog suspect that traffic jams delay the delivery of shipments and therefore, there are more truck drivers needed. Furthermore, fluctuations in the logistics process seem to play a role, like the number of pallets that should be transported and the time of the year. For example, logistics companies observed more activity at certain days, such as Christmas and King's Day (a Dutch national holiday).

Bricklog manages large data sets of different customers and would like to be able to offer forecasts based on these datasets. The datasets are each unique but contain similar information about the logistics processes of the customers. Logistics companies suspect they can save costs if they better predict the future. The better they can predict, the more costs they can save and better anticipate future developments. Such a forecast of future development could potentially be an as accurate as possible estimate of the future deployment of truck drivers. Deploying too many employees will potentially drive up costs, while during times with less activities insufficient incomes might be generated. Also, deploying not enough fix-contract employees will drive up costs since costs involved for temporary workers are significantly higher compared to fix-contract employees. Bricklog would like to make a forecast for their customers to predict how many truck drivers are needed per day. They want to be able to make this prediction a month in advance. It is expected that the forecast will be useful a month in advance because a company can start with more actively recruiting personnel or check whether a temporary contract will expire in the coming month. Also, Bricklog wants to offer the forecasting service in combination with scenario planning. With this, Bricklog wants to offer a total package for its customers, to make the best possible estimate of the future.

1.2 STRUCTURE OF THE THESIS

The outline of this thesis is based on the Design Science Research Methodology Process Model, abbreviated DSRM Process Model. This model was developed by Peffers, Tuunanen, Rothenberger, and Chatterjee (2007). The activities of this model are visualised in figure 1.

The structure above has been adopted in this study, and every activity is described in a separate chapter, except for the activity *Communication*. This entire thesis and its publication apply for the activity *Communication*. Also, some of the activities have been repeated; this is called iteration. Iteration is a possible part of Design Research. In the next chapter, Chapter 3, the DSRM Process Model is explained. Also, there is explained how this model is used in this research.

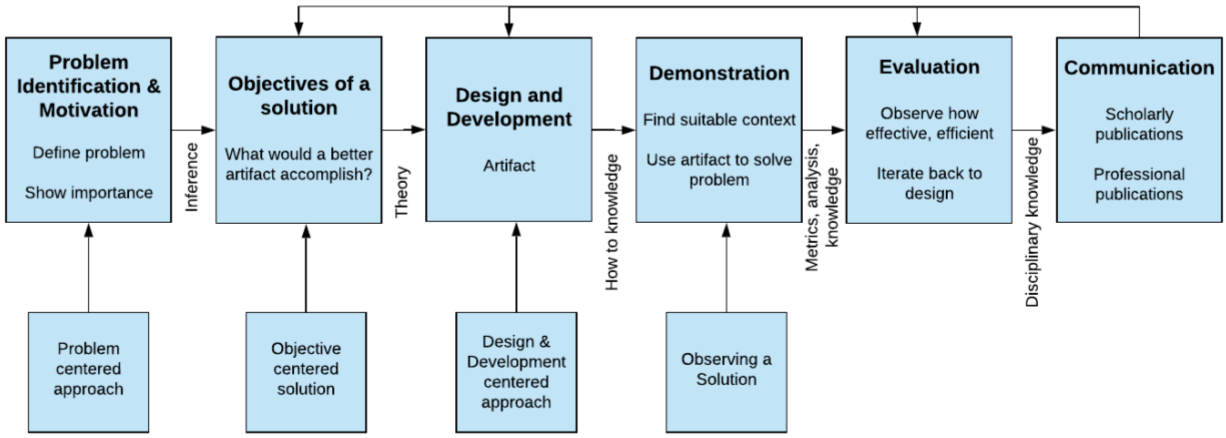

FIGURE 1: DESIGN SCIENCE RESEARCH METHODOLOGY (DSRM) PROCESS MODEL. ADAPTED FROM "A DESIGN SCIENCE RESEARCH METHODOLOGY FOR INFORMATION SYSTEMS RESEARCH", BY K. PEFFERS, T. TUUNANEN, M.A. ROTHENBERGER, AND S. CHATTERJEE, 2007, JOURNAL OF MANAGEMENT INFORMATION SYSTEMS, *24*, P.93. COPYRIGHT 2007 BY CLAREMONT GRADUATE UNIVERSITY.

1.3 DESIGN RESEARCH

Design research is chosen if there is a desire to improve the environment by introducing new and innovative artifacts and the introduction of the processes for building these artifacts (Simon, 1996). An artifact in the IT world is most of the time a construct, model, method of instantiations of new properties of technical, social of informational resources (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007). These innovative artifacts are used to solve real-world problems. Design research in the IT world focuses on the IT artifact in combination with high relevance for the application domain. In such an application domain, a specific goal is pursued with the use of organizational systems, people, and technical systems (Hevner, 2007). This research aims to investigate how the demand forecast for logistics can be forecasted accurately. For this reason, design research was chosen because various artifacts are tested for usability to solve a real-world problem. The use of a well-functioning IT artifact will be of high relevance to the application domain.

A design research approach is chosen to evaluate how different elements work in the design experiments carefully and then optimize the design as pleasant as possible (Collins, Joseph & Bielaczyc, 2004). In this investigation, combining different predictor variables and different forecasting techniques form the design experiments. These different design experiments are evaluated to arrive at the best working design eventually. To be more precise, there is investigated which dependent variables, which predictor variables and which forecasting technique will create the most accurate forecasting of the demand for truck drivers. In design research, the researcher will continually assess the design and then consider whether the design will have to be adjusted. The design will be adjusted as often as necessary (Collins, Joseph & Bielaczyc, 2004). Hence, for this research, it means that if the performance of the design is low, variables are removed to see if this improves the performance of the model. If this does not work, the choice will be made to use a different forecasting technique. Thus, the evaluation of the design is a relatively lengthy process that changes the design until the best outcome is clear (Collins, Joseph & Bielaczyc, 2004).

1.4 DESIGN SCIENCE RESEARCH MODEL METHODOLOGY PROCESS MODEL FROM PEFFERS, TUUNANEN, ROTHENBERGER, AND CHATTERJEE (2007)

The researchers aimed to create a transparent model for design research. They considered that this was lacking before. According to them, scientists who conducted design research were confronted with the lack of being able to refer to a generally accepted methodology for design research. As a result, design research was viewed by some as poor-quality empirical research. This model, which has similarities with the design research processes that have been used before in the IS discipline, has established a common framework for researchers that can validate design research. Peffers, Tuunanen, Rothenberger, and Chatterjee (2007) have compared and set out seven papers on the methodology of design research. Based on these seven papers, they have built a model that they believe is the most effective way to conduct design research (see figure 1). The model, abbreviated with DRSM, describes the structure that a scientist follows in the process of design research. The process has six activities in a nominal order. A researcher may choose to repeat some activities in the research process. This repetition is also called iteration. For example, a researcher finds out after evaluating the metrics of an artifact; the artifact is not yet working optimally. Therefore, he can decide to go back to the activity of Design and Development. Here, he can design a new artifact and then restart the process from 'design'. Also, the activity communication can be used to look back at the aim of the research and describe to what extent the aim of the research has been achieved (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007).

The DSRM model is structured in a nominal order. However, the researchers do not need to perform these steps in a specific order. It depends on the focus of the research with which step the researcher starts. If the research focuses on objectives for a solution phase, the research will start with that activity. The reason that the focus of a research is on objectives for a solution-phase is that the research is initiated because of a search for a proper solution for a particular problem. This solution will have to meet specific objectives to achieve what the researchers have in mind. The objectives of the desired solution are identified from the research question. These objectives may describe how a new artifact is supposed to support solutions to problems that have not been addressed so far. This artifact is designed in the design and development phase. This artifact is then demonstrated, evaluated, and communicated. Again, it is not necessary to follow this order. According to Peffers, Tuunanen, Rothenberger, and Chatterjee (2007), it does not matter which approach design research takes. They conclude that all approaches work equally well and that they are all effective in achieving the intended goal. Throughout this process, the focus is on achieving the objectives that the solution must meet. Researchers can categorize these objectives into the direct impact and the indirect impact of the design fact. It may, of course, be the case that the outcome of the study is that these objectives have not been achieved, for example, due to lack of time or possibilities (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007).

1.5 RESEARCH METHOD LITERATURE REVIEW

The most standard types of literature review methods are the systematic method and the narrative method. For quantitative research is the narrative method most common (Randolph, 2009). For that reason, the narrative style is used in the literature review of this thesis. Narrative literature reviews could include one or more questions, and articles could be selected without a precise specification of the selection criteria. The search words define the literature search and should be defined in such a way that all related articles will be found, and the irrelevant articles should not appear (Ferrari, 2015). The search words for the literature review of this thesis are the following:

- forecasting distributor supply chain
- forecasting logistics supply chain
- forecasting supply chain
- forecasting logistics
- machine-learning supply chain
- demand forecasting logistics
- demand forecasting supply chain
- performance measures forecasting
- accuracy measure forecasting

The search for relevant literature for this thesis is done via the websites Google scholar and Scopus.

CHAPTER 2: IDENTIFICATION OF PROBLEM AND MOTIVATION

⇒ **Problem**: an accurate method to forecast is missing for Bricklog and the logistics industry

Returning to the in the introduction described context of this study, this chapter will describe the problem in this context. This research is conducted to find a solution to this problem. Subsequently, in this chapter, there is described what this research will contribute, both in practical as theoretical way.

2.1 PROBLEM AND MOTIVATION

As described earlier, Bricklog wants to offer forecasts as a service. Nowadays, much data is available, and using this data can lead to benefits for the business. Analyzing and evaluating historical data can make the future of a business less uncertain. However, the problem is that the method of analyzing this data in a valuable way is missing. Commissioned by Bricklog, this research will therefore look for an accurate method to forecast logistics processes and specifically the demand for truck drivers. Besides, it is to be expected that other companies in the logistics industry will also want to know the potential of forecasting. The developed forecasting method can help Bricklog with forecasting. Also, there is intended that other companies in the logistics industry can use this method. Next, the structure of this thesis could be seen as an example of how to comprehensive and orderly set up a forecast that adds value to the business.

2.2 PRACTICAL CONTRIBUTION

There is a growing body of literature that recognises significant issues for companies in the logistics sector, caused by globalization and digitalization. First of all, supply chains have to deal with considerable flows in almost every industry (Hart, Lukoszová, & Kubíková, 2013). Secondly, there are more competitors in the market. In 2017, 5 thousand companies started in the logistics sector in the Netherlands, while in 2018, already 6.4 thousand companies started (Centraal Bureau voor Statistiek, 2019). Third, the logistics sector has difficulty recruiting personnel. There are 4.5 thousand more vacancies than a year ago (Centraal Bureau voor Statistiek, 2019).

To deal with these issues, owners or employees of these SMEs (small-medium enterprises) could try to predict the future. In general, forecasting is used to reduce the uncertainty that comes with trade-offs that the management of a company faces. Forecasting is making educated guesses for the uncertain future, and it is a rational process of extending historical information into the future (Hanke

& Wichern, 2014). These forecasts must be used in the decision-making process. A cost-benefit consideration is also essential here, which balances the costs of forecasting against the benefits it generates. Studies show the importance of accurate forecasting. Recent evidence suggests that accurate forecasting make a company more competitive because it could result in lower costs, more on-time deliveries, reduction of the inventory, higher satisfaction among customers and better supply chain relationships (Carbonneau, Laframboise, & Vahidov, 2008; Moon, Mentzer, Smith, 2003; Hanke & Wichern, 2014). Investigation showed that nowadays, forecasts are often calculated manually or estimated (so not calculated) based on previous experiences. In the last twenty years, statistical forecasting techniques have been improved and are becoming more accurate (Franses, 2014).

If an organization could make an informed decision about choosing and applying a proper performing forecasting technique to forecast developments in its supply chain, the organization could reap the benefits. Benefits of forecasting that could be expected from previous investigations are higher competitiveness, lower costs, more on-time deliveries, reduction of the inventory, higher satisfaction among customers, and better supply chain relationships (Carbonneau, Laframboise, & Vahidov, 2008; Moon, Mentzer, Smith, 2003). Additionally, every percentage that the accuracy of the forecast increases, the precision of the calculation for the needed inventory will also increase with one percentage (Kremer, Siemsen, and Thomas, 2015). Forecasting is of great importance in the current economy and society, which is continually changing and in the high interactive business environment (Hanke & Wichern, 2014). Forecasting is a process by which it is possible to get a presumption of analysing magnitude values evolution in the future (Hart, Lukoszová, & Kubíková, 2013).

2.3 THEORETICAL CONTRIBUTION

Studies over the past decades have provided valuable information on how well existing forecast techniques work and which one works best. With every new study in the field of forecasting, the academic world discovers more about the performance of those techniques. New techniques like Support Vector Machine came up and were compared with the existing older techniques. These techniques, in combination with the right features, can be used to predict the demand for truck drivers. In the context of forecasting the demand for truck drivers, there is little research into how the currently available techniques can optimally make this forecast.

