MASTER

Prediction of variable travel time components in distribution planning

Rijk, N.

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Prediction of Variable Travel Time Components in Distribution Planning

by N. Rijk

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Student identity number 0658074

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Supervisors:
dr. ir. R.M. Dijkman – Eindhoven University of Technology
prof. dr. T. Van Woensel – Eindhoven University of Technology
ing. J. Brouwer – TomTom N.V.
N. Cohn – TomTom N.V.

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Abstract

Daily execution in the logistics sector is subject to variability. This makes it difficult to predict the exact amount of time that a driver needs to complete his tasks. Currently, logistics companies (partially) rely on rules of thumb and job experience to plan their trips. Key activities in transport that are taken into account in distribution planning are: driving, (un)loading, pausing, and resting. This report describes the development of a prediction model for these variable truck travel time components based on a data set from a logistics company. Predictions of the variable truck travel time components by both the developed prediction model and the rules of thumb that are currently used in the logistics company were compared in terms of deviation from reality. Prediction of truck travel time components based on data has proven to be more reliable than prediction based on the current rules of thumb used by the logistics company which saves money. The quantitative analysis on the outcomes confirmed the potential of this prediction model for the logistics sector. It was recommended to develop tooling to enable use of the prediction model by logistics companies. In addition, it was advised to examine the predictions made with different rules of thumb and planning systems further in order to define the target group for the prediction model further.

Acknowledgements

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1. Introduction

The topic of this research: prediction of variable truck travel time components in distribution planning is introduced in this chapter. Some background will be given on the relevance of this research from both a scientific and business perspective in paragraph 1.2 and 1.3 respectively. Afterwards, the research questions and research method will be presented. Finally, the report outline will be given.

1.1 Topic

Distribution planning is an important topic in the logistics sector (Dinalog, DAIPEX). Pure travel times, waiting times, driver rest times, (un)loading times, (un)loading time windows, and physical characteristics of the vehicle play a role in distribution planning. These factors will influence the routing, departure times, and assignment of trucks to routes. The factors '(un)loading time windows' and 'physical characteristics of the vehicle' are fixed upfront. Factors such as pure travel times, (un)loading times, waiting times, and driver rest times are variable and should be estimated to enable distribution planning. These estimations can be based on experience and rules of thumb or on data of truck distribution (Planner interviews, 2015). Basing estimations on experience or rules of thumb is relatively quick and simple, but may give inaccurate and unreliable results. This does not necessarily mean that estimations based on experience are faulty. However, using data to make estimations may enhance accuracy and reliability of predictions. On the other hand, using data requires more effort than using experience. Nowadays, substantial amounts of data are available. It is important to filter these data and use representative data for the prediction of the variable truck travel time factors. After all, the representativeness of data influences the quality of predictions.

Next to data, algorithms also influence the quality of predictions. Logistics companies use suboptimal algorithms for distribution planning due to their reliance on experience. On the other hand, suppliers of travel time predictions (e.g. TomTom) use algorithms that are designed for passenger cars, but not for trucks. This would be due to the differences between passenger cars and trucks such as physical characteristics (e.g. dimension and maximum speed) and route requirements (e.g. (un)loading times and windows and routes with more than one stop).

Above-mentioned considerations lead to the research focus: prediction of variable truck travel time components (i.e. pure travel times, (un)loading times, waiting times and rest times). An example of a trip that includes different travel time components is represented in Figure 1: the blue dotted line represents an example of how a truck travels and the black crosses show where the truck stops for respectively loading at the home base, unloading at a harbour, pausing at a parking lot, and unloading at a distribution centre. The order and presence of travel time components differs per trip. Differences can be for example in whether or not the driver takes rest or the number of (un)loading events in a trip.

