MASTER

Improving the planning accuracy and route efficiency at a freight distribution company
a case study at Van Opzeeland

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Improving the planning accuracy and route efficiency at a freight distribution company

A case study at Van Opzeeland

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<td>Estimated Time of Arrival</td>
<td>4, 38</td>
</tr>
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<td>LSP</td>
<td>Logistics Service Provider</td>
<td>1, 2</td>
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<td>MAPE</td>
<td>Mean Absolute Percentage Error</td>
<td>14, 15, 18–20, 33, 35, 39</td>
</tr>
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<td>Mean Percentage Error</td>
<td>14, 15, 18–20, 33, 35, 39, 43</td>
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Abstract

This research is conducted at Van Opzeeland, a distribution company specialised in delivering to retail stores. The performance of the planning department in terms of planning accuracy and planning efficiency is researched and improved mainly using data-driven techniques. First, methods have been developed to validate the data that is entered in the computer terminal by drivers. Then, it has been found that the service time is highly variable and influences the planning accuracy. Statistical models have been developed to better predict the service time, the best model explains 35% of the variance. It is also found that not including the breaks in the planning is a major cause for delays and thus lower accuracy. Having a higher accuracy also leads to a greater efficiency. Finally, this research shows that some time window constraints greatly upset the planning efficiency and cause on average a detour of 20 kilometers each. During the research the planning accuracy has been improved and tools have been presented to measure the performance. The planning efficiency is improved by a more accurate planning and insights in the cost of time windows.
Management summary

This research is conducted at Van Opzeeland, a distribution company specialised in delivering to retail stores. The performance of the planning department in terms of planning accuracy and planning efficiency is researched and improved mainly using data-driven techniques.

Methods have been developed to validate data for future analysis. Currently about 70% of the service time data can be identified as valid and 40% of the driving time is identified as valid. Analysis is done on three areas of interest: service time, driving time, and time windows. An overview is presented in table 0.1.

<table>
<thead>
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<th>Service time</th>
<th>Driving time</th>
<th>Time windows</th>
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<tr>
<td></td>
<td>The service time is underestimated and predicted poorly.</td>
<td>The driving time is underestimated.</td>
<td>The cost of time windows is unknown.</td>
</tr>
<tr>
<td>Analysis</td>
<td>Service time is lognormal distributed; higher planning accuracy leads to higher planning efficiency.</td>
<td>Currently traffic does not influence the driving time; not including the breaks upsets the planning.</td>
<td>Government time windows are set correctly when looking at the pedestrian traffic; customer time windows occur throughout the day but have varying lengths and occur at different address densities.</td>
</tr>
<tr>
<td>Solution</td>
<td>Service time model with the shipper and amount of load as most important variables.</td>
<td>Include a break in the planning of 30 minutes around noon.</td>
<td>Use approximation models to describe the network.</td>
</tr>
<tr>
<td>Implementation</td>
<td>Preliminary model has been implemented in september 2015, new model should be implemented.</td>
<td>A driver break has been implemented in January 2016.</td>
<td>No action yet. Change tariffs when necessary to better reflect the costs.</td>
</tr>
<tr>
<td>Results</td>
<td>Preliminary results show that the predictive performance has increased and average delay has decreased.</td>
<td>Preliminary results show that the average delay has decreased.</td>
<td>Time windows of length 3 to 5 hours in rural areas are costly (20 km per order).</td>
</tr>
<tr>
<td>Future research</td>
<td>Further analyse the services that are offered to the customer and their effect on the service time.</td>
<td>When the driving time is explicitly administered more analysis can be done on deviations.</td>
<td>The extended approximation models can be confirmed by solving vehicle routing problems computationally.</td>
</tr>
</tbody>
</table>

Table 0.1: Management summary overview
Preface

Eindhoven, March 8th 2016

This report concludes my last 6 months working as a graduate intern at Van Opzeeland. It also signals the end of my 6.5 years as a student at the Eindhoven University of Technology and an exchange semester at UC Berkeley, USA. Therefore I would like to thank a few people who made this report and my enjoyable student chapter possible.

I would like to thank my first coach at the TU/e, Tom Van Woensel, for guiding me in my last student years. I appreciate your pragmatism and insights in the transportation research. I would also like to thank you for introducing me to Van Opzeeland. Also, I would like to thank Luuk Veelenturf, my second coach at the TU/e, for his critical view and very valuable notes in the last stages of writing this report.

At Van Opzeeland I would like to thank Theo Harmsen, my supervisor, for the freedom to execute this research project and valuable insights in the challenges the planning faces. I would also like to thank Bert Brouwers for his insights from a commercial perspective and the discussions about the ins-and-outs of the company. Finally I would like to thank Bert Boll and Gerrit Geenen for many insightful conversations about the IT and drivers, respectively.

During my time as a student I have been active in multiple student and sport organisations. Everywhere I have gained a lot of valuable experiences, had a lot of fun and made a lot of friends. I would like to thank all friends from Interactie, ESTIEM, Industria and Atletiek Vereniging Wijchen for making this possible.

Bram Vercammen
1 Introduction and research questions

1.1 Introduction

The transportation sector has been very competitive for years; prices are low and the demanded customer service is ever high. Customers require more and more accurate information than before about the status of deliveries, mainly concerning the estimate time of arrival. The transportation sector faces typical 'big data' problems; large amounts of data are available but it is not yet used to its maximum value, for example to increase the operational performance. Van Opzeeland, the company at which this case study is done, is no exception. In this research their will be a focus on empirical, data-driven, techniques to find value in the available data. The main objective is to increase the accuracy of the estimated time of arrival and through it also the route efficiency c.q. profitability.

The main driver for this research is the desire of the case company to enter the digital age and to do more with available data. This master's thesis is the first of a range of students doing research together with Van Opzeeland, including a granted project with two PhD and one PDEng student over the next couple of years. The goal is therefore not solely to research the problems at hand but also to provide a valuable backbone research of the basics that are related to the planning performance. Several subtopics are touched and tools are provided to monitor and improve performance on these subjects. Each subtopic in this research on its own could again be a subject for further research.

1.2 Company introduction

1.2.1 Van Opzeeland

Van Opzeeland is a logistics service provider (LSP) specialised in retail distribution. Daily, it delivers goods to clients in The Netherlands, Belgium and Luxembourg with the use of around one hundred trucks and trailers of varying size. It visits almost daily every large city center where its major clients are retail stores. After visiting the city center, which is often restricted to morning (un)loading, trucks visit more clients outside the pedestrian part of the center and also in suburban areas.

Van Opzeeland was founded in 1945 by the brothers Jan and Kees Van Opzeeland. It has since been part of Nimox BV and the Pax Group and is owned by the Nabuurs Group since 2011. It prides itself in its cost-leadership, mainly by combining freight from different shippers, and in its service oriented work methods. In the recent years it has been making improvements to its vehicle fleet by introducing long and heavy vehicles (Dutch: LZV, see figure 1.1). These large trucks can carry more load and are deployed on different long-distance and heavy traffic routes which include the provinces Groningen, Zeeland and Zuid-Holland. Van Opzeeland its main activity is freight distribution but it also executes warehousing activities for a part of its clients.

1.2.2 Nabuurs Group

Nabuurs has a vast distribution network and operates in multiple fields in transportation and warehousing. The Nabuurs Group is a family owned business, it has around 1200 employees
at around 20 sites. Nabuurs was the 13\textsuperscript{th} largest LSP of the Netherlands in 2015 (Logistiek.nl, 2015). Nabuurs its main focus is on the fast moving consumer goods market. Nabuurs offers integrated supply chain solutions at customer sites and it transports its goods throughout Europe as a logistic service provider. Nabuurs also operates with a network of regional distribution centers to deliver the goods for a major beer brewing company (Anheuser-Busch InBev). Van Opzeeland executes the fine-mazed distribution for its own clients but also executes orders with a small drop-size on behalf of Nabuurs. Currently, research is done to further integrate Nabuurs and its subsidiaries to increase operational efficiency.

1.2.3 Clients

The clients of Van Opzeeland can be organised in four categories:

- Retail chains, mainly shoe retailers and perfume stores often located in the pedestrian area of the city centers;
- Pet food wholesalers and large users, distribution to pet shops, veterinaries and kennels;
- Wine importers, distribution to liquor shops, hospitality industry, wholesalers and large clients;
- Tire centres, seasonal work to transport and store car tires for car garages for switching winter and summer tires.

The warehouse or central office from which the transportation orders originate will be referred to as the shipper. The delivery address to which the goods are delivered will be referred to as the client or customer.
Even though the content of the deliveries ranges from pet food to wine, they typically have the following characteristics:

- A delivery has a size of 1 to 5 pallets or trolleys;
- A delivery is made to a business address.

Dependent on the client there are fixed delivery times (mainly in city centers), just restricted by store opening hours or, even less restrictive, there might be a key to deliver the goods beyond opening hours. On a case-to-case base additional delivery time windows may be agreed upon. Some large shippers require a delivery appointment which is often strictly enforced. Aside from the restrictions set by clients there are also governmental restrictions, mostly in the pedestrian areas of the city centre. There restrictions include: vehicle size/length limitations, emission limitations, specific (un)loading hours and vehicle permits.

1.2.4 Vehicles

Van Opzeeland operates vehicles of varying size. For the line-haul operation to decentralised depots in The Netherlands long and heavy vehicles are used. The hauling from shipper warehouses to the central depot is done by semitrailers and the delivery of goods is done by trucks of sizes ranging from a delivery van to a semitrailer. All vehicle types for distribution and their corresponding capacity and required driver’s licence are listed in table 1.1.

<table>
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<tr>
<th>Name</th>
<th>Capacity (m²)</th>
<th>Dutch driver’s licence</th>
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<tr>
<td>Delivery van</td>
<td>4</td>
<td>B</td>
</tr>
<tr>
<td>Clickstar</td>
<td>8</td>
<td>BE</td>
</tr>
<tr>
<td>Truck</td>
<td>17</td>
<td>C</td>
</tr>
<tr>
<td>Semitrailer city</td>
<td>25</td>
<td>CE</td>
</tr>
<tr>
<td>Semitrailer</td>
<td>33</td>
<td>CE</td>
</tr>
</tbody>
</table>

Table 1.1: Van Opzeeland vehicles

1.3 Freight distribution

Van Opzeeland offers a 24-hour delivery service: orders are placed and delivered within 24 hours. For some shippers the warehousing activities are organised in-house. In most cases, however, the shipper operates its own warehouse and the goods are hauled to the central depot of Van Opzeeland in Hedel during the day.

Orders from the shippers are collected throughout the day parallel with the physical arrival of the goods. At night (currently 20:00 hour) the planning department starts planning the routes of the next day. This planning process continues throughout the night and is done mainly manually with the aid of specialised software. At night all vehicles are loaded such that in the morning drivers depart almost instantly with their loaded truck. Planned vehicles are released in batches to the warehouse for loading.

On the delivery day vehicles are typically assigned to a city center in the benelux where the first group of clients are retail stores. Because retail stores in city centres often have
restricted access roads, deliveries are made early morning in a predetermined sequence and timing. After the retail stores in the city center have been visited the vehicles move to less urban areas and deliver the rest of their goods.