Therefore, this research will investigate which available techniques will contribute to predict the demand for truck drivers accurately. The approach of design research science is used in this research. Design research is an effective way to make academic research more relevant, especially for research in management and information systems disciplines (Hevner & Chatterjee, 2010). With the knowledge that is gained in previous studies, an artifact will be designed and developed in this study. The artifact will contain a forecasting technique in combination with specific features. Then, that will be used and evaluated. The findings should make an essential contribution to the field of forecasting in the supply chain because there is tried to make an informed decision of how the demand for truck drivers could be predicted accurately. Next, there will be insights gained about the features (i.e. the weather, holidays) that influence the demand forecasting in the supply chain. Previous research did not succeed to formulate a clear and unambiguous answer to this question. By using design research in this thesis, the topic is systematically investigated. Every artifact that is executed will be evaluated. The evaluation is done using performance measurements.

CHAPTER 3: OBJECTIVES OF SOLUTION

⇒ **Solution:** a method for realizing an accurate forecast

⇒ **Objectives of solution:** accuracy with a minimum of 80%

⇒ **Other objectives**, with indirect impact:

- Cost reduction
- More on-time deliveries
- Reduction of the inventory
- Higher satisfaction among customers
- Better supply chain relationships for logistics companies.

A good result of performance measures of the forecast determines whether there is accurate forecasting or not. This study states that the objective of the solution is achieved when forecast is at least 80% accurate. The lower the accuracy, the higher the chance that a human being with an understanding of logistics can make the estimate better. The threshold is not set higher than 80%, because, at this threshold it is expected that the costs of deploying truck drivers can be reduced. Several outcomes of the forecast have been combined into one category. Also, Bricklog wants to offer the service of forecasting and thinks her customers will not be interested enough if the accuracy is lower than 80%.

3.1 OTHER OBJECTIVES WITH INDIRECT IMPACT

In addition to the direct objective as described above, secondary objectives are also pursued by conducting this research. Bricklog intends to contribute to the business of logistics companies with accurate forecasting. These secondary objectives will not be assessed in this research, but from the literature, these objectives, are expected as a result of forecasting. The expectation is that accurate forecasting causes lower operational costs, more on-time deliveries, reduction of the inventory, higher satisfaction among customers, and better supply chain relationships for logistics companies.

3.2 FOCUSSED CENTRAL RESEARCH QUESTION

For Bricklog, the solution to the problem is developing an accurate forecast to predict the demand for truck drivers. Therefore, finding an accurate way to forecast the demand is the purpose of this investigation. The research question is formulated based on this solution. The central research question of this research will be:

Consequently, the central research question of this research will be:

Research question: How can the demand for truck drivers in the logistics be forecasted accurately?

In the search for an accurate forecast, different forecasting techniques will be assessed. First, previous literature will be researched. Based on the literature, an appropriate forecasting technique will be chosen. Performance measures are used to assess the performance of the models. A selection of these performance measures will be extracted from previous academic literature, see chapter 3. Based on these performance measures, an answer will be given about the performance of the forecasting method. It is possible that when more than one method has a 'good' performance, methods will be combined.

To answer the research question, the question will be split into two sub-questions. The first sub-question is:

Sub question 1: Which forecasting technique performs well to predict demand for truck drivers accurately?

Next, there will be investigated which features influence the forecast of the number of truck drivers. From previous research, there is a choice made which features will be added to the forecast. Also, to find out how the demand for truck drivers in the logistics could be accurately forecasted, different dependent variables will be investigated. After all, the demand for truck drivers could be forecasted in different ways, and by comparing multiple variables, the best performing variable could be chosen.

So, the second sub-question is:

Sub question 2: What insights can be gained about forecasting the demand for truck drivers from the available dataset?

3.3 RESEARCH DESIGN

The reason this research is done is because Briclog wants to design an artifact that could realize an accurate forecast for the demand for truck drivers. Therefore, this research has a focus on the *objectives for a solution phase* of design research. This is because efforts are being made in this research to find a solution to a problem that has not been tackled before. In the academic world, there is comparable scientific research on the same topic, but no study investigated the problem with the most recent knowledge and techniques. This could be described as the problem of this research, the lack of knowledge about an accurate way to forecast demand for logistics with the use of most new knowledge and techniques. From knowledge of previous studies, it is not yet possible to give an unambiguous answer which forecasting techniques and which variables can best be used in demand for logistics. Also, there have been many developments in forecasting in recent years. That is why this research uses new knowledge to investigate which forecasting techniques and which variables can best be chosen. This combination will create an artifact. That new artifact is believed to support the solutions to the problem that has not been addressed so far. If it turns out that this artifact does not meet the stated objective, an accuracy of at least 80%, the theory will be reviewed. From there, an attempt will be made to create a new artifact. A new artifact will be again demonstrated and evaluated. In figure 2, this process is visualized.

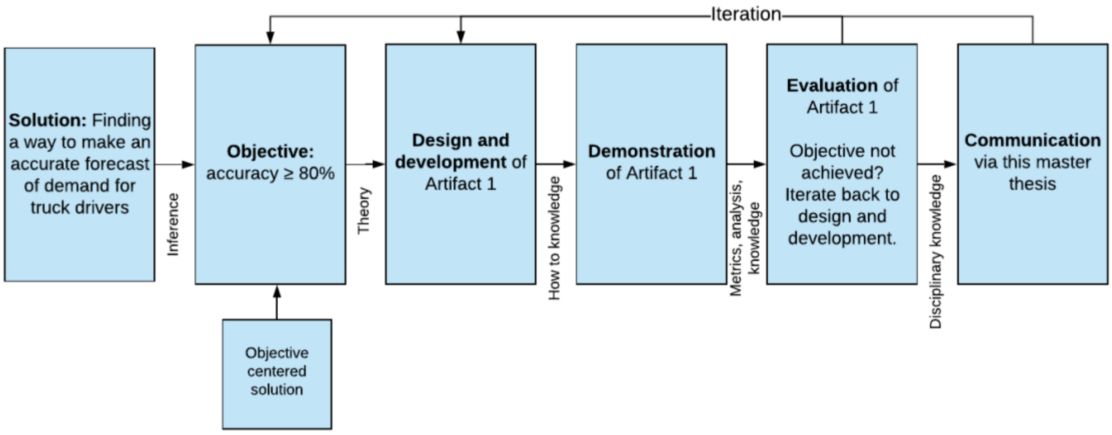

FIGURE 2: RESEARCH DESIGN OF THIS MASTER THESIS

CHAPTER 4: DESIGN AND DEVELOPMENT

4.1 THEORY

In this chapter, previous research about the topic demand forecasting in supply chain management is described. First, there will be explained what supply chain is. Secondly, there will be explained what is known about forecasting in supply chain, according to the literature. Third, the existing forecasting techniques will be explained. Fourth, several statistical forecasting techniques will be which statistical forecasting techniques exist.

4.1.1 SUPPLY CHAIN

In the last decades, there are many developments in the world of forecasting and supply chain management. Globalization and digitalization create new challenges in supply chain management and the internal logistics of companies worldwide. Nowadays, the supply chain has to deal with considerable flows in almost every industry. Managing these large flows can be done via forecasting (Hart, Lukoszová, & Kubíková, 2013). Before we delve deeper into forecasting in the supply chain, the supply chain itself will be explained first.

Supply chain management is a network of stakeholders that cooperate with the shared purpose to meet the customer demand (Perera, Hurley, Fahimnia, & Reisi, 2019). The most critical components of a supply chain are purchasing, manufacturing, packaging, inventory, logistics, and reverse material flow management (Hart, Lukoszová, & Kubíková, 2013). All parties in the supply chain are directly or indirectly concerned with meeting the demand of the consumer (Chopra & Meindl, 2012). Each party in the supply chain has a specific influence on the supply chain. It can be an organization, but also a business unit in an organization. The vast majority of supply chains can be divided into a stream of different parties; they are supplier, manufacturer, distributor, retailer, and consumer. Of course, this division cannot always be made, but in the context of this research, these categories will be used. The order of the parties in the supply chain is also critical. The sequence is shown in figure 3. Figure 3 shows a simplified version of a supply chain (Syntetos, Babai, Boylan, Kolassa, & Nikolopoulos, 2016).

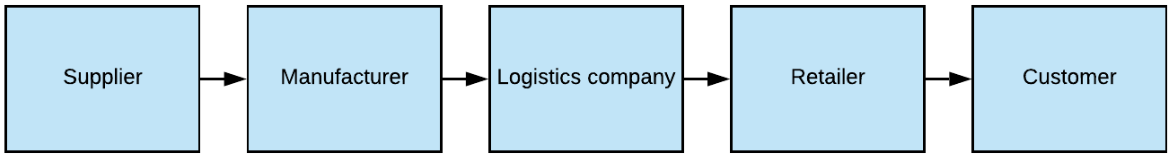

FIGURE 3: SIMPLIFIED MODEL OF PARTIES IN THE SUPPLY CHAIN MODEL

4.1.2 FORECASTING IN SUPPLY CHAIN

So, all parties in the supply chain directly or indirectly depend on consumer demand. Only the retailer has the exact and most actual information about this consumer demand because the consumer directly purchases from the retailer. The other parties in the supply chain do not have this information. Of course, these parties can ask for this information, but there is the risk that the quality or actuality of the data has deteriorated. Each party could try to predict what the purchasing party will demand, but how further away the party is from the customer in the supply chain, the more the forecast error and the demand distortion increases (Metters, 1997). This effect is called the Bullwhip Effect. This effect is often described in academic articles but might be overestimated according to other research (Sucky, 2009). Cachon, Randall, and Schmidt (2007) found evidence that only in wholesale industries, the bullwhip effect is present. In retail industries, the effect is most of the time not present.

All activities that a party in the supply chain does to predict the future situation is called supply chain forecasting (Ord & Fildes, 2013). Figure 4 shows how supply chain forecasting is for each party different. Each party could make a forecast based on the party that is before them in the supply chain. An example of such forecasting activity is a supplier who supplies to a manufacturer and tries to predict how much raw materials and goods the manufacturer will demand from him. This prediction often can be made by analyzing historical data. The demand for a particular product or service is influenced by various features. Those features need to be taken into account in the forecast of the demand. Such features are seasons, national holidays, characteristics of the weather (like temperature, rain, wind), promotions, promotions of the competitor(s), prices, past sales, the sale of similar products are influencers of the demand and the state of the economy (Aburto & Weber, 2007; Ord & Fildes, 2013).

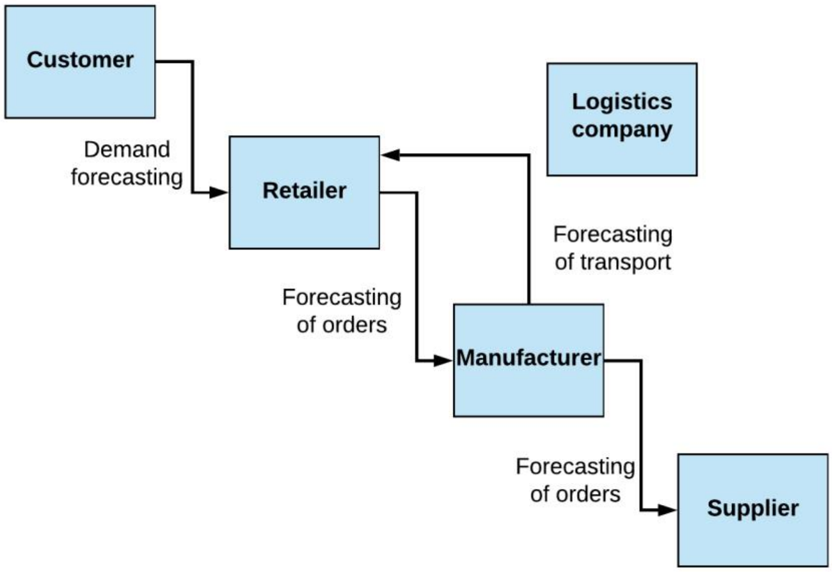

FIGURE 4: SIMPLIFIED MODEL OF POTENTIAL FORECASTING ACTIVITIES. BULLWHIP EFFECT MIGHT APPEAR IN FORECASTING ACTIVITIES FAR AWAY FROM THE CUSTOMER.

Supply chain forecasting includes dealing with complex issues, such as coordinating and sharing information among the various parties (Syntetos, Babai, Boylan, Kolassa, & Nikolopoulos, 2016). Sharing this accurate information among the parties in the supply chain in collaboration is vital to avoid the bullwhip effect. A problem that arises with these collaborations is that digitalization and globalization stimulate a trend towards dynamic and agile supply chain management. This leads to more flexible and adaptive business processes. It discourages companies from engaging in collaborations for the long term (Vakharia, 2002; Gunasekaran and Ngai, 2004). Another problem that may arise in the current situation of forecasting in the supply chain is the increase in the possibilities of artificial intelligence and machine learning. Because a multitude of possibilities can quickly generate predictions, it happens that there is less logical thinking is done. There is a lack of managerial supervision in forecasting and forecasting techniques can lead to expensive decisions, which yield relatively little (Hanke & Wichern, 2014).