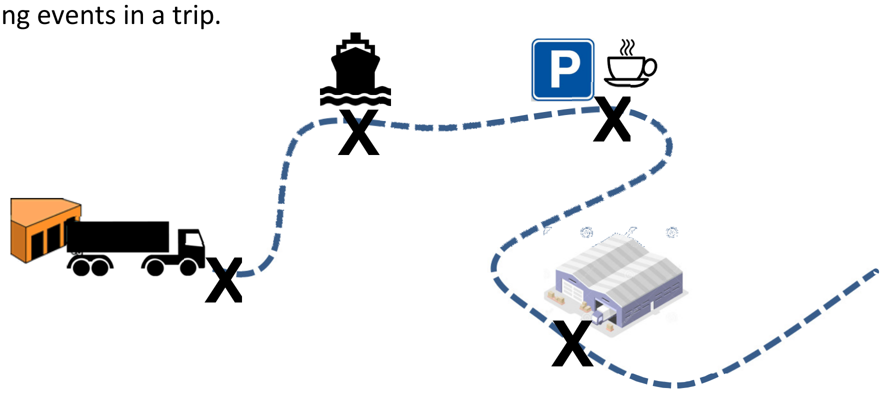

Figure 1 - Trip example

1.2 Rigour

Up to now, not much attention has been given to the prediction of truck travel times in academic papers. However, a vast amount of research addressed travel time prediction in general. Predictions are made by means of regression, time-series, and artificial intelligence. Input data for these types of research was gathered by sensors installed along roads, automatic vehicle identification on sites, and GPS devices in vehicles (W. Zhao, A.V. Goodchild, 2011). An example is a US patent that comprises a system to predict travel times for road segments based on traffic speed data for this segment (A. Gueziec, 2006). Another example distinguishes travel times for a particular time of the day and day of the week. The distributions over days and weeks are used as reliability measures for the prediction of travel times (J.W.C. van Lint, H.J. van Zuylen, 2006). Next to that, vehicle routing and scheduling problems with time windows that take the uncertainty of travel times into account are often discussed in articles (N. Ando, E. Taniguchi, 2006). In addition, the area of shortest paths in logistics, considering driving times, has been discussed extensively. In articles on this topic, no real traffic data is used for verification (H. Huang, S. Gao), (W. Dong, H.L. Vu, Y. Nazarathy, B.Q. Vo, M. Li, S.P. Hoogendoorn, 2012). Another interesting view on this topic describes how route choice is dependent on perceived travel time: a person's belief about the time it takes to travel a certain route (E.A.I. Bogers, M. Bierlaire, S.P. Hoogendoorn, 2008).

Several articles do discuss truck travel times. One article discusses how truck data can be used to produce travel time information and shows how travel times can be generated from these historical data (C.M. Monsere, M. Wolfe, H. Alawakiel, M. Stephens, 2009). A shortcoming of this research is the acquisition of data. This is done via sensors that are installed along connecting roads to identify passing trucks by means of transponders. These sensors are installed with spaces in between which causes inaccuracies in the acquired data. Another article proposes a technique for estimating the probability distribution of total network travel time (S.D. Clark, D.P. Watling, 2005). However, travel times are aggregated over the network instead of splitting them per day or origin-destination pair. In addition, no empirical data is used to verify the proposed technique. A research on data from GPS devices in trucks shows that speed estimations based on GPS data are sufficiently accurate in comparison with speed measured over a whole road segment with an absolute difference of less than 6%. GPS data is found to be a good alternative for measuring truck travel characteristics (W. Zhao, A.V. Goodchild, E.D. McCormack, 2011). An example where truck tracking data is used calculates travel time reliability by means of the coefficient of variation, which is the ratio of standard deviation of travel time and mean travel time. A 95% confidence interval was used to estimate truck travel time between a given origin-destination pair. This improved the information about truck arrivals for operators that have to handle the freight of these trucks (W. Zhao, A.V. Goodchild, 2011).

Literature on travel time valuation claims that requirements for reliability and flexibility in transport have increased. A reduction of travel time with one hour is valuated with €30-€45 per transport. An improvement in reliability of travel times with 10% is valuated with €1-€2 per transport per hour (G. de Jong, S. Bakker, M. Pieters, 2004). Around 9.5 billion kilometres is driven by Dutch trucks each year. Dividing this by an average of 65 km/h this indicates a total driving time of no approximately 150 million hours per year (Transport in Cijfers, 2014). This means an improvement in reliability of travel time predictions of 10% would have a value of €150-300 million a year for the Dutch logistics sector. These numbers justify research on the topic of truck travel times. After all, the research results can create benefits for the logistics sector.