Each vehicle route is executed by a driver, either internally employed or employed by a charter company. Drivers follow training programs to prepare them better for their work and to abide by government regulation. Whenever abnormalities occur during the driving or the servicing of a customer the planning department assists over the phone. The geographic location of all vehicles is known and vehicles are tracked throughout the day to ensure timely deliveries. Whenever possible Van Opzeeland will reach out to customers when a driver has a large delay.

1.4 Planning performance

The planning department is responsible for making an efficient routing of vehicles such that the cost of execution is as low as possible, while still meeting the customer requirements. In this report two measures for the planning performance are considered: the planning accuracy and the planning efficiency. The planning accuracy measures the correctness of the estimated time of arrival (ETA). The planning efficiency measures the extent to which an efficient routing, in terms of execution costs, is made given the set of orders and customer requirements. The current state of the planning accuracy and the planning efficiency are discussed below.

1.4.1 Planning accuracy

The goals of the planning department at Van Opzeeland are mainly to efficiently plan and execute deliveries. There is no systematic measurement of the ETA performance. In 2015 the average delay for orders increases throughout the day, as figure 1.2 displays. It shows that around 13:00 hour the average delay of a customer order is 40 minutes opposed to the planned arrival time. The main reasons for this inaccuracy are the high variability in service times and the large deviations in driving time. Figure 1.3 displays the standard deviation over time, one can see that the standard deviation also increases throughout the day.

![Figure 1.2: Average delay per order displayed per hour](image1)

![Figure 1.3: Standard deviation of delay per order displayed per hour](image2)

There are two types of time windows: (1) the time window restriction of the customer
and (2) the self-imposed time window. The time window imposed by the customer is most important and needs to be met, or a failed delivery may occur. The self-imposed time window (SITW) is a service proved to the customers and needs to be adhered to as much as possible. The concept of self-imposed time windows is described by Jabali et al. (2015). Van Opzeeland currently strives to always meet the delivery time window, but does not actively strive to meet the SITW as part of their daily business.

The time window imposed by the customer is restricted by either the opening hours of the customer site or by governmental restrictions for accessing the stores in busy shopping streets. The customer may also specifically request for a certain time window. The performance of delivering within the customer time window can be found in figure 1.4. On average 96% of orders are delivered before the end of the customer time window. Being too late however does not always result in a failed delivery. The closing time known by the systems may be incorrect or customers may wait for their deliveries. Therefore, the actual amount of failed deliveries due to delays is lower than 4%.

The SITW at Van Opzeeland is currently set with the start of the time window as the planned arrival time and the end of the time window two hours later. This has been a moderately reliable method since the service times were structurally underestimated and driver breaks were not taken into account. The time window performance is measured in three parts. Deliveries can be either: too early, within the time window or too late. For the SITW being too early is considered less problematic than in the case of delivery time windows set by the client, as the latter will probably incur waiting time. The performance of the self-imposed time windows can be found in figure 1.5.

Both the high uncertainty in service times and the certainty of a driver break, even though the break wasn’t incorporated in the planning yet, result in an early end of a planned shift. Figure 1.6 displays the distribution of the last order over time. As one can see most routes end at around 15:00. Though, most clients are open to receive goods until 17:00 or 18:00 hour. Increasing the certainty of service times and calculating the impact of driving deviations and incorporating breaks in the planning may greatly increase the planning efficiency.
1 INTRODUCTION AND RESEARCH QUESTIONS

1.4.2 Planning efficiency

Daily, the planning department has to make a planning given the current set of orders. The planning has to be feasible, that is, all orders have to be executed. Also, the planners have to plan and schedule all orders such that all customer requirements are met. Because the order set is different every day it is challenging to develop an efficient planning and maintain the desired level of profitability.

At Van Opzeeland the planning is currently made manually with the aid of vehicle routing software. Using the knowledge and experience of planners is crucial for Van Opzeeland to reach a feasible solution every night. Although there is abundant academic literature on solving vehicle routing problems computationally (e.g. Laporte (1992), Demir et al. (2014)), software providers have struggled to implement a workable solution at Van Opzeeland. As this research is focused on data-driven techniques to obtain valuable insights, the solving of vehicle routing problems is omitted. This research rather focuses on the impact of customer restrictions on the efficiency, in particular the impact of time windows.

Offering time window appointments to customers is closely related to the planning accuracy. One can not offer strict time windows when in fact they are hardly ever met. However, when the planning is very accurate also strict time windows can be agreed upon, for which shippers pay a premium. To determine the minimum price shippers should pay for this additional service it should be known what the cost of time windows are.

1.5 Research questions

At Van Opzeeland there is a desire to increase the planning performance using the data that is collected daily. Profitability margins are under pressure and to better identify the operational improvement areas a more accurate planning is needed. Also, it is found difficult to quantify the impact of customer restrictions, in particular custom time windows.
The main research question for this research is:

*How can the planning performance be improved?*

This research will focus on data-driven techniques to improve the planning accuracy and efficiency. The following subquestions are answered:

1. *How can reliable data for analysis be extracted from all available data?*

Currently whenever analysis are done at Van Opzeeland there is always a challenge with the reliability of data. There is the need for a systematic and single approach to validate reliable data to use for further analysis.

2. *How can the estimated arrival time of customer orders be made more accurate?*

Time reliability is highly valued by the freight transportation industry (Fowkes et al., 2004), this is also true for the customers of Van Opzeeland. Also, having a more accurate planning results in a lower uncertainty buffer, which increases the planning efficiency.

3. *How do time window constraints influence the planning efficiency?*

An important restriction that freight transportation companies face are time window restrictions. The additional cost of this restriction has been researched before, mainly using simulations (e.g. Deflorio et al. (2012), Muñuzuri and van Duin (2014)). In this report it is researched how historic data can be used to determine the costs of time window constraints.

The scope of this research is limited to the distribution activities of Van Opzeeland, in The Netherlands as well as in Belgium and Luxembourg. Figure 1.7 displays the transportation activities of Van Opzeeland. Within a route the research is limited to the part of the route that starts at the first order and ends at the last order, which is displayed in figure 1.8. The research is focused on this specific scope since it is the major contributor to turnover for Van Opzeeland. It is also the area which has the most, and best, registration of data. And, it is the area in which the customer service, in terms of estimated time of arrival, is most important.

The remainder of this research is organised as follows. Research question one is answered in section 2. Research question two is answered in section 3, here a model is developed for the prediction of service times. Also, contributing directly to the accuracy are the delays in driving time and the planning of breaks, which are discussed in section 4. Section 5 answers research question three. Section 3,4 and 5 are organised similarly, first the problem is stated, then the problem is further analysed and finally a solution design is suggested. Some of the solutions already have been implemented, these are discussed in section 6. Finally, this report is concluded by answering the research questions in section 7.
1 INTRODUCTION AND RESEARCH QUESTIONS

Figure 1.7: Scope of transportation

Figure 1.8: Scope of distribution route
2 Data Validation

During the delivery day the driver uses two types of administration: (1) a paper freight letter is used to get a customer’s signature and to give a receipt and (2) a computer terminal is used to register the service time and track the location of the driver, using GPS.

The usage of the data extracted from the computer terminals for analysis poses some challenges since not all data is entered (correctly). For further analysis three types of temporal data are discussed: (1) service time, (2) waiting time and (3) driving time. The service time is the time spend at the customer site, unloading goods and doing administration. The waiting time is the time spend on waiting for the customer to be ready to receive the goods, this may happen because a driver is too early or for example when the customer has limited staff to handle incoming goods. The driving time is the time between the servicing of subsequent customers. For each data type a method to extract valid data is discussed in the following sections.

2.1 Service time

The service time is manually registered by the driver. Upon arrival at the customer site the driver has to enter in the computer terminal that he starts unloading. When the unloading is done he registers the end of servicing the customer and does some additional administration.

Sometimes, there is more than one order for a single address, the driver will only start the first order (e.g. at time 10:00), and close the first order (e.g. at time 10:25), whereafter he will open and close the second order (e.g. both at time 10:25). Therefore, in the analysis one will have to take into account the total service time of a stop, combining all order information. Orders are identified as a single stop when subsequent orders have the same address and zipcode. Unfortunately, due to data inconsistencies multiple stops are not always automatically recognised as a single stop. This occurs for example when street names are written differently, or one address is with and the other without address number addition.

In order to separate valid from invalid data three types of invalid service time data are developed. Service time data can simply be missing, i.e. there is no digital administration of the servicing. The registration of the service time may also happen simultaneously for multiple stops at once. The last invalid type is for data that is simply invalid due to the length of the service time. All three types of invalid data are discussed below.

1. Missing data

Because the terminal computers are not always functioning and because charter drivers don’t always receive or use the terminal, overall 5-15% of orders don’t have a service time registered. These orders are excluded from further analysis.

2. Multiple stops

In most city centres the shops a truck delivers to are close to each other, here a driver delivers goods to multiple addresses without moving the vehicle. Since the computer terminal is located in the truck cabin, which the driver does not enter in between servicing different addresses, at the end of the service the driver will do its administration and open and close multiple orders at once. There is not a clear identifier for when multiple addresses are in practice combined. Therefor, the service time data for these
2 DATA VALIDATION

stops is unreliable. This is however a system imperfection rather than a driver error.

Stops that are closed within a timespan of 3 minutes (see appendix B) are considered to be closed at the same time and therefore all considered invalid. On average, 10-15% of stops is considered invalid due to logging multiple stops at once. These stops are removed from further analysis.

3. Invalid service times
For all remaining stops, not invalidated by the previous types, an additional measure is in place to remove unrealistic service times. To eliminate all invalid stops a minimum of 3 minutes and a maximum of 120 minutes service time is set (see appendix B). This invalidates 5-10% of the stops. The cause for these invalid stops is mainly human. The registration of a service time less than 3 minutes typically means that the driver forgot to start registering the service time in the computer terminal, and only does his administration after the servicing has been completed. The registration of service times larger than 120 minutes is rare and is mainly attributed to system errors.

Figure 2.1 displays the percentages invalid and valid service times.

![Figure 2.1: Service time validity](image)

2.2 Waiting time
The computer terminals have an option for drivers to register waiting time. The waiting time, however, is not widely used by drivers and is not used by the administration as a performance measure. There are several reasons for the waiting times to be hardly registered and used afterwards:

- Because the waiting time has to be started and stopped by the driver manually, with the computer terminal located in the vehicle, it is not convenient for a driver to register. For example, waiting time may occur when the driver has already left the vehicle during unloading.
• Waiting time is differently interpreted and used by drivers. About 50% of all registered waiting time is done by only 20% of the drivers.

• For a waiting time to be charged to the shipper, just the time registered is hardly enough. For a shipper to accept additional charges also the underlying reasons and actions taken have to be registered. This is only cost-effective when large waiting time occurs. In this case the driver will typically call the planning to notify them of the delay.

In some cases where there is excessive waiting time at a specific stop waiting time may be charged to the shipper.

The service time with the waiting time also gives a good representation of the required time spend on each stop. Some clients typically require more time, including waiting to be serviced, and this also has to be taken into account in the planning. Therefor, the registered waiting time will be ignored while analysing the service time.