It appears that stakeholders in the supply chain make decisions on operational, managerial, and strategic levels based on demand forecast data (Fildes, Goodwin, & Lawrence, 2006). In other words, the need for forecasts is in all functional lines in the organization, but it also appears to be needed for all types of organizations (Hanke & Wichern, 2014). Demand forecasting is predicting how much of a product or service will be needed in the future. The prediction is usually based on historical sales data (Perera, Hurley, Fahimnia, & Reisi, 2019). Demand forecasting is crucial for making the right decision cause the demand is a driving force for every component of a supply chain (Hart, Lukoszová,

& Kubíková, 2013). Some researches even take it a step further. Perera, Hurley, Fahimnia, & Reisi (2019) call demand forecasts the lifeblood of supply chains. Forecasting could give a company better competitiveness because it could result in lower costs, more on-time deliveries, reduction of the inventory, higher satisfaction among customers better supply chain relationships (Carbonneau, Laframboise, & Vahidov, 2008; Moon, Mentzer, Smith, 2003). Additionally, other research has shown that for every percentage that the accuracy of the forecast increases, the precision of the calculation for the needed inventory will also increase with one percentage (Kremer, Siemsen, and Thomas, 2015).

4.1.3 FORECASTING TECHNIQUES

There are three types of forecasting distinguished in the literature. Figure 5 presents these types of forecasting and their relationship to demand history and forecast horizon types are divided based on the two dimensions demand history and forecast horizon. In 1995 researchers Mentzer and Kahn (1995) found that back then the most popular technique in forecasting was *judgemental forecasting* (also called *expert judgment*). This type of forecasting, via human intervention, creates forecasts for the long term based on a low demand history (Syntetos, Babai, Boylan, Kolassa, & Nikolopoulos, 2016). Since the development of data-based methods, the importance of the judgemental method has also grown significantly. The judgment can be used to review and perhaps modify the forecasts that are made with data (Hanke & Wichern, 2014). This brings us to the next type of forecasting technique. The integration judgment in model-based statistical forecasting is called *integrated statistical judgmental forecasting* (Franses, 2014). This type is based on more extended demand history and predicts a shorter forecast horizon (Syntetos, Babai, Boylan, Kolassa, & Nikolopoulos, 2016). The third type of forecasting came up in the last decade and is called *statistical forecasting.* Many researchers try to improve existing statistical forecasting techniques or try to come up with new, better techniques. Statistical forecasting is usually preferred for short time horizons (like the upcoming week), under the condition that there is a vast demand history (Syntetos, Babai, Boylan, Kolassa, & Nikolopoulos, 2016).

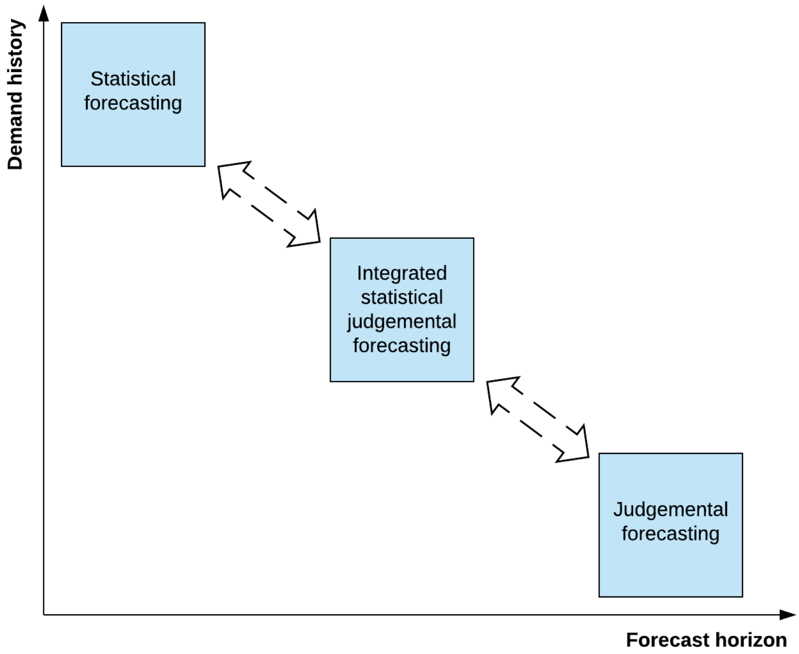

FIGURE 5: THREE TYPES OF FORECASTING AND THEIR RELATIONSHIP TO DEMAND HISTORY AND FORECAST HORIZON. ADAPTED FROM "SUPPLY CHAIN FORECASTING: THEORY, PRACTICE, THEIR GAP AND THE FUTURE", BY SYNTETOS, A. A., BABAI, Z., BOYLAN, J. E., KOLASSA, S., & NIKOLOPOULOS, K., 2016, *EUROPEAN JOURNAL OF OPERATIONAL RESEARCH, 252*, P.14.

4.1.4 STATISTICAL FORECASTING TECHNIQUES

There are different methods of statistical forecasting. Traditional statistical forecasting methods are Autoregressive Integrated Moving Average (ARIMA) models, created by Box and Jenkins (1994) and exponential smoothing, created by Winter (1960). Other, relatively simple, techniques are naïve forecast, average forecast, moving average forecast, and trend forecast. These traditional methods have compared to other forecasting techniques high levels of error, especially trend forecasting, and naïve forecasting. ARIMA is one of the most used techniques for forecasting (Carbonneau, Laframboise, & Vahidov, 2008). Research showed that these traditional methods do not perform well in the dynamic, non-linear, and complicated character of demand forecasting in the supply chain (Sarhani & El Afia, 2014). Techniques with significantly higher performances in supply chain demand forecasting are Support Vector Machines (SVM) and Multiple Linear Regression (Linear Regression) (Carbonneau, Laframboise, & Vahidov, 2008; Kandananond, 2012). The method Support Vector Machines (SVM) is still explored by many researchers nowadays (Maniatis, 2017). Another method that is often used in forecasting is Artificial Neural Networks (ANN) (Gupta & Pal, 2017). Kandananond

(2012) found that SVM performance better than ANN. Some researchers believe that Support Vector Regression, the regression variant of Support Vector Machines, will ultimately replace ANN (Maniatis, 2017). Carbonneau, Laframboise, and Vahidov (2008) found that RNN and SVM do outperform Neural Networks, but do not outperform Multiple Linear Regression. SVM seems to be a suitable method for forecasting, Villegas, Pedregal, and Trapero (2018) even call it the best method in a recent study. They state that SVM is most interesting in highly dynamic and inconsistent environments. They state that SVM is the best technique because it allows that the model could be changed when the model does not fit the data well.

4.2 ARTIFACT 1: SUPPORT VECTOR MACHINE

Following the theory, there is decided to use the Support Vector Machine for forecasting. SVM is new and seems promising, so this research uses this new forecasting technology to predict the demand for truck drivers. Also, Recurrent Neural Network appears to be a suitable method, but there is chosen not to use this technology as an artifact. The reason not to use a Recurrent Neural Network is that Bricklog customers have a basic knowledge of technology and machine learning. The execution and interpretation of the Support Vector Machine are a lot less complicated. In the next section, there will be explained how Support Vector Machine works.

4.2.1 TECHNIQUE: SUPPORT VECTOR MACHINE

A Support Vector Machine is an algorithm and a mathematical entity often used to assign labels to objects, also known as classifying. A mathematical function is maximized on a collected data collection. This chapter will provide a further explanation of how a Support Vector Machine works. To understand the essence of classification with the Support Vector Machine, four basic concepts are explained in the next sections: the separating hyperplane, the maximum margin hyperplane, the soft margin, and the kernel function.

4.2.1.1 HYPERPLANE

First of all, the Support Vector Machine divides the data into clusters. To explain the essential operation of a Support Vector Machine, an example of a two-class variable will be given. The mechanism of a Support Vector Machine with a two-class variable and is similar to a Support Vector Machine with a multi-class variable (Noble, 2006). Suppose that data is divided into two different classes of the dependent variable. The dependent variable in this example has the classes "red" and "green". Figure 6 shows a visualization of data that is divided into a green class and a red class. This visualization shows that each observation from the data set is red or green and shows that each observation is positioned on the graph. In this example, the classes are divided almost perfectly. A clean line can be drawn through these two classes, see figure 7, A Support Vector Machine uses this line to divide the data. This line is called a hyperplane. If the Support Vector Machine wants to predict the class of a new observation, the SVM determines which the class of this observation should have, based on the information of the predictor variables (Noble, 2006).

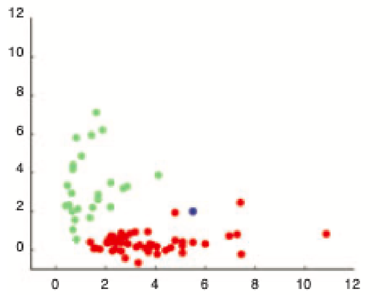

FIGURE 6: OBSERVATIONS HAVE THE CLASS "GREEN" OR CLASS "RED" AND ARE POSITIONED BASED ON THE PREDICTOR VARIABLES. ADAPTED FROM "WHAT IS A SUPPORT VECTOR MACHINE?," BY W. S. NOBLE, 2006, *NATURE BIOTECHNOLOGY, 24*, P. 1566. COPYRIGHT 2006 BY NATURE PUBLISHING GROUP.

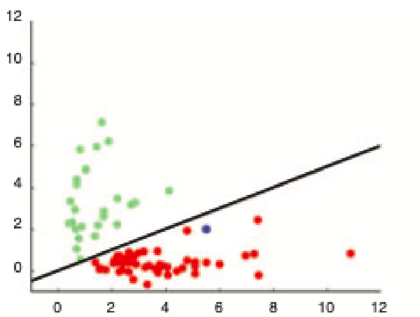

FIGURE 7: A LINE CAN BE DRAWN THROUGH THE TWO CLASSES. THIS LINE IS CALLED A HYPERPLANE. ADAPTED FROM "WHAT IS A SUPPORT VECTOR MACHINE?," BY W. S. NOBLE, 2006, *NATURE BIOTECHNOLOGY, 24*, P. 1566. COPYRIGHT 2006 BY NATURE PUBLISHING GROUP.

4.2.1.2 HYPERPLANE WITH MAXIMUM MARGIN

The method of classification, as described above, is not unique. Other algorithms also use this method of drawing a hyperplane between classes. Where SVM differs from these other algorithms is the way this hyperplane is selected. Figure 8 shows that a hyperplane could also have been positioned in other ways in the previous example. Which hyperplane is chosen is very important for the final prediction made by the SVM. The hyperplane selected by the SVM is the line with the most distance from the observations closest to the line. See figure 9 of a visualization of this line of the described example. This hyperplane is called the maximum margin hyperplane. The observations closest to the hyperplane are called support vectors. These support vectors are fundamental because they determine the final hyperplane. This mathematical approach does not assume that the variables in the data set follow a normal distribution (Noble, 2006).

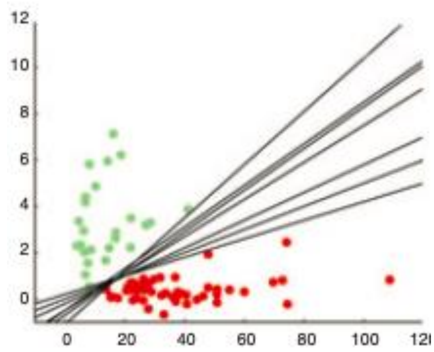

FIGURE 8: MANY POTENTIAL HYPERPLANES COULD BE DRAWN TO DIVIDE THE DATA. ADAPTED FROM “WHAT IS A SUPPORT VECTOR MACHINE?,” BY W. S. NOBLE, 2006, *NATURE BIOTECHNOLOGY, 24*, P. 1566. COPYRIGHT 2006 BY NATURE PUBLISHING GROUP.

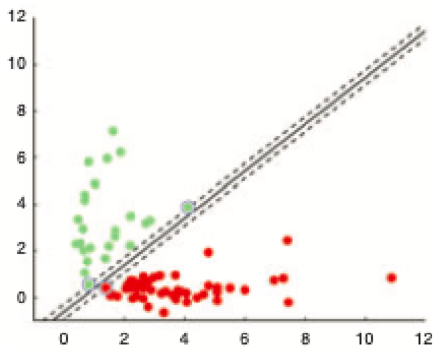

FIGURE 9: THE SUPPORT VECTOR MACHINE CHOOSES HYPERPLANE WITH MAXIMUM MARGIN. ADAPTED FROM “WHAT IS A SUPPORT VECTOR MACHINE?,” BY W.S. NOBLE, 2006, *NATURE BIOTECHNOLOGY, 24*, P. 1566. COPYRIGHT 2006 BY NATURE PUBLISHING GROUP.