As far as it is known, the research topic has not been dealt with before on a high level of detail. The research can enrich literature on the topic of truck travel times and their variable components.

1.3 Relevance

This research is relevant for organizations with logistics as core business as well as for TomTom. First of all, the research will provide a model that gives accurate and reliable information on variable truck travel time components. Organizations that are involved in distribution planning can possibly profit from such a model. Therefore, the research is relevant for logistics organizations. In addition, the research will provide TomTom with a business case that enables them to decide whether or not they are going to invest in a product that can be used in distribution planning. For this reason, the research is relevant for TomTom.

1.4 Research Questions

The problem statement can be described as follows:

- **Variable truck travel time components (i.e. pure travel times, (un)loading times, waiting times, and rest times) are currently not or sub-optimally integrated in distribution planning.** (Dinalog, DAIPEX)

Solving this problem will enhance both the accuracy and reliability of predicted variable truck travel time components. With a more accurate prediction of truck travel time components, buffer times in distribution planning could possibly be decreased, which will save time and thus money. In addition, these predictions can contribute to a more reliable prediction of expected time of arrival (ETA) for trucks which will result in less delivery fails and could therefore save both time and money.
The research question that follows from the problem statement is twofold and formulated as follows:

- **How can the duration of variable truck travel time components be predicted?**
- **What is the business case for a product that enables above-mentioned calculations?**

The first part of the research question has a theoretical nature and is aimed at developing a model. The second part of the research question has a more practical focus that is aimed at decision making. The research as a whole can be considered a preliminary investigation on the development of a new product or service.

The research is subject to several restrictions. The restrictions are as follows:

- Research will focus on distribution planning. Real-time information and changes in routes during trips will not be taken into account since this information is not available at the time of planning;
- Research will focus on optimization of truck travel times working with existing routing algorithms. Hence, optimization of routes will be out of scope;
- Research will focus on truck distribution planning in logistics companies.

1.5 Research Method

The research aims to develop a model where a new product or service can be built upon. The approach will therefore start with examination and assessment of the current situation followed by designing the new situation. Data plays an important role in this research. The Cross-Industry Standard Process for Data Mining (CRISP-DM) is used as guide line for this research (G. Mariscal, Ó. Marbán, C. Fernández, 2010). This process is schematically represented in Figure 2.

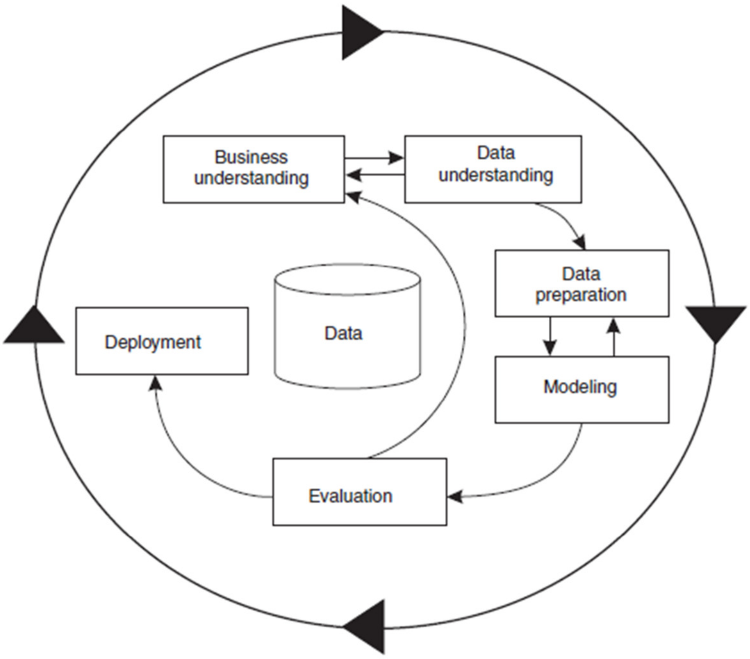

Figure 2 - Cross-Industry Standard Process for Data Mining (CRISP-DM)