2.3 Driving time

The driving time is not explicitly registered at Van Opzeeland but is the time between servicing two stops. The driving time is calculated by the planning software, the exact calculations are unknown and for this research the system is considered a black-box. The planned driving time is therefore used as an input and the expected driving time is not calculated afterwards. In order to analyse the difference in planned and actual executed driving time a few conditions need to be satisfied:

• The driving time between two stops can only be compared if the route is driven in the same order as planned. If the driver deviates from the planned order and services another stop in between two planned stop, the distance has changed. If the driver drives in the opposite direction, small deviations in distance and travel time may occur, therefore these instances are also omitted (see appendix B).

• Both stops need to have valid service times in order to be able to analyse the driving time. If either of the service times is invalid one does not know what happened exactly and whether the driving time might be upward or downward biased.

• Both the planned and actual driving time need to be greater than zero.

Figure 2.2 displays the percentages invalid and valid driving times.
3 Service time model

Using all valid data, analysis is done on the accuracy of the service time estimate. Currently at Van Opzeeland the service times are estimated per shipper based on historic averages. Sometimes also estimates are made on an address level if there are structurally high or low service times registered.

The service time estimate versus the actual service time as executed by the driver is currently inaccurate. The deviation of the actual service time from the estimate is biased (mean error = 1.5 minutes) and the standard deviation is high (10 minutes). The service time if further analysed and new service time models are presented to better estimate the service times.

3.1 Analysis

Before building service time models first the statistical characteristics of the service time are described. Then, the influence of increased accuracy on the planning efficiency is calculated to prove the importance of an accurate planning.

3.1.1 General characteristics

Figure 3.1 displays the histogram of service times of Van Opzeeland in 2015. The average service time is 14.44 minutes and can be best approximated by a lognormal distribution with parameters $\mu = 2.50$ and $\sigma = 0.57$ (figure H.1, appendix H). The right tail is bigger than the left tail, this is legitimate in reality since there will be a minimum service time (i.e. zero minutes). The right tail displays the low probability but large impact delays that occur in servicing a customer. The lognormal properties of the service time will be taken into account in developing advanced models for predicting the service time.
3. SERVICE TIME MODEL

3.1.2 Calculation example: the impact of service time variability on efficiency

By means of example the service time is assumed to be normally distributed with mean $\mu$ and standard deviation $\sigma$. Now assume a truck would execute $n$ stops in total, that is, $n$ random draws from the service times are done in a single route. The required buffer time, $b$, to account for variability in service times, taking into account a given service level, $s$, can be calculated. Let $Z$ be the corresponding standard score to service level $s$. First, the combined standard deviation can be calculated by summing the variances:

$$\sigma_n = \sqrt{n \cdot \sigma^2}$$

and the required buffer time can be calculated by:

$$b = Z \cdot \sigma_n.$$  \hspace{1cm} (1) \hspace{1cm} (2)

Calculation with original variability

Using the original data provided by Van Opzeeland the following buffer is required.

$\mu = 14.4$
$\sigma = 10$
$n = 15$
$s = 97.5\%$ (right tailed)
$Z = 1.96$

$$b_1 = 1.96 \cdot \sqrt{15 \cdot 10^2} = 76 \text{ minutes}$$ \hspace{1cm} (3)

Calculation with new variability

Now using the statistics for the variance of the service times after implementation of the service time model, the variance has been decreased, which in turn decreases the required buffer.
\( \mu = 14.4 \)
\( \sigma = 8.1 \)
\( n = 15 \)
\( s = 97.5\% \) (right tailed)
\( Z = 1.96 \)

\[
b_2 = 1.96 \times \sqrt{15 \times 8.1^2} = 61 \text{ minutes} \tag{4}
\]

Thus, increasing the estimation performance of the service times results in a lower required buffer \((b_2 - b_1 = 15 \text{ minutes})\), given a fixed service level. Having a lower required buffer means that more work can be planned for the same vehicle, in particular when a route is time restricted.

### 3.2 Solution

In this section a model for the service times is developed using order, shipper, address, driver, truck and weather information. The following models are covered in the next sections, the performance of which can be found in table 3.4 and the coefficients and their significance in appendix A.

1. A basic linear model which uses the same factors currently used in practice.
2. A basic linear model with a lognormal data transformation on the dependent variable to increase the model performance.
3. A model with all possible factors to identify factors that significantly influence the service time.
4. Model 3 with additional interaction factors.
5. A minimum viable model, deducted from the models above.

First, the modelling method is presented. Then, external data sources for weather information and address density statistics are presented. Finally, the model parameters and different models are discussed.

#### 3.2.1 Modelling method

The service time models are build using R Studio (RStudio Team, 2015). Using the build in multiple regression modeller (lm), which minimises the sum of squared errors, the models are tested. As the coefficient estimates are company specific and confidential these are omitted from this report. For each model the adjusted R-squared, hereafter referred to as the R-squared, Mean Percentage Error (MPE) and Mean Absolute Percentage Error (MAPE) are used as measures for the fitness of the model.

The R-squared measures the portion of variance explained by the model, versus the total variance in the dependent variable. The highest R-squared value is 1, the lowest sensible value is zero. Using the average as a model results in a R-squared of exactly zero. The MPE is a measure for the mean percentage bias of deviations and should be close to zero (either
positive or negative). The MAPE is a measure for the mean absolute percentage deviation, which should be as small as possible. The MPE and MAPE are calculated as follows:

\[
MPE = \frac{1}{p} \sum_{i=1}^{p} \frac{Y_i - E_i}{Y_i} \times 100%
\]

\[
MAPE = \frac{1}{p} \sum_{i=1}^{p} \left| \frac{Y_i - E_i}{Y_i} \right| \times 100%
\]

Where the actual distance for observation \( i \) is \( Y_i \) and the estimated distance is \( E_i \). The total amount of observations is \( p \).

### 3.2.2 Weather information

The influence of the weather on (un)loading conditions is currently unknown. Historical data is used to find possible influences. At the Dutch bureau for weather information (KNMI) publicly available weather data is available. Weather data from the central weather station (De Bilt) is collected over 2015. The extracted variables are displayed in table 3.1. There are different types of measures for the weather (e.g. temperature, windspeed). For each measure there are also different parameters available, for example the daily minimum or maximum. For each type of measure available the parameter is chosen that displays the mean during the day, since this best represents the (un)loading conditions throughout the day.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>FG</td>
<td>Daily mean windspeed (in 0.1 m/s)</td>
</tr>
<tr>
<td>TG</td>
<td>Daily mean temperature in (0.1 degrees Celsius)</td>
</tr>
<tr>
<td>SQ</td>
<td>Sunshine duration (in 0.1 hour) calculated from global radiation (-1 for &lt;0.05 hour)</td>
</tr>
<tr>
<td>RH</td>
<td>Daily precipitation amount (in 0.1 mm) (-1 for &lt;0.05 mm)</td>
</tr>
<tr>
<td>PG</td>
<td>Daily mean sea level pressure (in 0.1 hPa) calculated from 24 hourly values</td>
</tr>
<tr>
<td>NG</td>
<td>Mean daily cloud cover (in octants, 9=sky invisible)</td>
</tr>
<tr>
<td>UG</td>
<td>Daily mean relative atmospheric humidity (in percents)</td>
</tr>
</tbody>
</table>

Table 3.1: Weather information variables

### 3.2.3 Surrounding addresses density

Van Opzeeland delivers to addresses in very urban areas (e.g. city centres) but also in rural areas. Unloading conditions between urban and rural areas may differ, therefor information is gathered on the density surrounding an address.

The Dutch bureau for statistics (CBS) has defined a measurement for the density of an area called the Surrounding addresses density (OAD, Dutch: Omgevingsadressendichtheid). This is a measurement for the amount of addresses per square kilometer. The amount of addresses is calculated per address by counting the amount of addresses within a circle of a kilometer surrounding it. Next, the amount of addresses per squared kilometer is averaged...
over all addresses in the postal area (Centraal Bureau voor de Statistiek). Using the OAD, each zipcode can be classified from rural to very urban using table 3.2.

Table 3.2: Urban classes

<table>
<thead>
<tr>
<th>Class</th>
<th>Class name</th>
<th>Addresses per km²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Very strongly urban</td>
<td>&gt; 2500</td>
</tr>
<tr>
<td>2</td>
<td>Very Urban</td>
<td>1500-2500</td>
</tr>
<tr>
<td>3</td>
<td>Urban</td>
<td>1000-1500</td>
</tr>
<tr>
<td>4</td>
<td>Suburban</td>
<td>500-1000</td>
</tr>
<tr>
<td>5</td>
<td>Rural</td>
<td>&lt; 500</td>
</tr>
</tbody>
</table>

The information from the OAD can be used to attribute an urban class to addresses. One will see that typically each shipper operates in a specific range of address densities. Using these address attributes in the models, instead of using shipper-specific parameters, more general models can be obtained.
### 3.2.4 Model variables

<table>
<thead>
<tr>
<th>Name</th>
<th>Source</th>
<th>Variable type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shipper</td>
<td>Order</td>
<td>Category</td>
<td>Shipper name</td>
</tr>
<tr>
<td>StopDISOVE</td>
<td>Order</td>
<td>Number</td>
<td>Calculated $m^2$ load per stop to deliver</td>
</tr>
<tr>
<td>StopRETOVE</td>
<td>Order</td>
<td>Number</td>
<td>Calculated $m^2$ load per stop top pickup</td>
</tr>
<tr>
<td>StopRetOVEAdj</td>
<td>Order</td>
<td>Number</td>
<td>Adjusted return $m^2$ load per stop, including load for clients that always return their containers</td>
</tr>
<tr>
<td>hhstart</td>
<td>Order</td>
<td>Number</td>
<td>Calculated hour of start time of unloading</td>
</tr>
<tr>
<td>REMBOURS_JN</td>
<td>Order</td>
<td>Y/N</td>
<td>If Y then the customer is required to pay for the goods upon arrival.</td>
</tr>
<tr>
<td>Adr.code</td>
<td>Address</td>
<td>Category</td>
<td>Unique identifier for an address</td>
</tr>
<tr>
<td>PC1</td>
<td>Address</td>
<td>Category</td>
<td>First number of zipcode (Netherlands) or 'B' for Belgium.</td>
</tr>
<tr>
<td>Land</td>
<td>Address</td>
<td>Category</td>
<td>Country of destination</td>
</tr>
<tr>
<td>Bijrijder.f</td>
<td>Address</td>
<td>Y/N</td>
<td>If Y then address requires a second employee for unloading.</td>
</tr>
<tr>
<td>retplusdis</td>
<td>Shipper</td>
<td>Y/N</td>
<td>If Y then clients of a specific shipper always returns the same amount of $m^2$ load for each order</td>
</tr>
<tr>
<td>ZENDING_AFGESTAPELD</td>
<td>Order</td>
<td>Y/N</td>
<td>Registration of a driver for an order if the goods have been unstacked from its pallet or container</td>
</tr>
<tr>
<td>PlanLoad</td>
<td>Route</td>
<td>Y/N</td>
<td>If Y then the vehicle is loaded by the driver itself, otherwise by warehouse employees</td>
</tr>
<tr>
<td>Plan2nd</td>
<td>Route</td>
<td>Y/N</td>
<td>If Y then route is identified as a second route</td>
</tr>
<tr>
<td>Driver.f</td>
<td>Route</td>
<td>Category</td>
<td>Driver number categorised</td>
</tr>
<tr>
<td>DriverCount</td>
<td>Driver</td>
<td>Number</td>
<td>Calculated value of how many times a drives has driven this route</td>
</tr>
<tr>
<td>Age</td>
<td>Driver</td>
<td>Number</td>
<td>years since birthday year</td>
</tr>
<tr>
<td>YearsOfService</td>
<td>Driver</td>
<td>Number</td>
<td>years since year of first workday</td>
</tr>
<tr>
<td>VOERTUIG_SOORT</td>
<td>Route</td>
<td>Category</td>
<td>Vehicle type</td>
</tr>
<tr>
<td>DAGRAPPORT_TIJD</td>
<td>Route</td>
<td>Number</td>
<td>Total actual duration of the route</td>
</tr>
<tr>
<td>AANTAL_STOPS</td>
<td>Route</td>
<td>Number</td>
<td>Total amount of stops in route</td>
</tr>
<tr>
<td>Sted</td>
<td>CBS</td>
<td>Category</td>
<td>Urban category variable</td>
</tr>
<tr>
<td>OAD</td>
<td>CBS</td>
<td>Number</td>
<td>Surrounding Address Density, average amount of addresses in a $km^2$</td>
</tr>
</tbody>
</table>

Table 3.3: Model parameters
3.2.5 Model 1 and 2: Basic models

Using the same parameters as readily available in practice, being the shipper from which the order is originated and $m^2$ of load (OVE), a linear model is calculated to estimate the actual service time per stop. Using linear regression the $\beta$ estimates are derived.