4.2.1.3 THE SOFT MARGIN

So far, a linear line has been described in the example. However, an SVM is also able to analyse data that cannot be distinguished so straight and obvious. It is possible that the distribution of the classes "green" and "red" is a lot less clear to see with the naked eye. For this reason, an SVM algorithm can add a soft margin. This ensures that some observations can also be on the "wrong" side of the line, without changing the line and influencing the end result (Noble, 2006).

4.2.1.4 KERNEL FUNCTION

So, it is possible that a straight line cannot clearly split the data. The kernel function of SVM is also used for this. The kernel function is a solution to be still able to split the data into the different classes, adding an extra dimension to the data. The new dimension is constructed by squaring the original values of observations. The SVM continues with adding dimensions, with the goal that at some point the way to set the hyperplane is found. These kernels ensure that nonlinear data can still be analysed with a linear model. The flexibility of the kernels can transform the data into other dimensions. However, there is a downside to these kernels. A high number of dimensions in the data can provide dimensionality. This means that due to the increasing number of variables, the number of potential solutions to split the data also increases, but in an exponential manner. This could make it increasingly difficult for the algorithm to select a correct solution (or split) (Noble, 2006).

4.3 SAMPLE

To accurately forecast the demand for drivers in the Netherlands, a dataset from a logistics company in the Netherlands has been selected. This company logisticss refrigerated and frozen goods. The raw data in the original dataset was divided per shipment. Each row in the dataset contained data from a single shipment with associated variables. These associated variables are shown in appendix 1. Subsequently, the dataset has been transformed so that the data is categorized per day. In this way, a transformed dataset has been created that contains 730 lines (365 days times two years). The dataset goes from 2/01/18 to 2/01/20. The reason that the data has been transformed in this way is that the forecasting must also be determined per day. It must be possible to predict how many drivers will be needed in one day.

4.4 DEPENDENT VARIABLES

This study has attempted to develop an accurate forecast to predict the demand for truck drivers. Different dependent variables have been investigated to find out which of these variables can best be predicted. These dependent variables will be explained in this chapter. The context of each dependent variable is also shown in a visual representation. To understand this visual representation, figure 10 shows a legend, which explains the components in the visual representations.

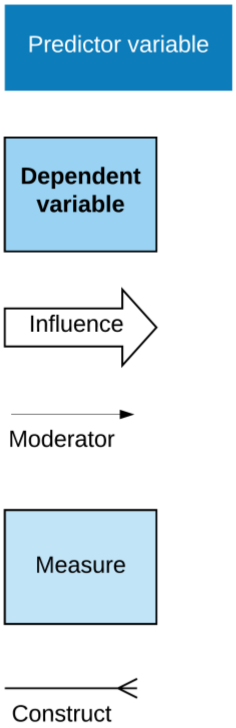

FIGURE 10: LEGEND FOR THE VISUAL REPRESENTATION OF THE DEPENDENT VARIABLES, WHICH ARE DESCRIBED IN THE FOLLOWING SUBSECTIONS

4.4.1 DEPENDENT VARIABLE 1: RATIO PALLETS DRIVERS

In order to be able to predict the demand for truck drivers, the number of truck drivers needed is compared to the number of pallets to be transported in a day. An example of this is that 100 pallets must be transported and that for which two drivers are deployed. The ratio will be 2 drivers / 100 pallets = 0.02. This ratio is used as one of the dependent variables and will be further referred to as Ratio Drivers / Pallets. Several variables have been used to predict future values about this ratio. For each day in the historical dataset, there is determined what the value of the Drivers/Pallets ratio was and what the value of these predictor variables was on that day. There is expected that the weather, traffic jam, seasonal or time-bound variables and holidays could contribute to predict ratio of drivers and pallets. See figure 11 for the visual representation of the context of the ratio Drivers/Pallets. All these variables could theoretically influence the ratio. For example, the ratio may be influenced by the weather. A lot of rainfall, limited visibility, high or low temperatures or strong wind could increase the number of drivers required to logistics one pallet. The heaviness of the traffic jam could do the same. Many traffic jams could cause an increase in required truck drivers because it takes longer to logistics a pallet. Besides, the number of drivers required to logistics a pallet may differ per quartiles, per month or working day. This could be due to differences that occur per period.

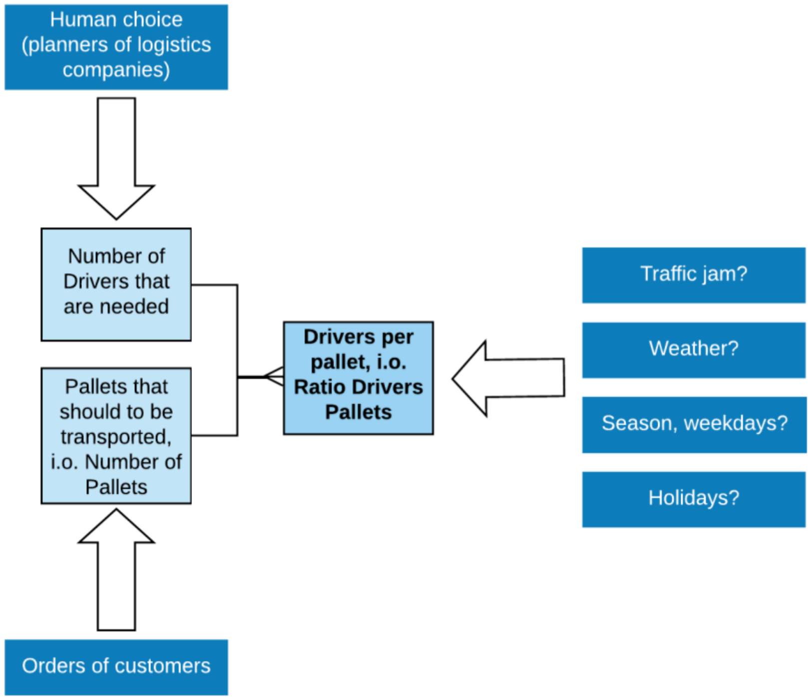

FIGURE 11: VISUAL REPRESENTATION OF DEPENDENT VARIABLE RATIO DRIVERS PALLETS

4.4.2 DEPENDENT VARIABLE 2: DRIVING HOURS PER PALLET

It is possible that the time that it took to logistics a pallet depends more on the external variables, than the number of drivers that have been deployed. That is why this study also examines how much time it took to logistics one pallet. For example, it will affect the amount of time that a pallet is delivered when the driver gets stuck in traffic or when he has poor visibility caused by fog, and therefore the pallets cannot be transported at the average speed. See figure 12, for a visual representation. The Ratio Drivers / Pallets will most likely experience a particular influence of human choice, because employees (humans) of a logistics company decide how much drivers will be deployed on one day. Therefore, there is decided to forecast the Time Per Pallet. This dependent variable is based on the total time of deployment of all truck drivers working that day, relative to the number of pallets that are transported that day. The predictor variables used to calculate the Time Per Pallet are the same as for the Ratio Drivers Pallets, see figure 12.

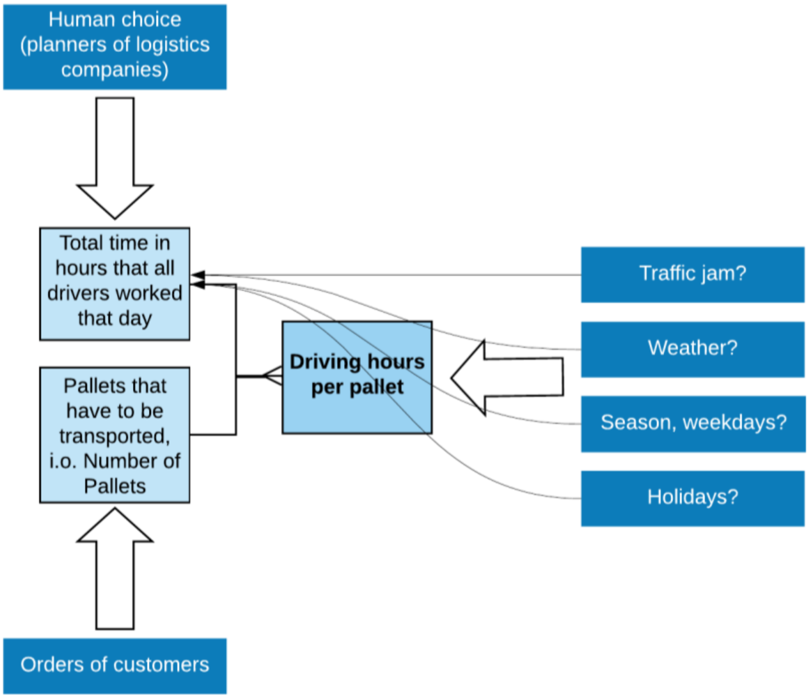

FIGURE 12:VISUAL REPRESENTATION OF DEPENDENT VARIABLE DRIVING HOURS PER PALLET

4.4.3 DEPENDENT VARIABLE 3: DRIVING HOURS

A third option to investigate the demand for drivers is to use simple analysis of the variable Driving hours, see figure 13. This variable is the total time of deployment of all truck drivers working that day. This variable is chosen to investigate whether the forecasting without the predictors used in the first and second dependent variable yields a better result. The variable Driving hours is predicted using the predictor variable Number of Pallets. This variable is the total number of pallets transported in one day. Also, two other predictor variables are used in the prediction of the variable Driving hours. These predictor variables are lags of the dependent variable, with a lag of t-1 and a lag of t-7. Using the observation of the day before (t-1) and the week before (t-7) makes sure that recent history is brought into the forecast. The predictor variable Yt-1 is used in the forecast because recent developments could have effect. It is possible that the situation of yesterday is a good indicator for today. The predictor variable Yt-7 is used in the forecast because last week: the same day of the week of the previous week could be an indicator for coming week. The most recent developments, like economic or climate developments, could count for last week and this week. For example, the situation around COVID-19 had influence on the number of shipments. Because of the worldwide outbreak of the virus and lockdowns of whole countries the number of shipments reduces radically, and the number of pallets that had to be transported remained low. From literature, there is expected that lagged dependent variables in general improve forecasts (Coulson & Robins, 1993).

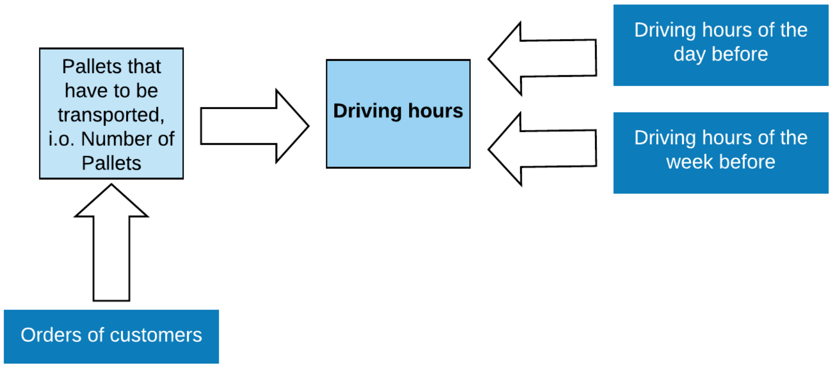

FIGURE 13: VISUAL REPRESENTATION OF DEPENDENT VARIABLE DRIVING HOURS

4.5 PROCESS OF ARTIFACT 1

Figure 14 shows a visualization of the process that is followed to demonstrate the process of forecasting with Support Vector Machine. The programming language R was used to realize the forecasting in this study. The package *readxl* is used for loading an Excel file in R. The package *dplyr* is used to clean and transform the data. The package *Caret* is used to apply various preprocessing techniques and to split data between a training dataset and test dataset. For the Support Vector Machine, the package *e1071* was installed and used. Furthermore, the package *Hmisc* is used to lagged the dependent variable in order to create new predictor variable.