The business understanding phase refers to the project objectives and requirements. In this research the objectives are prediction of duration of variable truck travel time components and a business case for a product that enables these predictions. The next step, data understanding, is used to get an overview of the current state of affairs. Therefore, data on trucks will be analyzed to get insight in the distribution of time over different activities. As stated before, the focus will be on driving, loading, unloading, waiting, and resting. Then, the data is prepared for modelling. During the modelling phase, the duration of the mentioned activities will be predicted based on the prepared data. After modelling, and evaluation phase is used to check whether the model is able to predict the duration of activities better than the rules of thumb that are currently used. Therefore, the outcomes of both the rules of thumb for planning and the new prediction model will be compared to reality. In this way, the potential of the prediction model can be quantified. Finally, the deployment phase is used to present the gained knowledge. This is done by means of this report.

Apart from data, this research will also use information from qualitative sources (e.g. planner interviews) to gain insight in the current state of affairs, trends and opportunities in the logistics sector.

1.6 Report Outline

The business understanding phase of the previous paragraph is discussed in paragraph 1.4. Hereafter, chapter 2 presents some research background. Chapter 3 presents the data understanding phase. This chapter includes an overview of the available data and an analysis of the variable truck travel time components that are present in the data. Chapter 4 describes the modelling phase in which a prediction model for different truck travel time components is developed and explained. After modelling, the evaluation phase starts. In this phase, the results of the prediction model are checked with the results of rules of thumb and with reality. Chapter 5 describes a proof of concept and its results. Furthermore, insights from different interviews with planners are discussed in this chapter. Finally, chapter 6 presents the conclusions, recommendations and possibilities for further research.

2. Research Background

This chapter provides background information about the project in order to enable a better understanding of the chapters that will follow. Firstly, some background on the DAIPEX project, a project where this research is part of, will be given. Secondly, the involved companies will be discussed.

2.1 DAIPEX

The research described in this report is part of a cross-organizational project that is focussed on enhancing efficiency and reliability in complex transportation planning. This project is referred to as DAIPEX (Data and Algorithms for Integration of Planning and Execution) and involves Eindhoven University of Technology and TomTom, among others. Transportation companies seldom find their transportation execution conform to the distribution planning made upfront. Time-dependency and stochasticity play a big role in transportation. However, existing transportation planning software does not take these two factors into account. The DAIPEX project is set up to develop algorithms and software that can handle time-dependent, stochastic planning problems based on big data. This project aims to enable handling of complex distribution planning with efficient algorithms in order to get executable plans within acceptable response times. (Dinalog, DAIPEX)

2.2 Companies

Multiple companies have contributed to this research. This paragraph will introduce the two companies that were involved during the larger part of the project: TomTom N.V., the principal of the research assignment, and Jan de Rijk Logistics, the subject of a case study that was performed for this project.

TomTom N.V.

TomTom is founded in 1991 and is a leading supplier of in-car location and navigation products and services. Headquartered in Amsterdam, TomTom has over 4,500 employees and sells its products in more than 100 countries. Over 70 million devices have been sold and hundreds of millions of people use the TomTom digital maps on the internet or mobile phones. TomTom's products include portable navigation devices, in-dash infotainment systems, maps and real-time services.

TomTom has a growing catalogue with currently more than 44 million Points of Interest (POIs) to the dynamic traffic content. TomTom maps are constantly refreshed with professional sources as well as real world experience and feedback from millions of drivers worldwide.

Tele Atlas, one of the largest digital mapping companies in the world, was taken over by TomTom in 2008. This enabled TomTom to speed up the release of new maps, increase map accuracy, and make the map production process more efficient.

TomTom is comprised of four different business units:

1. **Consumer**
   This business unit focuses on customer experience and integrated navigation services on platforms such as Personal Navigation Devices (PNDs), smartphones, and internet.
2. **Automotive**
   This business unit develops and sells navigation systems, services, and content to car manufacturers and their suppliers. This includes in-dash systems and aftermarket solutions (e.g. a multimedia navigation system) among others. Automotive services are currently offered to Renault, Fiat, Toyota, Mazda, Mercedes-Benz, Alfa-Romeo, VW, and Audi.