Model 1: $ST_1 = \beta_0 + \sum_{i=1}^{C} \beta_i * X_i + \beta_l * l + \epsilon$

(5)

Where,
$\beta_0$ = estimate intercept
$\beta_i$ = estimate per shipper
$\beta_l$ = estimate per load
$c$ = Shipper number
$C$ = Number of unique shippers
$l = m^2$ load

$X_i = \begin{cases} 1 & \text{if order originates from shipper } i \\ 0, & \text{otherwise} \end{cases}$

As one can see in figure 3.2 the predicted distribution and original distribution are not similar for model 1, especially in the higher quantiles. Also the MPE (-28%) and MAPE (48%) display large deviations. In the current model the high, uncommon, service times upset the model as their deviation weighs heavily opposed to smaller, more common, service times. Taking the natural logarithm of the service time makes the models perform better, the residual plot (figure 3.3) and model performance (table 3.4) are notably better. Therefore, in the next models the service time is estimated by first transforming it to the natural logarithm. Model 2 (equation 6) uses the same independent variables as model 1 (equation 5) but uses the natural logarithm. As table 3.4 displays the performance in terms of r-squared is a little worse, but the MPE and MAPE performance is remarkably better.

Model 2: $ST_2 = e^{(\beta_0 + \sum_{c=1}^{C} \beta_c * X_c + \beta_l * l + \epsilon)}$

(6)
3 SERVICE TIME MODEL

<table>
<thead>
<tr>
<th>Model</th>
<th>$R^2$</th>
<th>Adjusted $R^2$</th>
<th>MPE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1 (Basic)</td>
<td>.265</td>
<td>.265</td>
<td>-28.30</td>
<td>48.64</td>
</tr>
<tr>
<td>Model 2 (Basic lognormal)</td>
<td>.238</td>
<td>.238</td>
<td>-4.56</td>
<td>16.93</td>
</tr>
<tr>
<td>Model 3 (All parameters)</td>
<td>.336</td>
<td>.335</td>
<td>-3.95</td>
<td>15.53</td>
</tr>
<tr>
<td>Model 4 (All + interaction)</td>
<td>.354</td>
<td>.352</td>
<td>-3.84</td>
<td>15.28</td>
</tr>
<tr>
<td>Model 5 (Minimum viable)</td>
<td>.276</td>
<td>.275</td>
<td>-4.38</td>
<td>16.55</td>
</tr>
</tbody>
</table>

Table 3.4: Service time model overview

3.2.6 Model 3: All factors

In this model all available factors are added to find factors that significantly influence the service time. Also, the effect size of a factor is taken into account when considering adding factors in the final model. The $R$-squared measure for model 3 is .336 (table 3.4) and the MPE and MAPE performance are better than model 1 and 2. All factors that are included in the model are listed in table A.3, the explanation of the variables is listed in table 3.3. Most important factors, being significant and of relatively large effect size, are: Shipper, StopDisOVE, StopRetOVE and Driver.f. Driver characteristics age and years of service have a significant effect and a moderate effect size. The effect of age is positive (i.e. a higher age results in a higher service time) and the effect of years of service is negative. Both effects seem to balance one another.

Factors that are not significant or of very small effect size include geographic properties (country, zipcode, density), weather measures (table 3.1), truck characteristics (vehicle type) and total route statistics (amount of stops, total distance). Also driver-route combination characteristics such as if the driver loaded the vehicle himself or if a driver has driven a certain route before, show very small effect sizes.

3.2.7 Model 4: Interaction factors

From practice several interaction factors are derived and added to the model. The following factors are considered:

- Shipper number * StopDisOVE: The time spend per unloading unit may differ per shipper.
- Shipper number * StopRetOVE: The time spend per return loading unit may differ per shipper.
- Shipper number * ZENDING_AFGESTAPELD: The time spend on extra service may differ per shipper. The ZENDING_AFGESTAPELD variable is a somewhat ambiguous measure that captures if drivers have unloaded the good from the load carrying container or pallet. Drivers have to say either 'Yes' or 'No' to this after delivering each order. The measure is ambiguous because the exact meaning of 'unstacking' goods is not clear and the variable may capture also other services offered.
From table A.4 it can be seen that all three interaction factors have a significant effect and are of reasonable effect size. Therefore, all three interaction factors will be used in the final model.

3.2.8 Model 5: Minimum viable model

Using all information from the previous models a model is developed which best estimates the service time. This minimum viable model uses only significant factors with a high effect size and could be implemented in practice. One important factor, the driver, is excluded from the model as it is undesirable to adjust the service time to the speediness of specific drivers.

The performance of model 5 is less than the performance of the models 3 and 4, but has the advantage of being less complex. Also, the MPE and MAPE performance is quite similar (table 3.4). The model performs better than model 1 and 2. The mathematical formulation for model 5 is:

$$Model\ 5:\ ST_5 = e^{(\beta_0 + \beta_l l + \beta_u u + \sum_{i=1}^C X_i (\beta_{ci} + \beta_{cl_i} l + \beta_{cu_i} u) + \beta_s S + \epsilon)}$$

Where,
- $\beta_0$ = estimate intercept
- $\beta_{ci}$ = estimate for shipper $i$
- $\beta_l$ = estimate per load distribution
- $\beta_u$ = estimate per load return
- $\beta_s$ = estimate for unstacked load
- $\beta_{cl_i}$ = estimate for shipper $i$ specific load distribution
- $\beta_{cu_i}$ = estimate for shipper $i$ specific load return
- $i$ = Shipper
- $C$ = Number of unique shippers
- $l$ = m$^2$ load distribution
- $u$ = m$^2$ load return

$$X_i = \begin{cases} 1 & \text{if order originates from shipper } i \\ 0 & \text{otherwise} \end{cases}$$

$$S = \begin{cases} 1 & \text{if order unstacked at customer} \\ 0 & \text{otherwise} \end{cases}$$

3.3 Conclusion

Accurately estimating the service time is important for transportation businesses as it is an important, yet uncertain, part of the planning. When a more accurate planning is available the customer service is increased and less buffer time has to be scheduled. Using a ”big data” approach data from multiple sources has been gathered and tested for influence on the service time. Most external data, however, did not result in better performing models.

First the current model has been tested (model 1) and improved by doing a lognormal data transformation (model 2). Then, all possible factors and interaction factors have been investigated (model 3 and 4). Finally a model is presented (model 5) which incorporates the
most important factors which have a reasonable effect size.

The current theoretical maximum is reaching a R-squared of 0.35 (35% of variance is explained). When more factors that may influence the service time are captured by Van Opzeeland the explained variance in the service time may further increase. Examples of which are services offered (e.g. delivering to departments within a building vs. delivering to a warehouse) or address specific restrictions (e.g. parking, walking, elevators, stairs).

Since the service time is best modelled with the driver as an independent variable, reasonable effort should be spend to decrease the differences between drivers. When each driver would execute a planned route the same, the driver should no longer be a part of the service time estimate. More on this can be found in section 6.1.
4 Driving and breaks

Driving time is the time spend between servicing two stops, and also between the depot and the first and last stop. The driving time can be analysed and underlying causes for under- and overestimated driving times are researched.

The first results from the driving times show that the average deviation between the actual and planned driving time is 3 minutes, with a standard deviation of 12 minutes, assuming a normal distribution. Because the driving time is implicitly taken from the service time registration, additional time such as driver breaks are also attributed to the driving time. Because the break-time registration is not complete (60% logged) and drivers sometimes take their break at the middle of the day and sometimes at their end of the route, information is missing to accurately filter out the breaks from the driving time.

The deviation in driving times over time is displayed in figure 4.1. One can see that in the early morning the driving times are overestimated, which would normally be when cars and trucks are delayed because of rush hour traffic. Starting 9 o’clock every hour only delays are captured. The highest peak of delays is around 12 o’clock, which is the time most drivers take a break.

![Aggregate driving delta](image)

Figure 4.1: Sum of delayed minutes of driving time displayed per hour

4.1 Analysis

This analysis is separated into two parts. First the driver breaks will be analysed and the influence on the driving deviations will be shown. Next, information for traffic jams is presented and the influence of traffic jams on the driving deviations is discussed.

4.1.1 Break analysis

Apart from the logging of service times the drivers at Van Opzeeland also have to log their break time. The required break-time is heavily regulated and the company therefor acts on
drivers who do not take enough break-time during the day (by subtracting these minutes from their total paid time). In the computer terminal the start of the break is entered and the end of the break is signalled by either an end break event or some other activity (driving, opening an order, etc). All relevant events from the terminal are sent to the TMS of Van Opzeeland and are summarised per driver per day. From these summarised day-reports the start and length of the driver breaks are derived using a VBA macro.

Currently 60% of distribution routes have break-times registered, this is low mainly because of two reasons:

- Charter drivers who use the computer terminal are not mandatory to log their breaks, as they typically have to log breaks in the terminal of their charter company.

- Because of the policy of always deducting the break-time minutes, some drivers take their break throughout the day at their convenience without registering it. In the end, the drivers don’t have a direct interest in this administration if the end result (hours paid) is the same.

Drivers are under strict government regulations concerning their driving and break hours (Appendix E). After a certain amount of driving hours the truck driver is mandatory to take a break, or may face serious fines. In distribution, drivers generally have their longest drive between their base and the first and last stop. In between stops the driving is typically relatively short and a driver may spend up to 30% servicing the customers. Therefore, the maximum allowed hours of driving is often reached only at the end of the day. At Van Opzeeland drivers are currently free to take their break whenever it is most convenient, some will do so around noon, but others will finish their whole route first and take their break-time at the end. Because of the company’s policy for a driver to be mandatory to take a break, whether or not it is commanded by law, drivers will be deducted hours anyway if no breaks are logged.