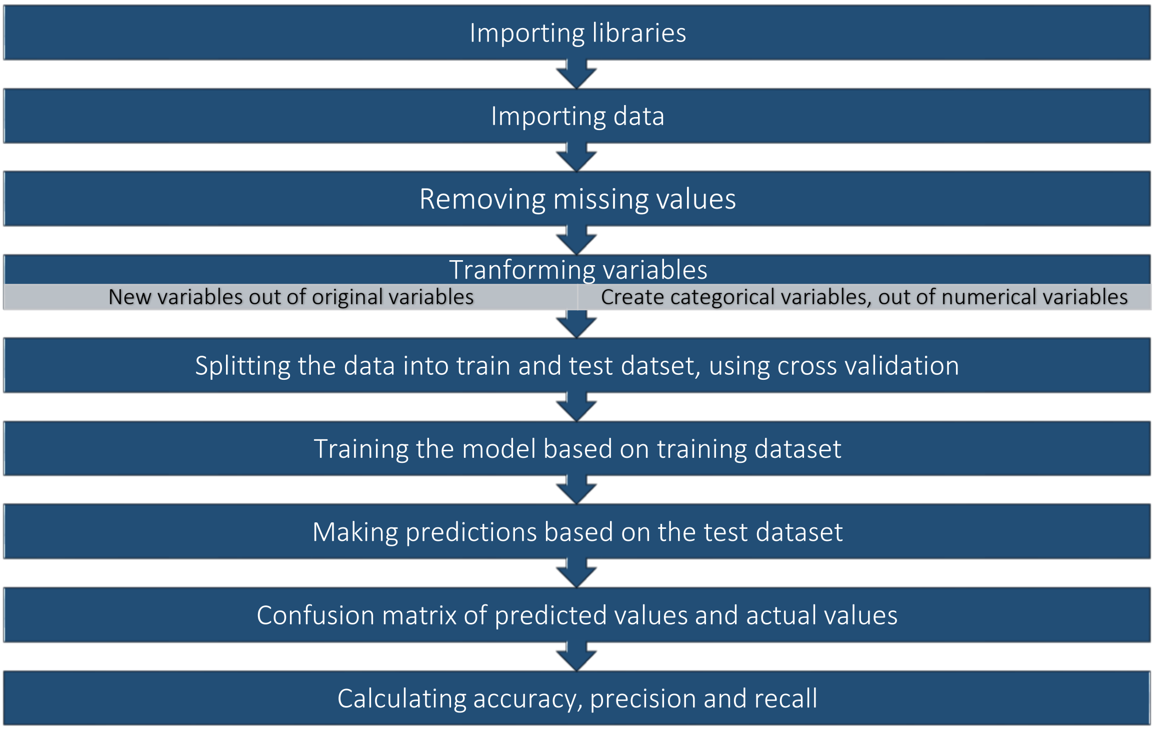

FIGURE 14: EXECUTION PROCESS OF THE FORECAST WITH SUPPORT VECTOR MACHINE

4.5.1 MISSING VALUES AND TRANSFORMATION OF VARIABLES

There are 69,946 rows in the raw data, five of which contain missing values. This means that 0.007% of the data contained missing values. Because this percentage is meagre, there is decided to remove these five observations (shipments) from the data. There is expected that removing those missing values has a minimal impact on the outcome of the study. After removing missing values, the raw data has been transformed into a dataset that is ordered by date. The raw data was a dataset with 69,946 rows; the transformed dataset contained 730 rows. There are 730 rows because the dataset contains two years of data, in other words, twice 365 days. After this transformation, new variables were then developed from the raw data. For example, it was determined in which month and in which quartiles each observation lies. The variables *Day of the week, Months,* and *Quartiles* are set up in this way. The variable *Number of Drivers* is created by adding up the unique personnel numbers of drivers that worked that day. The variable *Number of Pallets* was created by adding together the number of pallets transported that day. The *Driving hours* variable was created by adding together the number of hours that the logistics of all shipments took in one day. The variable *Holiday* was created by designating the dates that were a holiday. In appendix 1 there is shown which days have been designated as a holiday. Besides, five variables were retrieved from external datasets. Four of these variables are weather variables, and these are retrieved from a dataset from KNMI. This is the Dutch weather station of the government. It concerns the variables *Temperature, Wind speed, Rainfall, and Minimal visibility*. Appendix 1 shows what the variables mean precisely. The fifth variable, retrieved from an external data set is *Traffic Jam*. These variables are obtained from a dataset of the Dutch government agency Rijkswaterstaat, obtained through Network Management Information System (NIS). In appendix 1, there is described what this variable means. At first, all predictor variables are used. The multicollinearity was checked and turned out to be too high for the variable *Months*. So, there is chosen to delete this variable from the forecast.

Adding too many predictor variables than needed could lead to overfitting. Overfitting happens when your suggested prediction model is too much "fitted" on your test data. The result is excellent results when you apply your model on your test data, but less good results on real data. Adding many predictor variables as such is not called overfitting, as long as they are available and relevant and effective in "the wild" using them is fine. The smaller the sample size, the higher the risk of overfitting, especially if a large number of predictor variables are included in the model. To prevent the problem of overfitting, a solution is to have a balance in the dataset, where for each predictor variable there are at least ten observations in the dataset. So, if the dataset has five predictor variables, a sample size of at least 50 is recommended (Hanke & Wichern, 2014). To avoid overfitting in this study, this rule is adhered and applied. In the forecasts, there is a maximum of seven predictors used, while the dataset contains 730 observations. According to the rule, this should be at least 70 observations, so this rule is amply satisfied.

The technique Support Vector Machine is a classification method and therefore the dependent variables of this research are split into three categories. The categories for the dependent variable Drivers / Pallets are *low, medium,* and *high.* The variable is rounded to two decimal places so that the variable has values between 0.02 and 0.16. These numbers are then divided into three categories, each consisting of a range of 5 numbers. Each category is then given a name; these names are *low, medium,* and *high*. With the division in the categories logistics companies could forecast how busy the day is going to be. With a *low* Ratio Pallets/Drivers, not many drivers are needed in comparison with the number of pallets. When the company knows how much pallets there have to be transported, they could estimate in what range the number of drivers will be. For example, based on the predictor variables the forecast is that the Ratio Pallets/Drivers will be classified as *low*. Low means the Ratio Pallets/Drivers is in a range of 0.01-0.06. When it becomes clear that the number of pallets that should be transported is 50, the calculation will be 0.01 to 0.06 = Drivers/50. Solving this calculation, the company know that 0.5 to 3 drivers are needed for this day. Then it is the choice of the logistics company, how much drivers are going to be deployed.

The same has been done for the variable Driving hours per pallet; this distribution of categories can be found in appendix 1. A distribution has also been made for the variable Driving hours, see appendix 1. A disadvantage of the Support Vector Machine is that it only classifies, which can make the forecast less predictable because the Support Vector Machine scales the dependent variables in a different class. For example, a regression method could predict the exact number.

4.5.2 TRAINING AND TEST DATASET

Before, there is described what overfitting means and how it can be avoided. Another way to avoid overfitting is to build the model on one part of the dataset and then apply the model to another part of the dataset (Hanke & Wichern, 2014). This was done in this study by splitting the data into a training dataset and a test dataset. The training dataset contains 70% of the total dataset, and the test dataset the other 30%. The split of data is standard. It does prevent not only overfitting but also measures the performance of the model. If the model is built based on the training dataset, it can then be difficult to test on the training dataset whether the model works correctly (Muller & Guido, 2017).

4.5.3 PERFORMANCE MEASURES FOR SUPPORT VECTOR MACHINE

To measure the performance of the forecast with the Support Vector Machine, three performance measures are used, Recall, Precision, and Accuracy. To understand what these performance measures mean and how they are calculated, there will be explained first what a confusion matrix is. First, an explanation will be given using an example with a dependent variable with two classes. Next, it will be explained how the confusion matrix and the accuracy came about with a dependent variable with multiple classes. A confusion matrix shows how often in the forecast, the correct class is predicted and how often this was not the case. Table 1 shows a confusion matrix with two classes. The table has two dimensions "predicted" and "actual". At first, the forecasting technique builds a model that is created by analyzing the training data set. Then, this model is tested on the test dataset. The confusion matrix shows how often the model predicted the correct class and how often that was not the case. Under the dimension "predicted" each observation is sorted by the class that is predicted. In this example, the classes “positive” and “negative” are chosen. After this, there is determined which class the observation actually had in the test dataset, which is the dimension "actual" in the confusion matrix. If the model has predicted an observation under the class positive and the observation subsequently turned out to actually belong to the class positive, then this observation is added up in the confusion matrix as True Positive (TP). If it turns out that the observation was predicted under the positive class, but in reality turned out to be negative, then it will be added up in the confusion matrix under False Positive (FP). For the observations predicted in the negative class, the effect is the same. If it turns out that such an observation actually belonged to the positive class, then the observation belongs to False Positive. Should the observation actually belong to the class negative, then this observation will be added up by True Negative.

The performance measures Recall, Precision, and Accuracy can be calculated after drawing up a confusion matrix. The calculation of accuracy is True Positive + True Negative / total observations of the test dataset. In other words, the number of correctly predicted observations is added up and divided by the total observations. In this way, a percentage of correctly predicted observations is calculated, and a statement can be made about the performance of a forecasting technique. In this study, multiple classes were used for the dependent variable. Table 2 gives an example of a confusion matrix with multiple classes. The difference now is that there are multiple combinations of predicted and actual classes. More combinations indicate an incorrect prediction. To calculate the accuracy, we also look at the correctly predicted observations. Also, in the example of table 2, these are the combinations in which the class that is predicted corresponds to the actual class. In table 2, the blue combinations indicate the correctly predicted class. The calculation for accuracy with three classes is now: AA+BB+CC/Total. The calculation for Precision (for class A) is the following: Precision = AA/(AA+AB+AC). Precision measures: of all the times a class (in this case, class A) has been predicted, how often was it actually that class? The third performance measure is Recall. The calculation for Recall (for class A) is the following: = AA/(AA+BA+CA). It measures what percentage of the classes that were actually that class, were correctly is predicted.

		Predicted	
		Positive	Negative
Actual	Positive	True positive (TP)	False positive (FN)
	Negative	False positive (FP)	True negative (TN)

TABLE 1: EXAMPLE OF A CONFUSION MATRIX WITH TWO CLASSES

		Predicted		
		Class A	Class B	Class C
	Class A	AA	BA	CA
Actual	Class B	AB	BB	CB
	Class C	AC	BC	CC

Accuracy = AA+BB+CC/Total.

Precision Class A = AA/(AA+AB+AC).

Precision Class B = BB/(BA+BB+BC).

Precision Class C = CC/(CA+CB+CC).

Recall Class A = AA/(AA+BA+CA).

Recall Class B = AA/(AB+BB+CB).

Recall Class C = AA/(AC+BC+CC).

TABLE 2: EXAMPLE OF A CONFUSION MATRIX WITH THREE CLASSES, AND FORMULAS FOR ACCURACY, PRECISION AND RECALL

CHAPTER 5: DEMONSTRATION ARTIFACT 1

5.1 RESULTS DEPENDENT VARIABLE: RATIO DRIVERS PALLETS

The dependent variable Ratio Drivers Pallets is predicted with the use of Support Vector Machine and eight predictors: Traffic jam, Temperature, Wind speed, Quartiles, Rainfall, Minimal visibility, Holiday and Days of the Wee. Table 3 shows the confusion matrix of this forecast. The blue values in the confusion matrix are the number of observations per class that are correctly predicted in the forecast. It is striking that the number of observations that are predicted in the class low and actually fell in the class medium, is relatively high with 30 observations.

Conversely, the number that is also high is the number of observations predicted in the medium class while the actual class was low, this number is 18 observations. Based on the confusion matrix, the performance measures are calculated and shown in table 4. Both Precision and Recall are relatively low for all classes, except for the Recall of the low class. The percentage of observations predicted in the low class and actually belonging to this class is 76%. Also, the overall accuracy of the forecast is 0.61, which means that 61% of all predicted observations from the test data set have been a correct prediction.

		Prediction		
		Low	Medium	High
Actual	Low	57	18	0
	Medium	30	27	2
	High	1	5	4

TABLE 3: CONFUSION MATRIX OF THE FORECAST OF DEPENDENT VARIABLE RATIO DRIVERS PALLETS

	Class: Low	Class: Medium	Class: High
Precision	0.64	0.54	0.66
Recall	0.76	0.47	0.4
Accuracy	0.6111111 (for all classes)		

TABLE 4: PERFORMANCE OF THE SUPPORT VECTOR MACHINE ON THE TEST DATASET, FOR THE FORECAST OF DEPENDENT VARIABLE RATIO DRIVERS PALLETS

5.2 RESULTS DEPENDENT VARIABLE: DRIVING HOURS PER PALLET

Subsequently, a forecast was made with the Support Vector Machine for the dependent variable Time Per Pallet. The predictors in this forecast are Traffic jam, Temperature, Wind speed, Quartiles, Rainfall, Minimal visibility, Holiday and Days of the Week. Table 5 shows the confusion matrix. In this confusion matrix, there is shown that by far the highest number of observations is predicted as class medium, while it was actually class low. This becomes clear when looking at the Precision of the class medium, see table 6. The number of times that the class medium was predicted medium and it actually was this class is 36%. This can also be seen in the Recall of the class low, the percentage of observations that was actually low and also predicted in the class low is 15%. In general, the performance of the Support Vector Machine for this dependent variable is poor. Only the recall of the class high is good, but this looks to be caused by the fact that there were only ten actual observations in this class. The accuracy of this forecast is almost 50%.