3. **Geospatial & Traffic**
   This unit delivers digital maps and content to customers such as PND manufacturers, internet companies, mobile phone handset manufacturers, network operators, governments and enterprises. Services include Speed Profiles and real-time traffic service.
4. **Telematics**
   This business unit offers solutions for fleet management and efficiency control for commercial fleets. (TomTom Solutions Technical Documentation, 2014)

Jan de Rijk Logistics
Jan de Rijk Logistics was founded in 1971. Between the 1980s and 1990s Jan de Rijk Logistics expanded its network by targeting the high-end industries and diversified its product portfolio acquiring warehousing and developing Benelux distribution.

Jan de Rijk Logistics is based in the Netherlands and operates a fleet of over 550 motorized vehicles and 750 (semi-)trailers across Europe. The firm now boasts a range of services, which include intermodal solutions, international transport, warehousing, Benelux distribution, container transport, retail distribution, event logistics and forwarding. Jan de Rijk Logistics has 25 offices in 15 countries and employs more than 1,000 staff in Europe.

Jan de Rijk Logistics aims to provide qualitative, reliable, cost-efficient, innovative, sustainable logistics solutions to their customers. The company seeks to reduce the environmental impact – in terms of emissions and the exhaustion of natural materials - of core activities by managing energy and fuel consumption. (Jan de Rijk Logistics)

3. Analysis

A data dump from Jan de Rijk Logistics was obtained in order to analyze the current state of affairs concerning distribution planning and execution. This data dump consists of different tables that contain multiple measurements. The available data was organized and prepared for analysis. Preparation comprises coupling data from different tables in order to get an overview. The information of interest includes factors such as time, location, and activity. This chapter is focused on quantitative analysis. Qualitative analysis is done by means of planner interviews and will be discussed in chapter 5.2.

3.1 Data preparation

Data of trip planning and execution is needed. The data on trip execution should give information about where each truck was on what time and which activity was executed on that time. Activities include driving, loading, unloading, and resting among others. Classification of these activities will help to analyze driving speed and average durations of (un)loading, and resting. For trip planning, information about the planned times and locations to (un)load is needed. This enables comparison of planning and execution in a later stage.

Information in the data dump includes:

- Logs of truck events that comprise times, GPS locations, and activities that were carried out.
- Addresses that were part of an executed task such as (un)loading or resting.
- Information about shipments such as the amount of freight, the pick-up and delivery location, and the planned and actual (un)loading duration.

Instances from different tables in the data dump were coupled to each other to enable a better overview. Attempts to couple information about shipments to the logs of truck events were terminated because of problems with data quality: Planned and actual (un)loading start and end times in the data dump were found to be unreliable since the data are a combination of old and updated information. This leads to mismatches with other tables and for example a planned end of a loading activity that takes place even before that same loading activity was planned to start. Consultation with Jan de Rijk confirmed aforementioned irregularities and justifies exclusion of time-related shipment data from the research.

Detailed information on tables, variables, and the coupling of those can be found in Appendix A. This preparation resulted in a table with matched information as shown in Table 1.

Table 1 - Result of data preparation

Variable	***Explanation***	***Data type***
Id	Log identifier	Integer
Latitude	Part of GPS coordinate	Decimal (WGS-84)
Longitude	Part of GPS coordinate	Decimal (WGS-84)
City	Part of address	String
Street	Part of address	String
Country	Part of address	String (length 2)
Heading	Direction of truck in degrees	Integer
Mileage	Traveled distance in meters	Integer
Speed	Speed at certain moment in km/h	Integer
Time	Date and time of measure	dd-mm-yyyy, hh:mm:ss
Type	Start/end of activity	Integer
PropertyValue	Name of activity	Character
TruckNumber	Identifier for truck	Integer (length ≥ 4)

The table with information as presented in Table 1 was sorted by TruckNumber, and within TruckNumber by Time. Then, the following modifications were made:

First of all, a day separator was built in to distinguish days from each other. For practical reasons, the transitions between days are used as boundaries for trip length. Other definers for the start/end of a trip are ambiguous which makes it hard to implement a separator for these definers.