![Figure 4.2: Break duration histogram](image)

**Figure 4.2: Break duration histogram**
A further analysis is done of the breaks in week 50 of 2015. Figure 4.2 displays the amount (y-axis) of breaks logged per break length (x-axis). Break durations are centred amongst three types of breaks: 15, 30 and 45 minutes, which is in correspondence with the legislation. The breaks are divided into three groups, referred to as type 1, 2 and 3 respectively. The cutoff points between type 1 and 2 and between type 2 and 3 are chosen to be 23 and 36 minutes, respectively. Each break type represents the break lengths that are recognised by legislation (15, 30 and 45 minutes).

Figure 4.3 displays the time at which each break type is started. It can be seen that the shortest break is taken throughout the day, the 30 minute break (type 2) is mainly taken at lunchtime but also at the end of the shift. Breaks of 45 minutes (type 3) is about equally registered at around noon and at the end of the day. Long breaks registered after 15:00 hours typically are a direct consequence of the administrative policy to make breaks mandatory as the drivers after this break no longer have work to fulfil.

With the current data of Van Opzeeland the deviations in driving time are largely influenced by the breaks a driver takes. With the current method of registration it is cumbersome to extract more information about deviations rather than those caused by breaks. Figure 4.4 displays the overlap of percentage break minutes registration and percentage delays in driving time. From this figure it can be concluded that breaks that are taken throughout the day upset the planning and cause most of the current driving time deviations. Breaks taken at the end of the shift (normally starting at 15:00) do not seem to influence the driving deviations.
41.2 Traffic jams

At Van Opzeeland there is a lot of knowledge from drivers and planners concerning routes and traffic. This personal knowledge is used to optimise routes. Generally, trucks depart from their base at an early time as to avoid traffic jams, even though this might cause some waiting time at the customer. However, to quantify the influence of jams on the performance, more information needs to be captured. For the use of traffic information, which is not widely available in free datasets, the free RSS feed from the Dutch traffic information services at vid.nl (Dutch: Verkeersinformatiedienst) is used. Using a php script (Appendix D) the amount of traffic jams and the total kilometers of traffic jams is captured every 5 minutes and stored in a database. The data is used to show the trends of traffic jams and the consequences in the distribution routes. Figure 4.5 displays all measured points for week 50, 2015. This data is later aggregated over the weekdays and used to explain deviations in the driving time.
The influence of traffic on the driving deviations can be inspected by overlaying the total traffic profile over the total driving delays. As one can see from figure 4.6 there is no apparent correlation between traffic and driving delays. However, remarkably, in the morning there is an overestimation of the driving time during the rush hour. As the exact calculation of the current planning software in use is unknown, further investigation is required to find the source of this overestimation.

The reason why Van Opzeeland does not seem to be affected by traffic jams is because they have structured their deliveries in such a way that each vehicle arrives at its first destination (between 7 and 8 a.m.) while traffic jams surge. Using the knowledge of drivers and planners the departure time of each vehicle is set such that traffic jams are avoided and the arrival time at the first address is accurate.
4.2 Solution

In the previous section it has been shown that the largest contributor to the deviations in the driving time is the lack of including the break in the planning. For Van Opzeeland it is important to know how they should include the break in the planning to lower the large deviations that occur early afternoon. Therefore, the next section calculates the optimal break that should be included in the planning, using historic data.

4.2.1 Planning with breaks

A break will be included in the planning shifting all orders after the start break time with a certain amount of minutes. For this analysis all orders of 2015 are used. The objective is to minimise the expected delay in the afternoon by incorporating a break in the planning at start $s$ of duration $b$. Equation 8 describes the objective function, and minimises the delay over all orders $i$, denoted by $|i|$. The idea is to use historic data to find the best break that would have fitted the execution better. Needless to say it would be best if breaks are planned and the driver would (be able to) take his break at exactly this time.

The optimal break duration is found by first setting the break start, $s$, and setting the input variable $X_i$ to '1' whenever the planned arrival time, $A^p_i$, is later than the break start. Then, the objective function is minimised using the GRG nonlinear solver in Excel.

$$\text{minimise } \sum_{i} (A^a_i - A^c_i)^2$$

(8)

$$A^c_i = A^p_i + X_i \times b$$

(9)

Where,

$A^p_i$ = Original planned arrival time of order $i$

$A^c_i$ = Corrected planned arrival time of order $i$

$A^a_i$ = Actual arrival time of order $i$

$b$ = Length of break

$s$ = Start of break

$i$ = Order

$$X_i = \begin{cases} 
1 & \text{if } A^p_i > s \\
0 & \text{otherwise}
\end{cases}$$

The results from the optimal break duration to plan with are displayed in table 4.2. From this result it is concluded that planning with a break of 30 minutes that starts between 11:30 and 12:30 is best, using historic data. Whenever drivers are instructed to take the break at noon, instead of after their shift, it is important to reset the break time. The minimum break duration a driver is currently mandatory to take is 45 minutes, it depends on when the driver actually takes this break in whether and when to include the break in the planning. This approach assumes that the average delay is not biased by other factors such as the service time. Therefore, the average and variance of the delay should be monitored continuously to finetune the optimal set of planning parameters.
4 DRIVING AND BREAKS

<table>
<thead>
<tr>
<th>i</th>
<th>$A^e_i$</th>
<th>$A^p_i$</th>
<th>$X_i$</th>
<th>$A^c_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10:03</td>
<td>10:05</td>
<td>0</td>
<td>10:05</td>
</tr>
<tr>
<td>2</td>
<td>11:49</td>
<td>11:41</td>
<td>0</td>
<td>11:41</td>
</tr>
<tr>
<td>3</td>
<td>12:44</td>
<td>12:03</td>
<td>1</td>
<td>12:33</td>
</tr>
<tr>
<td>4</td>
<td>13:15</td>
<td>12:51</td>
<td>1</td>
<td>13:21</td>
</tr>
<tr>
<td>5</td>
<td>14:30</td>
<td>14:23</td>
<td>1</td>
<td>14:53</td>
</tr>
</tbody>
</table>

Table 4.1: Example data for calculating optimal break with start 12:00 hour.

<table>
<thead>
<tr>
<th>Break start</th>
<th>Optimal break duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>11:30:00</td>
<td>00:30:44</td>
</tr>
<tr>
<td>12:00:00</td>
<td>00:30:58</td>
</tr>
<tr>
<td>12:30:00</td>
<td>00:30:09</td>
</tr>
<tr>
<td>13:00:00</td>
<td>00:28:27</td>
</tr>
<tr>
<td>13:30:00</td>
<td>00:25:28</td>
</tr>
</tbody>
</table>

Table 4.2: Optimal planned break duration per start time using 2015 data.

4.3 Conclusion

This chapter has shown that Van Opzeeland faces inaccuracies of its driving times that are likely to be very company specific. It has been found that the company has been very good at avoiding traffic early morning and also does not face large delays due to evening rush hour traffic. However, not including breaks in the planning is found to be a major cause for current deviations in driving time. Using historic data it has been found that including a break of 30 minutes at around 12 o’clock is best to optimise the estimated time of arrival.

In the future Van Opzeeland should incorporate breaks in the planning and may instruct drivers to follow this schedule as strict as possible. Also, effort should be spend to explicitly administer the driving time, deducting any planned and actual breaks. This may make future data available for more advanced analysis of deviations in planned versus actual driving time.
5 Time windows

In this section the influence of time windows on the route efficiency is discussed. Currently there are time windows restrictions because (1) the government has restricted traffic to the shop, for example in city centers, or (2) the customer has requested a specific time window. Currently the exact influence of having these customer time windows on the planning efficiency is unknown.

5.1 Analysis

In this analysis governmental and customer time windows are discussed. It is generally accepted that increasing the restrictions leads to a less optimal solution. Therefore, it is researched if governmental time windows are currently set at reasonable times. It is also shown when and where customer currently occur at Van Opzeeland.

5.1.1 Governmental time windows

Large city centres in The Netherlands have developed their own body of rules to regulate the freight traffic. The most popular measure is to assign pedestrian areas to the shopping streets where freight trucks are only allowed to deliver goods until a certain time (Muñuzuri and van Duin, 2014). As figure 5.1 displays the most popular time to close the shopping streets for traffic is around 11 o’clock.

Figure 5.1: Percentage of a representative sample of Dutch cities that allow access to the center at each time of the day (Muñuzuri and van Duin, 2014).

The reason for local governments to restrict traffic to early morning is usually to protect pedestrians. To quantitatively contribute to the discussion there is an interest in the pedestrian traffic throughout the day.
The debate between municipality and logistic companies has been the same for years, outweighing the (perceived) inefficiency of logistics companies with the (perceived) benefits for shops, environment and pedestrians. In recent years more data has become available, instead of taking samples of pedestrian traffic currently technology exists, and is in place, that continuously monitors the amount of traffic in city centres. For the Netherlands and Belgium a data set is purchased from the company CityTraffic. The average amount of pedestrians, shown in percentage of registrations per hour, is displayed in figure 5.2.

![Figure 5.2: Percentage of registrations in the Kalverstraat, Amsterdam. October 2015.](image)

CityTraffic is a company that registers the amount of pedestrians in all major shopping streets in The Netherlands and Belgium. The registration is done by automatically counting the nearby cellphones and other devices that are detectible by bluetooth or Wi-Fi. At CityTraffic there is an estimated factor per measurement location for the percentage of actual pedestrians that are detectible. The purchased dataset includes the percentage of registrations over time (per half hour), for 189 locations during October 2015. An example of city traffic data for a single location, for a single week can be found in figure G.1 (appendix G).

From both figure 5.1 and 5.2 it can be seen that the closing of shopping streets for traffic coincides very closely with a steep increase in pedestrian activity, both around 11 o’clock. The same pattern holds for most Dutch and Belgium city centres. No causality can be proven either way (e.g. it may be that pedestrians know that the trucks leave at 11 a.m. and therefore start entering the center at that time).

Thus, time window restrictions set by governmental bodies have proven to be consistent with their reasoning of restricting the vehicle access when most pedestrians are present. Therefore in further analysis the time window set by governments for highly populated areas (i.e. city centres) will be taken as a given. More effort will be spent on time window restrictions explicitly set by customers that may decrease the vehicle routing efficiency.
5.1.2 Customer time windows

Customers have varying reasons to ask for a small delivery time window. Some customers have restricted warehouse opening hours, others may need goods early morning to restock their inventory for afternoon sales. At Van Opzeeland the length and start time of the time window is related to the location of the customer. As one can see in figure 5.3 the shortest time windows are planned early morning. Figure 5.4 displays the address density in which the time window is set. From both figures it can be derived that routes at Van Opzeeland start with strict time windows in the urban areas, having time windows more strict than required by the government. Then, the vehicle routes move to less urban areas where wider time windows are set.

Figure 5.3: Start of time windows grouped per time window length of an hour

Figure 5.4: Address density of time windows grouped per time window length of an hour
5.2 Solution

In this section a general model is shown and calculated to determine the total amount of kilometers travelled to execute a certain set of orders on a single delivery day. Next, an extension to the general model is provided that takes time window requirements set by the customer into account. Using this model conclusions can be made about the efficiency of the network and, in specific, the costs of orders bounded by strict delivery time windows.