		Prediction		
		Low	Medium	High
Actual	Low	11	62	2
	Medium	14	36	9
	High	0	2	8

TABLE 5: CONFUSION MATRIX OF THE FORECAST OF DEPENDENT VARIABLE DRIVING HOURS PER PALLET

	Class: Low	Class: Medium	Class: High
Precision	0.44	0.36	0.42
Recall	0.15	0.61	0.8
Accuracy	0.4930556		

TABLE 6: PERFORMANCE OF THE SUPPORT VECTOR MACHINE ON THE TEST DATASET, FOR THE FORECAST OF DEPENDENT VARIABLE DRIVING HOURS PER PALLET

5.3 RESULTS DEPENDENT VARIABLE: DRIVING HOURS

First, the Support Vector Machine has also performed a forecast for the variable Driving Hours. Only one predictor was used in this forecast, the variable Number of Pallets. Table 7 shows the confusion matrix. Most notably, the class high was zero times correctly predicted. That is why both the Recall and the Precision are zero, which can be seen in table 8 It is striking that the class high was predicted 36 times while it should actually be the class medium. Apart from these incorrect predictions, the performance of the Support Vector Machine is in general good. The Precision and Recall of the other two classes are high. The accuracy is also generally high. Overall, the forecasting is performing well, except for the class high. After this forecast, the same dependent variable is predicted again, but this time with two additional predictors. The predictors are based on the dependent variable but then lagged with t-1 and t-7. The results show in table 9 and table 10 that the forecast with predictors based on the lagged dependent variable, have positive influence on the forecast. All results of precision, recall and accuracy are better compared with the previous forecast with only one predictor.

		Prediction		
		Low	Medium	High
Actual	Low	46	3	2
	Medium	8	79	5
	High	1	36	0

TABLE 7: CONFUSION MATRIX OF THE FORECAST OF DEPENDENT VARIABLE DRIVING HOURS

	Class: Low	Class: Medium	Class: High
Precision	0.84	0.67	0
Recall	0.90	0.86	0
Accuracy	0.7333333		

TABLE 8: PERFORMANCE OF THE SUPPORT VECTOR MACHINE ON THE TEST DATASET, FOR THE FORECAST OF DEPENDENT VARIABLE DRIVING HOURS

		Prediction		
		Low	Medium	High
Actual	Low	49	2	0
	Medium	6	81	4
	High	0	35	3

TABLE 9: CONFUSION MATRIX OF THE FORECAST OF DEPENDENT VARIABLE DRIVING HOURS, WITH PREDICTOR VARIABLES YT-1 AND YT-7

	Class: Low	Class: Medium	Class: High
Precision	0.89	0.69	0.43
Recall	0.96	0.89	0.08
Accuracy	0.77325581		

TABLE 10: PERFORMANCE OF THE SUPPORT VECTOR MACHINE ON THE TEST DATASET, FOR THE FORECAST OF DEPENDENT VARIABLE DRIVING HOURS, WITH PREDICTOR VARIABLES YT-1 AND YT-7

CHAPTER 6: EVALUATION OF ARTIFACT 1

⇒ Artifact shows lower accuracy than 80%, so objective is not achieved

⇒ Second artifact will be designed and demonstrated

In summary, from the literature, the Support Vector Machine seemed to be one of the most promising techniques. In this study, the result of the method was disappointing; two of the three variables were not predicted accurately with the Support Vector Machine. All forecasted dependent variables have an accuracy of less than 80%. The threshold was determined at 80% at the beginning of the study as the minimum to label a forecast as "successful". Also, for many classes, Precision and Recall were also low. Although, the artifact did not achieve the objective, there could be concluded that the simplest forecasting seems to be the most promising. The dependent variable Driving Hours is best predicted with three predictor variables, where lagged dependent variables are included as predictors. So, the only data that a company needs are two variables, the dependent variable Driving Hours which could be lagged and used as a predictor variable and the variable Number of Pallets. Additionally, it should be noted that the class *high* was not very common in the dataset. This may have influenced the research and is related to a significant disadvantage of a Support Vector Machine: it is a classification technique. In this study, therefore, this method only predicts the classes *low*, *medium*, or *high*. A regression technique could predict the exact number. Due to previous limitations of the Support Vector Machine artifact, there is therefore decided to design a new artifact.

CHAPTER 7: DESIGN AND DEVELOPMENT ARTIFACT 2

- ⇒ Design of a new Artifact: Linear Regression
  Compared with Support Vector Regression
- ⇒ Performance measures for comparison of the forecasting techniques:
  - Root Mean Square Error (RMSE)
  - Mean Absolute Error (MAE)
  - R-squared
- ⇒ Performance measures which determine when objective is achieved:
  - Mean Absolute Percentage Error (MAPE)
    - ≤ 20% means objective has been achieved
  - Aggregate forecast accuracy
    - ≥ 80% means objective has been achieved

The literature showed that next to the technique Support Vector Machine, the techniques Recurrent Neural Networks and Multiple Regression have shown proper performing techniques in previous studies. As explained earlier, this research attempts to find a well-performing technique that is not too complicated for people with basic knowledge. The preference will, therefore go to Linear Regression and not the Recurrent Neural Network technique. That is why the Linear Regression technique will be used in this chapter for forecasting the truck drivers demand. A large part of the performance measures of Linear Regression is designed to compare forecasting techniques, so, therefore, it was decided to use the Support Vector method again, but this time with the regression variant. An additional advantage for this choice is that the regression variant of the Support Vector technique also will be tested. This technique, Support Vector Regression, has emerged in recent years and is therefore relatively little researched.

7.1 TECHNIQUE: LINEAR REGRESSION

This section describes the forecasting technique Linear Regression. Unlike the previously described Support Vector Machine technique, the dependent variables are not split into categories. This technique, Linear Regression, is intended for regression problems (James et al. 2013). The Linear Regression technique is a technique that can predict a dependent variable based on one or more predictor variables. The multiple Linear Regression model looks like this: $Y = a + bX$, where Y denotes the dependent variable and X denotes the predictor variables. The forecaster could take several steps to determine which predictor variables will be included in the regression model. In this selection of predictor variables, he will probably be faced with the dilemma of the most accurate forecast for the lowest costs. All potential and available predictors must add a forecaster to the forecast. This is also done in this study. The list of predictors is then assessed based on four criteria. If an predictor variable did not meet one or more criteria, this variable has been removed. The criteria are that a variable…

- …must have a plausible explanation that it affects the dependent variable
- …may not be subject to considerable measurement errors for any reason
- …does not have a relationship with another predictor variable (multicollinearity). There is multicollinearity if the VIF value is higher than 5. If the predictor variables overlap, a less reliable result will come from the Multiple Linear Regression.
- …is too challenging to measure accurately (for example because it is not available or too expensive) (Hanke & Wichern, 2014)

Next, it is essential in a Linear Regression model to determine which predictor variable is significant. This means: taking into account the other predictor variables, is the effect of a single predictor variable important for the model, or can this variable be removed from the model? This question can be answered by determining the t-value for each variable. Additionally, there is a value that indicates the proportion of the variance for a dependent variable that is explained by the predictor variables; this value is R-squared. The R-squared is denoted with a value between 0 and 1, where 1 means that all observed Ys are precisely in the regression model.

7.2 TECHNIQUE: SUPPORT VECTOR REGRESSION

The Support Vector Machine technique can also be used for regression problems, as described by Vapnik (1995). The regression variant of Support Vector Machine is called Support Vector Regression. The technique works the same as Support Vector Machine, except for a significant difference. Similar to the Support Vector Machine, the hyperplane and support vectors are used to separate the data and discover a pattern in the data. Also, kernels can still be used in the Support Vector Regression. The difference lies in the way the data is split. While the Support Vector Machine determines via a margin where the separation is made in the data, the Support Vector Regression does this via a loss function. A value is calculated with this loss function. The values that are not greater than the value that is calculated with the loss function determine the split in the data. The errors that are greater than this value are not taken into account.

7.3 PERFORMANCE MEASURES

This research is looking for a way to accurately predict the demand for drivers, using statistical forecasting techniques. To determine whether a forecasting technique works well, or in other words, can predict, performance measures can be assessed. For the regression techniques, there are different performance measures used, then for artifact 1. The reason that different performance measures are used is that the dependent variable in the Support Vector Machine should be divided into classed, while regression models could preserve the numeric state of the variable. The use of multiple performance measures allows users to focus on those features of a forecasting procedure they consider most relevant, as well as to check the robustness of their conclusion. For example, a user can appreciate the simplicity and be willing to accept somewhat reduced accuracy to keep things simple. Another wants to avoid major mistakes, in which case a different performance measure becomes the most relevant (Ord & Fildes, 2013).

The most straightforward measurement to measure how proper a forecasting technique is is an absolute error (AE). If we generate a forecast with a forecast = 100 and the actual value turns out to be 80 or 120, then the absolute error is 20. Although this method is straightforward, the performance of a forecasting technique can be measured more accurately. According to Bloom, Canning, Fink, and Finlay (2007) there is for several years a debate about determining the most appropriate performance measure for forecasting. Looking into different studies, it shows that there are indeed some contradictions in the researcher's opinion concerning performance measures. Bloom, Canning, Fink, and Finlay (2007) say that Root Mean Squared Error (RMSE), is an excellent measure to measure how well the model fits in the first period after the historical data. They make the critical note that this measure is susceptible to outliers. Next, they state that the mean absolute error (MAE) is less sensitive for outliers. In 1993, Makridakis reported that the measure Mean Absolute Percentage Error (MAPE) is the most appropriate measure. They state that MAPE could be done in a meaningful and straightforward manner and that it meets theoretical and practical concerns. Six years later, Tayman and Swanson (1999) found that MAPE does have many desirable criteria, it is well known among users, it is used a lot, and it is easy to apply and present. In recent studies, there is found that there is no one best accuracy measure, that is in general accepted for choosing the best forecasting technique (Mehdiyev, Enke, Fettke & Loos, 2016; Xu & Ouenniche, 2012).

Additionally, Xu and Ouenniche (2012) state that in several studies different rankings for different criteria are used, which leads to the problem that there cannot be made an informed decision about the performance of forecasting techniques. Therefore, they suggest an approach called Multi-Criteria Decision Analysis (MCDA). This would solve the problem, because this approach compares the performance of forecasting techniques with multiple criteria, to make an informed decision. The results from the study of Xu and Ouenniche (2012) show that MCDA is a valuable tool. Therefore, this study follows the MCDA method, and various performance measures are used in this study to determine how well a technique can predict and compare the forecasting techniques.

7.3.1 PERFORMANCE MEASURES FOR ARTIFACT 2

A total of five different performance measures were used to assess the regression methods for their performance. These measures are RMSE, MAE, MAPE, Forecast Aggregate Accuracy, and R-squared. These performance measures are presented in table 9, shown with the corresponding calculation and features. Three out of five performance measures use the mean deviation from the predicted value to the actual value. The Root Mean Square Error (RMSE) averages the square of these differences and then takes a square root. The RMSE has the same unit as the dependent variable. The Mean Absolute Error (MAE) takes the average of the absolute errors and also has the same unit as the dependent variable and is therefore of the same order of magnitude as the RMSE. The mean absolute percentage error (MAPE), is the mean value of the absolute percentage differences between the predicted values and actual values. (Fildes & Goodwin, 2007; Klimberg et al., 2010) For MAPE there is a generally accepted scale that indicates how good a forecast is, see table 12. The MAPE value makes it easy to calculate another value: the aggregate forecast accuracy, which can be calculated via 1-MAPE. The fourth performance measure is the R-squared, which has already been explained in the regression section. In short, the R-squared means how the predictor variables explain much of the variance in the dependent variable (weight). A low R-squared is generally a bad sign for a forecasting model. It depends on the user of the forecasting, which performance measure weighs more heavily because the importance of an 'error' in the forecasting differs per situation (Chai & Draxler, 2014). It depends on the user of the forecasting, which performance measure weighs more heavily because the importance of an 'error' in the forecasting differs per situation (Chai & Draxler, 2014).

7.3.2 THRESHOLD FOR ACHIEVING THE OBJECTIVE OF THIS RESEARCH (ARTIFACT 2)

The performance measures RMSE, MAE, and R-squared were used in this study to compare the two forecasting techniques of Artifact 2. For MAPE and the associated forecast aggregate accuracy (1-MAPE), a threshold has been set for this study to determine whether the forecast is performing sufficiently. This is done because this research aims to find an accurate forecast. The threshold is set at a MAPE value below 20%, based on the scale of Lewis (1982). According to this scale, a forecast is a

‘Good Forecast’ if the MAPE value is below 20%. Also, this automatically means that the aggregate forecast accuracy is satisfactory if it is above 80%.