5.2.1 Distance approximation model

The general model developed by Daganzo (1984) to estimate the total distance traveled for a set of orders has recently been completed with an extension to include time window requirements by Figliozzi (2009). The basic idea is that the total distance travelled consists of (1) a connecting and (2) a local distance. The connecting distance is the distance from the depot to the delivery area, the local distance is the distance within the delivery area. For time windows there is a ‘penalty’ distance caused by more inefficient routing. Both the connecting and local distance can be described with different mathematical formulations. Using historical data and linear regression factors for the connecting distance, local distance and time window penalty can be found. Using these case specific factors future estimates can be made. For known benchmark instances (e.g. Solomon’s) benchmark factors are presented in Figliozzi (2009).

The model in its most basic form developed by Daganzo (1984) is depicted in equation 10. Given a set of orders, \( V^n \), the total amount of distance travelled using a vehicle routing problem, \( VRP(V^n) \), is approximated. In the basic model only an estimation factor for the local distance is calculated, while assuming a fixed connecting distance based on the average distance to the addresses.

\[
VRP(V^n) \approx k_l \sqrt{An} + 2m\bar{r}
\]  

(10)

Where,
- \( n \) = amount of orders
- \( k_l \) = estimate for local distance
- \( m \) = amount of vehicles
- \( \bar{r} \) = average distance to customer

Other models displayed in table 5.1 use additional factors:
- \( k_m \) = estimate for connecting distance per truck
- \( k_b \) = estimate for local distance (2)
- \( k_d \) = estimate for connecting distance
- \( k_t \) = estimate for time window penalty
- \( m_d \) = amount of vehicles required without time window restrictions
- \( p_t \) = fraction of orders with time windows

All estimate factors are determined through linear regression, the amount of orders, \( n \), amount of vehicles, \( m \), and fraction of orders with time windows, \( p_t \), are extracted from...
available data. The average distance to each customer that was visited in 2015 from the central depot is calculated. For the calculation of the unique addresses (tens of thousands) a local distribution of the opensource java map program GraphHopper was used, running an opensource map of the Benelux provided by OpenStreetMap®.

5.2.2 Model comparison

All 12 models presented in Figliozzi (2009) are recalculated using real-life data made available by Van Opzeeland. In table 5.1 the adjusted R-squared, MPE and MAPE are presented for the calculations. The average results from Figliozzi (2009) serve as a benchmark.

The 12 models can be split into two groups: the first group consists of general distance models; the second group includes time windows in the distance model. Each model describes the interaction between the variables differently. For example, the \( \frac{n-m}{m} \) fraction aims to control for differences in the orders \( n \) per truck \( m \). All models are tested because using the data of Van Opzeeland the most favourable model may differ than the tested benchmark instances.

The results of the models are similar when comparing R-squared measures between the benchmark and Van Opzeeland data. The MPE performs generally better and the MAPE generally worse. The high MAPE signifies larger deviations that occur in reality. Also, part of the inaccuracy of the model might be caused by data inaccuracies and limitations of the model (see section 5.2.6). In general the model performs well when using all data points to develop the model (i.e. in-sample performance) and results are comparable to the benchmark. Model 3 and model 10 are chosen for further analysis for their relatively high performance combined with their mathematical simplicity.

5.2.3 Time window extensions

In practice different kind of time window lengths with corresponding tariffs are employed. The length of the time window and occurrence using data provided by Van Opzeeland is displayed in figure 5.5.
5 TIME WINDOWS

<table>
<thead>
<tr>
<th>Model</th>
<th>(R^2)</th>
<th>MPE</th>
<th>MAPE</th>
<th>(R^2)</th>
<th>MPE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. (VRP(V_n) \approx k_i \sqrt{An} + 2m\bar{r})</td>
<td>0.985</td>
<td>0.80%</td>
<td>3.30%</td>
<td>0.9976</td>
<td>0.48%</td>
<td>4.23%</td>
</tr>
<tr>
<td>2. (VRP(V_n) \approx k_i \frac{n-m}{n} \sqrt{An} + 2m\bar{r})</td>
<td>0.981</td>
<td>1.40%</td>
<td>2.90%</td>
<td>0.9976</td>
<td>0.50%</td>
<td>4.28%</td>
</tr>
<tr>
<td>3. (VRP(V_n) \approx k_i \sqrt{An} + k_m m)</td>
<td>1.000</td>
<td>-1.00%</td>
<td>3.10%</td>
<td>0.9978</td>
<td>0.02%</td>
<td>3.68%</td>
</tr>
<tr>
<td>4. (VRP(V_n) \approx k_i \frac{n-m}{n} \sqrt{An} + k_m m)</td>
<td>1.000</td>
<td>0.10%</td>
<td>3.90%</td>
<td>0.9978</td>
<td>-0.21%</td>
<td>3.40%</td>
</tr>
<tr>
<td>5. (VRP(V_n) \approx k_i \sqrt{An} + k_b \sqrt{A/n} + k_m m)</td>
<td>1.000</td>
<td>-0.40%</td>
<td>2.90%</td>
<td>0.9976</td>
<td>-0.08%</td>
<td>3.81%</td>
</tr>
<tr>
<td>6. (VRP(V_n) \approx k_i \frac{n-m}{n} \sqrt{An} + k_b \sqrt{A/n} + k_m m)</td>
<td>1.000</td>
<td>-0.10%</td>
<td>1.70%</td>
<td>0.9976</td>
<td>-0.21%</td>
<td>3.40%</td>
</tr>
<tr>
<td>7. (VRP(V_n) \approx k_i \frac{n-m}{n} \sqrt{An} + k_d m d \bar{r} + k_t p^2 t\bar{r})</td>
<td>0.989</td>
<td>13.70%</td>
<td>8.00%</td>
<td>0.9976</td>
<td>-0.08%</td>
<td>3.81%</td>
</tr>
<tr>
<td>8. (VRP(V_n) \approx k_i \sqrt{An} + k_d m d \bar{r} + k_t p^2 t\bar{r})</td>
<td>0.989</td>
<td>13.30%</td>
<td>7.40%</td>
<td>0.9976</td>
<td>-0.11%</td>
<td>3.78%</td>
</tr>
<tr>
<td>9. (VRP(V_n) \approx k_i \sqrt{An} + k_d m d 2\bar{r} + k_t p^2 2\bar{r})</td>
<td>0.994</td>
<td>9.60%</td>
<td>5.20%</td>
<td>0.9976</td>
<td>-0.04%</td>
<td>3.88%</td>
</tr>
<tr>
<td>10. (VRP(V_n) \approx k_i \sqrt{An} + k_d m d 2\bar{r} + k_t p^2 n \bar{r})</td>
<td>0.996</td>
<td>7.00%</td>
<td>2.70%</td>
<td>0.9976</td>
<td>-0.05%</td>
<td>3.90%</td>
</tr>
<tr>
<td>11. (VRP(V_n) \approx k_i \sqrt{An} + k_d m d 2\bar{r} + k_t p^2 n^2 \bar{r})</td>
<td>0.997</td>
<td>6.70%</td>
<td>1.80%</td>
<td>0.9976</td>
<td>-0.10%</td>
<td>3.85%</td>
</tr>
<tr>
<td>12. (VRP(V_n) \approx k_i \sqrt{An} + k_d m d 2\bar{r} + k_t p^2 n^2 \bar{r})</td>
<td>0.996</td>
<td>7.30%</td>
<td>1.70%</td>
<td>0.9977</td>
<td>-0.14%</td>
<td>3.82%</td>
</tr>
</tbody>
</table>


![Time window length histogram](image)

Figure 5.5: Time window length histogram

Time windows are split into 4 categories, based on their length (i.e. the latest arrival time \(l_i\) minus the earliest arrival time \(e_i\)) in minutes:

1. \(0 < (l_i - e_i) \leq 60\); time appointment
2. $60 < (l_i - e_i) <= 180$; small time window
3. $180 < (l_i - e_i) <= 300$; average time window
4. $300 < (l_i - e_i) <= 420$; large time window
5. $420 < (l_i - e_i)$; no time window.

Using model 10 from table 5.1 a new model is formulated, taking into account a distance penalty estimate for each type of time window. Model 13 is formulated in equation 11, the performance in terms of R-squared, MPE and MAPE are displayed in table 5.2.

\[ \text{Model 13: } VRP(V^n) \approx k_l \sqrt{An} + k_d m_d \bar{r} + \sum_{i=1}^{4} k_{t_i} n_{t_i} 2 \bar{r} \]  

Where,
\[ k_{t_i} = \text{estimate for distance penalty per time window orders of type } i \]
\[ n_{t_i} = \text{amount of time window orders of type } i. \]

<table>
<thead>
<tr>
<th>Model</th>
<th>$R^2$</th>
<th>MPE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>13. $VRP(V^n) \approx k_l \sqrt{An} + k_d m_d \bar{r} + \sum_{i=1}^{4} k_{t_i} n_{t_i} 2 \bar{r}$</td>
<td>0.9981</td>
<td>-0.16%</td>
<td>3.42%</td>
</tr>
</tbody>
</table>

Table 5.2: Vehicle routing distance estimates. Time window extension model

5.2.4 Results

Using extended model 13 lessons can be learned about the network and buildup of distance, more specifically the penalty costs of time windows. As four different types of time windows are added to the model, one can see what the penalty costs are per time window type. Using data provided by Van Opzeeland it is found that mainly type 3 time window, being time windows of length 3-5 hours, influences the total distance significantly and with the largest effect size (compared to for example type 1 time window). The estimate factors for model 13, using all 2015 data can be found in model 5.3.

From these factors, and specifically factor $k_{t_3}$ it can be learned that each additional time window ($n_{t_3}$) results, on average, in an additional 20 ($k_{t_3} \times \bar{r} = 0.200 \times 103 = 20.6$) kilometers of distance. Time windows of longer length (> 5 hours) which occur in the same type of rural areas have shown no significant effect. This is an important number for a transporter since it has a direct relation to the (additional) cost of execution. Van Opzeeland should be aware of these costs and adjust its tariffs accordingly.

5.2.5 Predictive performance

For the most attractive models (3, 10 and 13) also the out-of-sample performance is measured, by first training the model on 70% on the data and then testing the model on 30% of the data. The training and test data are chosen at random, an arbitrary large number (one
Table 5.3: Model 16 output

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>km</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_l$</td>
<td>1.203*** (0.087)</td>
</tr>
<tr>
<td>$k_d$</td>
<td>1.071*** (0.067)</td>
</tr>
<tr>
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<tr>
<td>$k_{t4}$</td>
<td>−0.030 (0.067)</td>
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Observations: 254  
$R^2$: 0.998  
Adjusted $R^2$: 0.998  
Residual Std. Error: 1,161.127 (df = 248)  
F Statistic: 22,424.360*** (df = 6; 248)  

Note: *p<0.1; **p<0.05; ***p<0.01

A thousand) of repetitions is done to find the average out-of-sample performance displayed in Table 5.4. The performance is somewhat lower than the in-sample performance, as can be expected, but is still very solid for practical prediction applications.

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Table 5.4: R-squared out-of-sample (1000 samples)

5.2.6 Limitations

The basic nature of the model is very attractive. There are, however, limitations and data inconsistencies that are important to the (future) usage of the model.

- Line-haul locations
  Several locations are served with a nightly line-haul service. By a single large vehicle a load of up to 3 distribution vehicles is brought to a decentralised depot. From hereon drivers will drive their route. These types of routes are 10-20% of the total amount of routes.

  The depot through which the order is executed is however not stored in the TMS. Therefore all distances from depot to customer are calculated from the central depot
in Hedel, whereas actual measured distances are registered from the line-haul depot. The kilometers of the line-haul services are not added to the total amount of kilometers because they are not available for analysis.

• **Backhauling**
  Backhauling is often planned ad-hoc based on the availability of vehicles and the amount of load. Backhauling orders are generally believed to decrease the total amount of distance travelled, including distribution and line-hauling, but increase the total distance driven by distribution vehicles. In this model the total travelled distance of all vehicles is used, including those kilometers caused by backhauling. In an improved version of the model backhauling kilometers could be removed from the data to better predict the travelled distance a group of customers orders requires.

• **The delivery area**
  The delivery area (variable $A$ in the model) is kept constant for all data points, while in practice the outskirts of the delivery area are not served daily. Also, the model assumes an even distribution of orders in the area, but in practice the amount of orders may differ per region. Both issues may be solved by separating the orders in geographical regions and calculating the amount of orders and exact delivery area for each.

• **Data availability**
  Each day of planning (and execution) will yield one additional data point. At least several months of data are required to build the model, but since the composition of orders may change more rapidly the model may not always appropriately represent the current network structure.

### 5.3 Conclusion

Using the models formulated by Figliozzi (2009) an accurate estimate for the total distance travelled with a set of orders using data provided by Van Opzeeland can be found. An extension to the model has been made to find the effect of time windows of different lengths, which resulted in a significant and large contribution of orders with time window lengths of 3 to 5 hours. Each additional time window of this length attributes 20 additional kilometers, according to the statistical model.

Remarkably, there is a very small, or no significant effect for very tight time windows (length shorter than 3 hours). It has been found that very small time window orders are only made in the early morning in city centres, where a group of time window orders is executed in a fixed order.

The out-of-sample performance of the best performing distance approximation is good (R-squared = 0.90), therefore these models may be used to calculate the effects of changes to the network, for example adding a new customer. Future efforts should be put into increasing the reliability by finding solutions to properly describe the multi-depot structure with line-hauling. Also, a correction for distance travelled for backhauling could be included in the model.
6 Implementation

During the course of this project most findings have been shared with the management of Van Opzeeland. Several conclusions from data analysis and models have been adopted to support decisions in improvement projects. In this section first the implemented measures are discussed, then an overview is presented of the tooling that is made available to Van Opzeeland.

6.1 Improvement projects

Partly based on this research several project have been started to improve the operational efficiency. The most important projects are discussed and preliminary results are presented.

6.1.1 Service time models

During the course of the project the service time estimates have been updated. As the newly developed models theoretically have a higher r-squared performance they could be implemented as well. Adding new independent variables should outweigh the costs of implementation. It must also be noted that recent changes in the policy of sharing ETA information with drivers may change the service times. The results of the implementation of a new service time model in September 2015 can be found in figure 6.1. As one can see the predictive performance up until then was poor (i.e. taking the average as a predictor would have been better). Since the implementation the predictor performance is between the 0 and 20% of variance explained, which is in coherence with the theoretical performance of the model in place.

Up until the start of this project (September 2015) the service time at Van Opzeeland was set per shipper and did not take additional time for large loads into account. The TMS and route planning software were equipped to calculate more advanced service times but due to a bug this function was never actually executed. The performance of this model over time is displayed in figure 6.1. For each day the R-squared measure is calculated and plotted. During this project (halfway september 2015) an initial update has been done on the implemented service time model, as figure 6.1 displays this greatly increases the performance of the service time estimation.
The R-squared is a measure for how well the data fits a model. In this usage case the model is the prediction of the service time and the data is the actual service time. The R-squared value describes the fraction of explained variance by taking the ratio of the residual sum of squares of the model and the sum of squared errors of the data. The R-squared is calculated as follows:

\[ R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \]  \hspace{1cm} (12)

\[ SS_{res} = \sum_i (y_i - f_i)^2 \]  \hspace{1cm} (13)

\[ SS_{tot} = \sum_i (y_i - \bar{y})^2 \]  \hspace{1cm} (14)

Where,

- \( y_i \) = actual value of observation \( i \)
- \( f_i \) = predicted value for observation \( i \)
- \( \bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i \)

Typically, when designing a model the R-squared value will be between 0 and 1 since the lowest value, zero, is obtained by using the average of observations, \( \bar{y} \), as a model. However, in the case of Van Opzeeland the model in place was behaving such that the R-squared value was below zero, signalling that it would have been better to simply use the average as a model. Having a negative R-squared is possible when the residual sum of squares, \( SS_{res} \), is larger than the total sum of squares, \( SS_{tot} \).

Figures 6.2 and 6.3 display the MPE and MAPE performance of the service time prediction over time. It can be seen that the mean percentage error has moved close to zero starting September 2015. Also the absolute percentage error has improved, moving from +/- 52% to +/- 42%.
Accurately predicting the service time is beneficiary to the efficiency of the planning. Combined with the incorporation of the breaks in the planning the planning performance should increase. The next section discusses the planning of breaks and displays more general measures for the planning performance.

6.1.2 Planning with breaks

Starting halfway January 2016 breaks are incorporate into the planning. At 12:00 hour a break of 30 minutes is planned for all drivers. Also, the planned departure time at each stop is placed on the route overview a driver receives. The expectation is that the planning will better fit the drivers behaviour (i.e. account for breaks), but also it is expected that sharing the planned arrival time at customer sites increases the timeliness of drivers. Figure 6.4 displays a great decrease in the average delay. The difference between the last months of 2015 compared to the first weeks of 2016 can be attributed to planning with breaks and a more strict management of drivers who are delayed. At 15:00 hour the average delay is below zero, this is because only a small amount of orders is planned after three o’clock. Only vehicles of which the planning thinks that generally are on time have orders planned after this 15:00 hour.

As can be seen in figure 6.5 the variance of the delay remains the same compared to the baseline of 2015. This is likely attributed to (1) differences between speediness of drivers or (2) cases where a driver deviates from the planning and delivers goods either way too early or way too late.
From figure 6.6 it can be seen that because the planning is made more accurate the current setup of the time windows that are communicated to the customer performs worse, as more orders are delivered before the start of the self-imposed time window. Adjustments to the setup of these time windows will improve the percentage that is delivered within this time window.
6.2 Tooling

During this research project multiple methods and measures have been developed to prepare and analyse data in a structured manner. To support the business several small tools are developed and implemented.

6.2.1 Data selection

Using the methods developed in the data selection of this research a tool is developed to standardise the data preparation for further analysis. Management is trained to periodically transfer new data from the ERP system to the data selection tool. This order data is also used in other tools. When operational and successful, the organisation might consider building a similar solution into their own enterprise software.

6.2.2 Data monitor

The data monitor presents an overview of the state of the data provided by the computer terminals. A percentage score is given for the amount of valid data. Using this graph future efforts to improve data validity can be monitored. To increase the data reliability an improvement project has been started in 2015 week 45. During a 6 week period the data quality was monitored by this author. The planning handed out computer terminals to charter drivers and checked that all computer terminals on the road would perform. Also, drivers have received feedback on their usage of the computer terminals (see below).

During this period the valid data has been increased from about 65% to 75% (figure 6.7 shows the validity over time), mainly driven by making sure that also charter companies had access to a computer terminal. Unfortunately, when handing over the tools and methods to the planning and management the efforts have decreased and the data quality is back to its original levels. The project did, however, prove the potential for improvement when reasonable effort is spend on data quality. From informal interviews it is also concluded that administrative burden (e.g. corrections done by the administration because of missing information) decreased slightly for vehicles that carried a computer terminal.
6.2.3 Driver feedback

As a measure to decrease driver induced data inconsistencies a tool is developed for the transportation manager. Using the tool a letter can be created per driver which displays data inconsistencies. The letter has been, and will be, used to (1) inform drivers of the importance of data consistency, (2) show concrete examples of inconsistencies and (3) to coach drivers to improve. An example of a driver feedback letter can be found in appendix F.

6.2.4 Potential customer calculations

Using the methods developed in section 5 it is possible to estimate the costs (i.e. additional distance) of adding a new customer. Actual data can be combined with expected additional orders for a new customer. Using the amount of orders, the distance to depot, amount of load and amount of time windows (dependant on the model to be used) a new total distance is calculated. The total amount of additional distance created by adding the orders can be averaged over relevant days (e.g. a single weekday). As the models typically show a MPE of less than 1%, the calculations will give a good estimate. One has to consider however that the estimated parameter values that are used in the model are based on the current network and road structure. Therefor, it is unclear how good the results of the model are when a relatively large amount of orders is added. Before offering a price to new customers based on this tool an additional validation by actually planning a set of orders seems appropriate. Also, the parameters of the statistical model should be recalculated every few months to reflect the current state of the network.
7 Conclusion

This research is concluded by answering the research questions.

Research question 1

How can reliable data for analysis be extracted from all available data?

Qualifications for valid and invalid data have been introduced. Service time administration is affected by (1) missing data, (2) data invalidated by registering multiple stops at once and (3) data invalidated by unrealistic service times. The validity of driving times is affected by the validity of service times, by executing the route differently than planned and by breaks. Tools have been provided to measure the data validity and tools have been introduced to decrease the driver-induced errors. Other recommendations concerning the data structure and storage can be found in appendix C.

Research question 2

How can the estimated arrival time of customer orders be made more accurate?

To increase the accuracy of the planning (1) a model is developed to more accurately predict the required service time for a single stop and (2) it is shown that not including the breaks in the planning greatly upsets the planning accuracy.

For the service time model different data sources have been tested to better explain the service time. There was a very small to no effect from weather, city characteristics (i.e. density) and the experience of a driver on a route. The most important factors that have been found are the shipper from which the order is originated, the amount of load, extra service offered and by which driver the order is executed. The prediction performance has already been greatly improved during this project (moving from a negative predictive performance to $\pm 20\%$ variance explained), the newly presented models promise even better performance ($35\%$ of variance explained).

It has been found that using historic data the planning would benefit from a 30 minute break at around 12:00 hour. It has been found that traffic jams do not or hardly influence the planning at Van Opzeeland, routes are currently scheduled such that traffic jams are mostly avoided. Combined with the service time model the average delay should go close to zero and the variance in delay is expected to decrease. Having a lower delay and decreased variance will increase the time window performance. It will also decrease the necessary buffer time to cope with variances, thus increasing the possible output.

Research question 3

How do time window constraints influence the planning efficiency?

Using a general model to estimate the total distance travelled for a set of orders it has been found that time windows of length 3 to 5 hours greatly influence the planning efficiency.
Each order of this time window length attributes an additional 20 kilometers distance to the total distance travelled, which is found using linear regression on data provided by Van Opzeeland.

It has been found that the distance approximation models perform well on data provided by Van Opzeeland and it advised to use these models to make broad network calculations. Although results are likely to be case specific it may also be interesting for other transporters to fit these models to their data and derive their cost structure.

7.1 Future research

Future research may focus on any of the following topics:

• Service offerings
  When predicting the service times there is still a lack of information about the exact services that are offered at the customer site. Structuring the service offerings and corresponding additional service time may increase the predictive performance of the service time.