Performance measure	Calculation	Features
Root Mean Square Error (RMSE)	The rooted average of the square of the differences	1. The same unit as the dependent variable, therefore easy to interpret 2. One of the most common 3. Sensitive for outliers 4. The lower, the better.
Mean Absolute Error (MAE)	The average of the absolute errors	1. The same unit as the dependent variable, therefore easy to interpret 2. Less sensitive for outliers. 3. The lower, the better.
MAPE: mean absolute percentage error	The mean of the absolute percentage differences between predicted values and actual values	1. Easy to interpret. 2. There is a commonly used scale of judgment 3. The lower, the better.
Aggregate forecast accuracy	(1 – MAPE)	1. Easy to interpret. 2. The higher, the better.
R-squared	Subtract the average actual value from each of the actual values, square the results, and sum them (this is variance). Divide the first sum of errors (explained variance) by the second sum (total variance), subtract the result from one.	1. Says something about the selection of predictors. 2. The higher, the better.

TABLE 11: DESCRIPTION OF PERFORMANCE MEASURES USED IN THIS RESEARCH

MAPE	Aggregate forecast accuracy	Judgment of Forecast Accuracy
Less than 10%	More than 90%	Highly accurate
11%-20%	80%-89%	Good forecast
21%-50%	50-79%	Reasonable forecast
51% or more	Below 49%	Inaccurate forecast

TABLE 12: A SCALE OF JUDGEMENT OF FORECAST ACCURACY. "ADAPTED FROM INDUSTRIAL AND BUSINESS FORECASTING METHODS: A PRACTICAL GUIDE TO EXPONENTIAL SMOOTHING AND CURVE FITTING," BY C.D. LEWIS, 1982. COPYRIGHT 1982 BY BUTTERWORTH-HEINEMANN.

7.4 PROCESS REGRESSION TECHNIQUES

The dataset that was made for Artifact 1 was also used in the execution of Artifact 2, which reduced the steps in the process. Also, the split of training and test dataset has already been done for Artifact 1, and for this artifact, the same training and test dataset is used. The R-package for Support Vector Regression is the same as for Support Vector Machine, namely, package *e1071*. No special package is loaded for Linear Regression; this function is automatically included in the program R. Other performance measures are used for this artifact. Those performance measures are already described above. In figure 11 is the process of the two regression techniques visualized. Furthermore, the package *Hmisc* is used to lag the dependent variable in order to create new predictor variables.

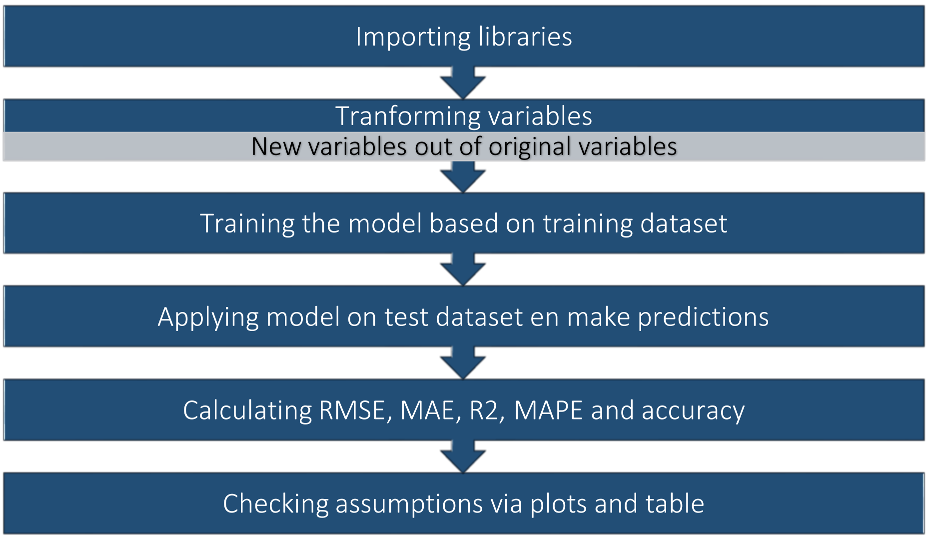

Figure 15: Execution process of the forecast with Regression Techniques

CHAPTER 8: DEMONSTRATION ARTIFACT 2

In this chapter artifact 2 will be demonstrated. The forecast is executed in the program R and the same three dependent variables are forecasted. The results of these forecasts are described in this chapter.

8.1 RESULTS DEPENDENT VARIABLE RATIO DRIVERS PALLETS

The predictors used to predict the dependent variable Ratio Drivers Pallets are shown in table 13. There is chosen to use the variable Quartiles and not the variable Months because the latter variable causes multicollinearity. In table 13 the VIF-value of the variable *Months* is higher than 5, which indicates high multicollinearity. Table 14 shows that the variable *Quartiles* causes no multicollinearity, because the VIF-value is below 5.

From the results of the performance measures, see table 15, it becomes clear that the Linear Regression model outperforms the Support Vector Regression. For all performance measures the Multiple Regression technique scores better than the Support Vector Regression. The R-squared of the Linear Regression is at an acceptable level. For 67%, the variance of the Ratio Drivers Pallets is explained by these variables. On the other hand, the R-squared of SVR Is low with 47%. A low R-squared is generally a bad sign for a forecasting model. Finally, the aggregate forecast accuracy of both techniques can be scaled to *Good Forecast* for both techniques on the scale of Lewis (1982).

	VIF
Traffic jam	2.651264
Temperature	3.848776
Wind speed	1.586373
Months	6.740730
Rainfall	1.229959
Minimal visibility	1.371736
Holiday	1.105300
Day of the week	2.347274

TABLE 13: VIF VALUES FOR THE FORECAST OF RATIO PALLETS DRIVERS WITH PREDICTOR MONTHS INCLUDED

	VIF
Traffic jam	2.369919
Temperature	2.589257
Wind speed	1.501524
Quartiles	3.381715
Rainfall	1.211133
Minimal visibility	1.298180
Holiday	1.074043
Day of the week	2.166956

TABLE 14: VIF VALUES FOR THE FORECAST OF RATIO PALLETS DRIVERS WITH PREDICTOR QUARTILES INCLUDED

	SVR	Linear Regression
RMSE	0.211789	0.01257021
MAE	0.1012598	0.006944909
R-squared	47,22%	67,36%
MAPE	19,67%	15,13%
Aggregate forecast accuracy	80,33%	84,87%

TABLE 15: PERFORMANCE OF FORECAST FOR RATIO DRIVERS PALLETS WITH SVR AND LINEAR REGRESSION BASED ON PERFORMANCE MEASURES.

8.2 RESULTS DEPENDENT VARIABLE: DRIVING HOURS PER PALLET

The results of the dependent variable predicted with the techniques SVR and Linear Regression are shown in table 17. The predictors and other characteristics of the forecast are described in table 16 and also the VIF-values are shown here. There does not seems to be multicollinearity. Here too, it can be seen that the Linear Regression performs better, with the exception for the R-squared. The R-squared is less good for Linear Regression compared to the SVR. This means that the predictor variables less explain the variance in the dependent variable in the Linear Regression method than with SVR. The R-squared is still quite low in both forecasting models, with 29% for Linear Regression and 47% for SVR. The variance of time per pallet is likely explained by other variables not included in this study. A low R-squared is generally a bad sign for a forecasting model. According to the aggregate forecast accuracy, both forecasts are Reasonable. This is not as good as the forecast than of Ratio Drivers Pallets.

	VIF	Df
Traffic jam	2.373872	1
Temperature	2.587866	1
Wind speed	1.504403	1
Quartiles	3.368141	3
Rainfall	1.210578	1
Minimal visibility	1.299056	1
Holiday	1.077813	1
Day of the week	2.181450	6

TABLE 16: VIF VALUES FOR THE FORECAST OF DRIVING HOURS PER PALLET

	SVR	Linear Regression
RMSE	0.211789	0.1608651
MAE	0.1012598	0.07214653
R-squared	47,22%	29,07%
MAPE	34,75%	26,79%
Aggregate forecast accuracy	65,25%	73,21%

TABLE 17: PERFORMANCE OF FORECAST FOR DRIVING HOURS PER PALLET WITH SVR AND LINEAR REGRESSION BASED ON PERFORMANCE MEASURES

8.3 RESULTS DEPENDENT VARIABLE: DRIVING HOURS

The results of the performance of the variable Driving hours are shown in table 17. First, the forecasting was done using one predictor: Number of Pallets, in contrast to the two previous dependent variables. The forecast is done via Linear Regression and Support Vector Regression and these results are shown in the first two columns of table 18 The third and fourth column of the table, show the second forecast. In this forecast the variable Number of Pallets is used but also is the dependent variable lagged with t-1 and t-7. So, in total there are three predictor variables. Several things are striking when predicting this dependent variable Driving Hours. First of all, the RMSE of the two techniques is very close to each other, so looking at this performance measure the techniques do not differ much in performance. Furthermore, the Linear Regression performs slightly better than the SVR technique on all performance measures, except for one measure. The MAE scores better for the SVR technique than for the Linear Regression technique. MAE is a lot less sensitive to outliers than the RMSE so that this difference may have been caused by the presence of outliers in the dependent variable. If we look at the histogram of residuals, there are indeed much more outliers than for the previous two dependent variables. Looking at the MAPE and the aggregate forecast accuracy, the SVR technique can be scaled into a Reasonable Forecast, while the Linear Regression can be labelled as Good Forecast. Also, looking at the difference of the forecasts without lagged dependent variables and with lagged dependent variables, the latter performs best. The difference is not great, but it is clearly there. In table 19 there is shown that there is no multicollinearity among the three predictor variables in the second forecast, because the VIF value is below 5.

	Linear Regression	SVR	Linear Regression with variables Yt-1 and Yt-7	SVR with variables Yt-1 and Yt-7
RMSE	30.25757	30.69671	27.62364	29.45621
MAE	22.43069	19.93564	18.99387	16.75776
R-squared	74.76264	73.13545	78.7242	75.89867
MAPE	13.92790	21.46742	12.67389	19.45985
Aggregate forecast accuracy	86.08%	78.53%	87.33%	80.54%

TABLE 18: PERFORMANCE OF THE FORECAST FOR DRIVING HOURS WITH SVR AND LINEAR REGRESSION BASED ON PERFORMANCE MEASURES

	VIF
Number of Pallets	2.372831
Yt-1	1.092583
Yt-7	2.291540

TABLE 19: VIF VALUES FOR FORECAST OF DRIVING HOURS

CHAPTER 9: EVALUATION OF ARTIFACT 2

- ⇒ In general, artifact performs well
- ⇒ Objective has been achieved for variables Ratio Drivers Pallets and Driving hours
- ⇒ Objective has not been achieved for Driving hours per pallet
- ⇒ Linear Regression outperforms Support Vector Regression

Looking back at the results of the Linear Regression and the Support Vector Regression, there can be concluded that Linear Regression outperformed the Support Vector Regression. All dependent variables have a lower MAPE-value and a higher aggregate forecast accuracy with the Linear Regression technique, compared to the Support Vector Regression. Looking at the dependent variables, the variable Time Per Pallet scores below the previously set threshold of 80% accuracy. It is therefore advisable that this variable is not forecasted in the future if the goal is an accurate forecast. Also, the variable Ratio Drivers / Pallets are accurately predicted. Both techniques provide a forecast with sufficient accuracy. If the choice between Linear Regression and Support Vector Regression has to be made, Linear Regression should be chosen. This technique scores overall better, looking at the used performance measures.

Considering the results of all dependent variables, the dependent variable Driving hours is calculated most accurately. With Linear Regression, this variable can be accurately calculated with an accuracy of 87%. Looking at MAPE, this forecast can be scaled in Good Forecast, and even comes close to Highly Accurate Forecast. The forecast with lagged dependent variable as predictor variables, with t-1 and t-7 is better than the forecast without these predictors. The outcome that this dependent variable Driving Hours could better be forecasted than than the other two dependent variables, which indicates that the external variables such as weather and traffic jam make the forecast less accurate and can better be left out of the forecast. This can also be seen in the R-squared value, which is much higher in the forecast with only one predictor: Number of Pallets. It can be concluded that a logistics company would only need the number of pallets to predict how many hours truck drivers have to drive. This prediction can be used to determine the deployment of truck drivers. Also, it will be much simpler to make a forecast with one predictor than with multiple predictors. In summary, there can be stated that this artifact, using two Regression techniques, is thriving. This is in contrast with the first Artifact Support Vector Machine. Both the Linear Regression and the Support Vector Regression provide accurate forecasts.

CHAPTER 10: CONCLUSION AND DISCUSSION

Answer to research question:

The demand for truck drivers can be forecasted best by predicting the dependent variable Driving Hours with variable Number of Pallets and lagged dependent variables functioning as predictors, and also using the techniques Linear Regression or Support Vector Regression.