• Cost calculation
  Van Opzeeland offers a large distribution network (Benelux) for its customers and prices are based on the division of the customers over the delivery area. It is likely that routes that are further away from the central depot are more costly than routes that stay close-by. Calculating the costs of a single order and comparing it with the actual income generated may generate valuable knowledge in analysing the efficiency of the network and the prices that should be offered to customers. The distance approximation model presented in section 5 may be used as starting point.

• Time window valuation
  The distance approximation model used in this report to estimate the additional distance travelled for specific time windows can be further investigated by doing simulations. Simulations can be done to solve the vehicle routing problems for different (real-life) problem instances. Problem instances may vary customers with different time window lengths and locations at which the restrictions occur.
References

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Logistiek.nl (2015). Top 100 logistiek dienstverleners 2015. www.logistiek.nl. 2


Appendices

A  Service time models

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Table A.1: Model 1: Basic linear model

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<td>0.170</td>
</tr>
<tr>
<td>Sted</td>
<td>1</td>
<td>66.432</td>
<td>66.432</td>
<td>336.793</td>
<td>0</td>
</tr>
<tr>
<td>Oad2010</td>
<td>1</td>
<td>8.734</td>
<td>8.734</td>
<td>44.280</td>
<td>0</td>
</tr>
<tr>
<td>FG</td>
<td>1</td>
<td>0.318</td>
<td>0.318</td>
<td>1.612</td>
<td>0.204</td>
</tr>
<tr>
<td>TG</td>
<td>1</td>
<td>0.939</td>
<td>0.939</td>
<td>4.762</td>
<td>0.029</td>
</tr>
<tr>
<td>SQ</td>
<td>1</td>
<td>0.568</td>
<td>0.568</td>
<td>2.880</td>
<td>0.090</td>
</tr>
<tr>
<td>RH</td>
<td>1</td>
<td>0.001</td>
<td>0.001</td>
<td>0.004</td>
<td>0.950</td>
</tr>
<tr>
<td>PG</td>
<td>1</td>
<td>0.196</td>
<td>0.196</td>
<td>0.996</td>
<td>0.318</td>
</tr>
<tr>
<td>NG</td>
<td>1</td>
<td>0.427</td>
<td>0.427</td>
<td>2.163</td>
<td>0.141</td>
</tr>
<tr>
<td>UG</td>
<td>1</td>
<td>0.573</td>
<td>0.573</td>
<td>2.904</td>
<td>0.088</td>
</tr>
<tr>
<td>Client:StopDisOVE</td>
<td>50</td>
<td>306.854</td>
<td>6.137</td>
<td>31.113</td>
<td>0</td>
</tr>
<tr>
<td>Client:StopRetOVE</td>
<td>34</td>
<td>118.801</td>
<td>3.494</td>
<td>17.714</td>
<td>0</td>
</tr>
<tr>
<td>Client:ZENDING_AFGESTAPELD</td>
<td>56</td>
<td>102.369</td>
<td>1.828</td>
<td>9.268</td>
<td>0</td>
</tr>
<tr>
<td>Residuals</td>
<td>94,335</td>
<td>18,607.430</td>
<td>0.197</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table A.4: Model 4: All factors + interaction factors
Appendices

<table>
<thead>
<tr>
<th></th>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shipper</td>
<td>55</td>
<td>11,084.910</td>
<td>201.544</td>
<td>852.358</td>
<td>0</td>
</tr>
<tr>
<td>StopDisOVE</td>
<td>1</td>
<td>8,100.010</td>
<td>8,100.010</td>
<td>34,256.110</td>
<td>0</td>
</tr>
<tr>
<td>StopRetOVE</td>
<td>1</td>
<td>679.140</td>
<td>679.140</td>
<td>2,872.182</td>
<td>0</td>
</tr>
<tr>
<td>ZENDING_AFGESTAPELD</td>
<td>2</td>
<td>185.622</td>
<td>92.811</td>
<td>392.511</td>
<td>0</td>
</tr>
<tr>
<td>Client:StopDisOVE</td>
<td>53</td>
<td>1,533.240</td>
<td>28.929</td>
<td>122.345</td>
<td>0</td>
</tr>
<tr>
<td>Client:StopRetOVE</td>
<td>38</td>
<td>224.309</td>
<td>5.903</td>
<td>24.964</td>
<td>0</td>
</tr>
<tr>
<td>Client:ZENDING_AFGESTAPELD</td>
<td>63</td>
<td>401.779</td>
<td>6.377</td>
<td>26.971</td>
<td>0</td>
</tr>
<tr>
<td>Residuals</td>
<td>246,911</td>
<td>58,383.210</td>
<td>0.236</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table A.5: Model 5: Minimum viable model

B Assumptions

<table>
<thead>
<tr>
<th>Number</th>
<th>Description</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Driving time is a-symmetric</td>
<td>The calculated driving time is based on a single-direction driven route. Because the calculation of driving times is a black-box it is unclear if the driving time is symmetric (a-symmetric is the weaker assumption).</td>
</tr>
<tr>
<td>2</td>
<td>Minimum service time is 3 minutes</td>
<td>To validate the data a minimum service time is used. All service times have to be at least 3 minutes to filter out the orders where the start and end of the service time have been logged simultaneously.</td>
</tr>
<tr>
<td>3</td>
<td>Minimum time between stops is 3 minutes</td>
<td>In order to be able to identify invalid service times due to processing multiple stops at once a minimum of 3 minutes (i.e. the minimum service time) between subsequently processed stops is used.</td>
</tr>
</tbody>
</table>

Table B.1: Table of assumptions
Appendices

C System recommendations

• Zipcode information.
  At the moment customers send in their own address information, which does not always follow the standard formatting. This sometimes results in the same address being handled by the TMS and planning software as two separate addresses, creating additional (redundant) service time.

• Address information.
  Address identifier: Currently an address is identified by the zipcode, street name and number. When different shippers send goods to the same customer address information may be stored duplicate, causing systems to misidentify multiple orders as a single stop. A system should be developed such that addresses can be uniquely identified, the Dutch system is based on unique combinations of zipcode and house number.

• Transportation information.
  The structure of different types of transports should follow the MECE (Mutually Exclusive, Collectively Exhaustive) standard. The recommended transportation types: Dedicated, Line-haul, Distribution and, Parcel. A transport may carry a subcategory for the country.

• Transportation information.
  Transports should have information fields for: 1st/2nd/3rd trip, to load in warehouse and general direction, which could be a shortlist of predetermined directions. Currently this information is solely stored in a single textfield (the transport ‘title’), which makes it difficult for future analysis to automatically extract the right information. Even though a standard format for these textfields is used, human errors are inherent to the current process of storing this information.

• Time formatting.
  Break-times are logged in the daily report using two different time formats, separating hours and minutes with either a semicolon or a point (i.e. 12:34 versus 12.34). It is recommended to use only one format and to validate the correct entry of the format throughout the TMS, the semicolon is the international standard for time notation.
D Vid.nl RSS feed reader

```php
<?php
include_once('simple_html_dom.php');

$target_url = 'http://www.vid.nl/VI/rss';

$html = new simple_html_dom();
$html->load_file($target_url);
foreach($html->find('item') as $item)
{
    // echo $source->outtext; //->plaintext;
    foreach($item->find('title') as $source)
    {
        $findme = 'file';
        $haystack = (string)$source->plaintext;
        $pos = strpos($haystack, $findme);
        if ($pos > 0) {
            $pos = $pos - 4;
            $length = 4;
            $str = substr($haystack, $pos, $length);
            // preg_match('!\d+!', $str, $matches);
            $ParseJams = array_shift($matches);
            echo 'Files: ', $ParseJams, '<br/>';
        } else {
            $ParseJams = 0;
            echo 'no Jams found';
        }
    }
    $pos = 0;
    $findme = 'km';
    $haystack = (string)$source->plaintext;
    $pos = strpos($haystack, $findme);
    if ($pos > 0) {
        $pos = $pos - 4;
        $length = 4;
        $str = substr($haystack, $pos, $length);
        // preg_match('!\d+!', $str, $matches);
        $ParseKm = array_shift($matches);
    } else {
        $ParseKm = 0;
        echo 'no km found';
    }
}

$servername = "LOCALHOST";
$username = "username";
$password = "password1";
$dbname = "database";

// Create connection
$conn = new mysqli($servername, $username, $password, $dbname);
// Check connection
if ($conn->connect_error) {
```

Appendices

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die("Connection failed: ". $conn->connect_error);
}
$mysql_date = date("Y-m-d H:i:s");
$sql = "INSERT INTO vid_n1 (timestamp, JamAmount, JamKm) VALUES ('$mysql_date','$ParseJams','$ParseKm');"
if ($conn->query($sql) === TRUE) {
    echo "New record created successfully";
} else {
    echo "Error: ". $sql . "<br>" . $conn->error;
}
$conn->close();
?>
E Driving and break regulations

Driving and break regulations as extracted from ILENT (2015):

Rij- en rusttijden vrachtauto en touringcar (Vo. (EG) nr. 561/2006)

Dagelijkse rusttijd
- Normaal: periode van 11 uur aaneengesloten rust
- Mag gesplitst worden in 2 perioden:
  - 1e minimaal 3 ononderbroken uren
  - 2e minimaal 9 ononderbroken uren
- Verkorte dagelijkse rust: minimaal 9 uur, en minder dan 11 uur (max. drie maal tussen twee wekelijkse rusttijden)
- Meervoudige bemanning: minimaal 9 uur (periode 30 uur), 1 uur facultatief (wanneer 2e bestuurder binnen 1 uur wordt toegevoegd, geldt voor beiden vanaf aanvang van ieders werkzaamheden de periode van 30 uur)

Wekelijkse rusttijd
- Normaal: periode van 45 uur aaneengesloten rust
- Verkorte wekelijkse rust: minimaal 24 uur aaneengesloten rust (mits compensatie voor einde derde week en bloc)
- In iedere periode van twee weken 2 x een normale wekelijkse rusttijd, of 1 normale en 1 verkorte wekelijkse rusttijd
- Uiterlijk na iedere periode van 6 x 24 uur dient een nieuwe wekelijkse rusttijd aan te vangen

Dagelijkse rijtijd
- Totale rijtijd tussen 2 rusttijden (dagelijks of wekelijks)
- Normaal: maximaal 9 uur
- Maximaal 2 x per week: 10 uur

Ononderbroken rijtijd
- Na 4,5 rijtijd neemt bestuurder onderbreking van 45 aaneengesloten minuten
- Mag worden vervangen door onderbreking van 15 minuten, gevolgd door één van 30 minuten (totaal minimaal 45 minuten)

Wekelijkse rijtijd
- mag niet meer bedragen dan 56 uur

Twee wekelijkse rijtijd
- mag niet meer bedragen dan 90 uur

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F Driver feedback letter

Figure F.1: Example of a driver feedback letter to improve data consistency
G CityTraffic data example

Figure G.1: Example of CityTraffic data for week 42, 2015. Location: Demer, Eindhoven.
Appendices

H Figures

![Histogram and theoretical densities](image1)

![Q-Q plot](image2)

![Empirical and theoretical CDFs](image3)

![P-P plot](image4)

Figure H.1: Service time fitting