The research question of this study was *How can the demand for truck drivers in the logistics be forecasted accurately*?,The research question was divided into two parts. Sub-question A was: *Which forecasting technique performs well to forecast the demand for truck drivers accurately?* Furthermore, subquestion B was: *What insights can be gained about the features when forecasting the demand for truck drivers from the available dataset?* In this chapter, there will be an answer formulated to the research question and its sub-questions. This structure of this thesis was based on the Design Science Research Model. Therefore, this research should be seen as exploratory research to achieve a solution with associated objectives. In this study, the solution that was attempted to achieve was "an accurate forecast". This solution is achieved with the forecasting techniques Linear Regression and Support Vector Regression. There is shown that Linear Regression outperformed the Support Vector Machine and the regression variant of Support Vector Machine.

10.1 THREE DIFFERENT DEPENDENT VARIABLES

Three dependent variables have been predicted with these forecasting techniques. First of all, the dependent variable Ratio Drivers Pallets, which indicates the ratio of the number of drivers deployed to the number of pallets. Various predictors have been used to predict this variable. The Ratio Drivers Pallets is well predicted with Linear Regression and Support Vector Regression techniques used. The second dependent variable that is predicted is Driving hours per pallet, which shows a weaker performance. The variable Driving hours per pallet does not meet the threshold set earlier in this study. It is, therefore, advisable not to predict this variable with the predictors and techniques used in this study. Next, it is advisable to use lagged dependent variables as predictors, because the results of the forecast with these predictors are better than forecasts without them. The third dependent variable shows the best performance. Driving Hours can be predicted accurately with Linear Regression and Support Vector Regression. Of these two methods, Linear Regression is the best method, and the forecast comes close to a Highly Accurate Forecast.

10.2 ANSWER TO RESEARCH QUESTION AND SUBQUESTIONS

To formulate the answer to the research question, the demand for truck drivers can be accurately predicted by predicting the variable Driving hours with one predictor Number of Pallets using the techniques Linear Regression or Support Vector Regression. To answer sub-question A, the techniques that perform well are Linear Regression and Support Vector Regression. Looking at sub-question B, it is striking that the variable Driving Hours is best predicted and that this variable is predicted with the variable Number of Pallet and two predictors based on lagging the dependent variable. Next, external variables such as weather and traffic jams seem to ensure lower accuracy. This is contradictory to the expected results because experts from Bricklog, customers, and similar logistics companies such as Picnic expected external variables to have a good effect on the accuracy of the forecast. On the other hand, this outcome can be seen as an advantage. A large part of the logistics companies will keep track of how many shipments (in the case of the sample of this study: how many Pallets), which makes it relatively easy and cheap to obtain this information if the forecast has to be made. Another advantage of this result is that Linear regression is relatively simple and is already widely used. Because it is widely used, the technique will therefore already be known to many people, which can be advantageous in the implementation and interpretation of the forecast.

10.3 LIMITATIONS AND FUTURE RESEARCH

This study had a few limitations. This section will describe the limitations of this study and recommendations for future research. First of all, it is crucial to take into account that the sample is from a company active in logisticsing refrigerated and frozen goods. In this sample, the predictor Number of Pallets represents the number of shipments that the logistics company logisticss. In the case of the dataset, this was the number of pallets, but it is possible that other logistics companies do not logistics pallets but logistics other shipments. These shipments have not been tested in this study. The results may be different for other logistics companies with different shipments, but also because of other differences like other customers. It is therefore advised to investigate the influence of these differences.

Another side note is that the Support Vector Machine did not necessarily perform poorly. In this study, this technique performed below par, but perhaps in other contexts, the Support Vector Machine does provide high accuracy. This being the case in other academic studies, so it may depend on the context in which the Support Vector Machine was used. Future research could investigate what characteristics the context should have to make sure a Support Vector Machine performs well. Another side note is that in this research, much time was spent on the program R. In R, the forecast must be executed via programming. Employees at logistics companies may not have programming skills. It is therefore advisable to investigate whether it is more efficient to use so-called low coding programs. Low coding programs require little or no programming skills from the user, which can mean that less time is needed to realize the same forecast. Also, it may be that the user performs the forecast more correctly because programming involves the risk of making mistakes if the user does not understand the program fully. Additionally, it appears from this research that a simple forecast yields the best result, and therefore, a complicated program with many functionalities should not be necessary.

Another limitation of this research could be that a forecasting technique was sought with excellent performance and a simple elaboration as well. This simple elaboration was sought because employees of the logistics company need to understand the execution and the interpretation of the forecast to some extent. These employees often have basic knowledge of machine learning and technology. It may have had a significant effect on this research that more complicated forecasting techniques, such as the Recurrent Neural Network, have therefore not been investigated, while the literature research showed that this technique performed well in other studies. It may be that in the end, these complicated forecasting techniques give better results in terms of performance. Also, it has not been investigated what the knowledge of this personnel of logistics companies is. Future research could do additional research to determine whether they master the techniques better or worse than expected.

Also, a side note to this research is that the data quality may have been influenced because the data was supplied to the researcher via Bricklog. Because the researcher was not able to communicate directly with the logistics company, it may be that the interpretation or quality of the data has been negatively influenced. Also, there are certain drawbacks associated with the use of design research. There are often many variables that influence the success of the design, and many of these variables cannot be controlled (Collins, Joseph & Bielaczyc, 2004). This may also be the case in this study. Also, researchers conducting design research often have to deal with a large amount of data to understand what happens in detail. This can result in them being flooded with data, which they cannot process due to too little time or resources. This can make conducting design research difficult and influence the reliability of the conclusions (Collins, Joseph & Bielaczyc, 2004). Many observations and many predictor variables are also included in this study. Also, various forecasting techniques are used. All this could cause problems with data processing and ultimately concluding. Ultimately, this research is a Design Research, and this research serves as an orientation on the topic of forecasting the demand for truck drivers. It is therefore recommended to re-examine the results of the well-performing artifact in a test study.

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APPENDICES

APPENDIX 1: DESCRIPTION OF VARIABELS

1.1 PREDICTOR VARIABLE HOLIDAY

Dummy variable with values:

- 1 = holiday
- 0 = no holiday

Dates that are marked as holiday in the dataset:

- 1 January 2018
- 30 March 2018
- 1 April 2018
- 2 April 2018
- 27 April 2018
- 5 May 2018
- 10 May 2018
- 20 May 2018
- 21 May 2018
- 5 December 2018
- 25 December 2018
- 26 December 2018
- 31 December 2018
- 1 January 2019
- 19 April 2019
- 21 April 2019
- 22 April 2019
- 27 April 2019
- 5 May 2019
- 30 May 2019
- 9 June 2019
- 10 June 2019
- 5 December 2019
- 25 December 2019
- 26 December 2019
- 31 December 2019 (Wettelijke vakantiedagen, 2020)

1.1 PREDICTOR VARIABLE HEAVINESS TRAFFIC JAM

Description: The total heaviness of the traffic jam (the product of the duration of the traffic jam and the length of the traffic jams of the individual traffic jam messages) in kilometre minutes (Rijkswaterstaat, 2020).

Range: from 184,52 to 144.767,07 kilometre minutes.

1.2 PREDICTOR VARIABLES RAINFALL SUM, TEMPERATURE AVERAGE, WIND SPEED AVERAGE, MINIMUM VISIBILITY

1. Variable Rainfall sum

Description: Daily sum of the rainfall (in 0.1 mm) (-1 for <0.05 mm) (KNMI, 2020)

Range: from -1 to 408

2. Variable Temperature average

Description: Daily mean temperature (in 0.1 degrees Celsius) (KNMI, 2020)

Range: from -66 to 297

3. Variable Wind speed average

Description: Daily mean wind speed (in 0.1 m / s) (KNMI, 2020)

Range: from 9 to 94

4. Variable Minimum visibility

Description: Minimum visibility due to fog (KNMI, 2020)

Range: from 0 to 80

1.3 PREDICTOR VARIABLES QUARTILES, MONTHS, DAY OF THE WEEK

Values of predictor variable Months:

- January
- February
- March
- April
- May
- June
- July
- August
- September
- October
- November
- December

Values of predictor variable Quartiles:

- Q1 = January, February and March
- Q2 = April, May and June
- Q3 = July, August and September
- Q4 = October, November and December

Values of predictor variable Day of the week:

- Monday
- Tuesday
- Wednesday
- Thursday
- Friday
- Saturday
- Sunday

1.4 PREDICTOR VARIABLES NUMBER OF PALLETS

Values of predictor variable Number of Pallets:

- 0-100 Pallets
- 101-200 Pallets
- 201-300 Pallets
- 301-400 Pallets
- 401-500 Pallets

- 501-600 Pallets
- 601-700 Pallets
- 701-800 Pallets
- 801-900 Pallets
- 901-1000 Pallets

APPENDIX 2: DESCRIPTION OF RAW DATA FROM BRICKLOG

Name	Description	Type
Planning group	The organizational group under which the ride falls (there is no relationship between the groups)	Nominal
Plan group name	Name of the group	Nominal
Date	Date on which the ride was driven	Nominal
Shipment no	Shipment ID	Nominal
Ride no	Ride number of the shipment	Nominal
Driver ID	Number of the driver. Each driver has his own number.	Nominal
WagenID	Number of the car. Each car has its own number.	Nominal
Customer Name	Name of customer for which is driven	Nominal
Number of shipments	Number of shipments	Discrete
Unit	Pallets, pieces, kilos etc.	Nominal
Loadmeter	Number of meters of the pallets in the truck	Discrete
Pallet places	Number of pallet spaces in use	Discrete
LoadingTripID	Trip number	Nominal
LoadingZipcode	Postcode loading address	Nominal
LoadingCountry	Country of loading address	Nominal
UnloadingZipcode	Postcode unloading address	Nominal
UnloadingCountry	Country of unloading address	Nominal
Plangroupname	Name of the group	Nominal

Tabel … Variables in the original dataset

APPENDIX 3: CATEGORIES OF DEPENDENT VARIABLES

	Name of category
0.01-0.06	Low
0.07-0.12	Medium
0.11-0.16	High

Table 1: *Division of dependent variable Ratio Drivers Pallets in three categories*

	Name of category
0.1-0.9	Low
0.9-1.7	Medium
1.7-2.5	High

Table 2: *Division of dependent variable Driving hours per pallet in three categories*

	Name of category
3-80	Low
80-157	Medium
157-234	High

Table 3: *Division of dependent variable Driving hours in three categories*

APPENDIX 4: KEY QUESTIONS FOR FORECASTING

Key questions for forecasting according to Hanke and Wichern (2014) answered for the forecasting case in this research.

Question	Answer
1. Why is this forecast needed?	Predicting the demand for truck drivers. Deploying too many employees costs money, and hiring employees at the last minute (mainly temporary workers) costs a lot of money.
2. Who will use the forecast, and what are their specific requirements?	Logistic companies: they want to save costs. Bricklog: will offer forecasting as a service to these logistics companies. Business model is offering such it-related services. Requirements: an accurate forecast that is not too complicated
3. What level of detail or aggregation is required, and what is the proper time horizon?	It must be possible to calculate the demand for the number of drivers. Details that must be available, are the number of shipments that has been made on a day and the duration in time that it took to logistics the shipments. Time horizon: monthly forecasting
4. What data are available, and will the data be sufficient to generate the needed forecast?	Data from the past two years is available. On the one hand, this may be insufficient data, because discovering patterns in, for example, seasons, requires older data. On the other hand, the world and especially the world of logistics is changing very quickly, so

		older data does not necessarily have to be a good predictor for the future.
5.	What will the forecast cost?	The forecasting in this study was done through the R program, which is a free program. The logistics companies will have to pay the costs of hiring Bricklog, if forecasting will be done by them in the future.
6.	How accurate can we expect the forecast to be?	The higher the accuracy, the better. This allows a logistics company to save costs and anticipate the future. However, it is expected that the accuracy is not 100. It is not needed that the accuracy comes close to 100%. However, looking at the costs for logistics companies to hire Bricklog, there is strived to an accuracy of 80%. In order to make the forecast profitable.
7.	Will the forecast be made in time to help the decision-making process?	Because the deployment of drivers is an on-going process of the logistics companies, the forecast will arrive on time in the decision-making process. However, the situation is that the sooner the company knows how many drivers have to be deployed, the more favorable the forecast will be. It is not easy to let go or attract drivers, and this cannot be done just one month in advance. Nevertheless, the forecast can contribute to the decision-making process, by recruiting more actively

		or seeing whether a temporary contract will expire in the coming month.
8.	Does the forecaster clearly understand how the forecast will be used in the organization?	The forecaster has researched the scientific theory and was informed by Bricklog about the current situation and the desired forecast.
9.	Is a feedback process available to evaluate the forecast after it is made and to adjust the forecasting process accordingly?	Forecasting is systematically investigated through the use of design research. Every deployed artifact (forecasting technique) will be evaluated. The evaluation is done using performance measures.