Secondly, time intervals between two consecutive rows are deduced based on the Time variable and distance intervals are deduced based on the Mileage variable. Next to that, the interval speed was calculated for each interval by dividing the interval distance in kilometers by the interval time in hours. In subsequent calculations, interval speed will be used rather than Speed from Table 1. The reason behind this is that Speed is a snapshot value, hence less accurate than interval speed.

Thirdly, a distinction between several key activities was made. This was done in order to enable analysis of the duration of the variable travel time components in a later stage. Key activities that were distinguished are: loading, unloading, waiting, pause, and resting. Pausing is considered a break between two tasks on one day whereas resting is considered a break between two working days. As a consequence, pausing will have a much shorter duration than resting. Driving is also marked as activity, but does not cover all time intervals in which the truck has covered distance. Therefore, intervals in which the truck has moved are also considered driving intervals unless these intervals are classified as loading, unloading, waiting, pause or resting intervals. Intervals in this last group of activities are considered stopping intervals. Figure 3 shows the distribution of time over activities.

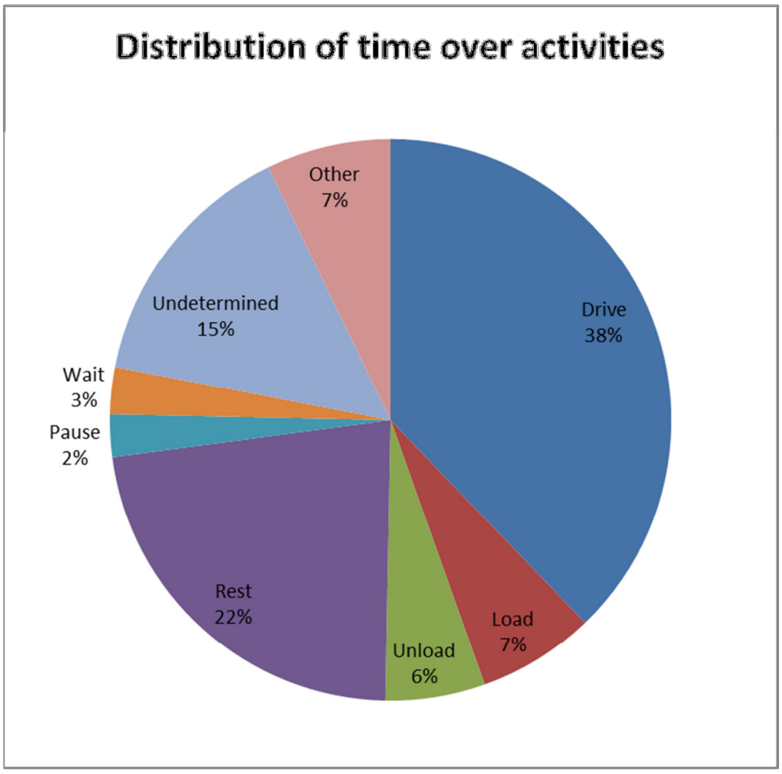

Figure 3 - Distribution of time over activities

Note that two categories in the pie chart were not discussed before: Undetermined and Other. Other is a composite of different activities such as fuelling, maintenance and logging in/out. The rule as described above holds for both Undetermined and Other; time intervals in which distance is covered are considered driving intervals. The other intervals are considered stopping intervals. The figure shows that most of the time, around 40%, is spent on driving. This confirms the importance of prediction of driving times. Pausing and resting cover approximately one fourth of the time. Furthermore, around 15% of the time is spent on loading and unloading. While this amount of time is not as large as the amount of driving time, it covers around 16,000 (un)loading events. The considerable amount of events makes loading and unloading interesting components to explore in more depth. Waiting covers 3% of the time, which makes it a relatively small component. Unfortunately, 15% of the time is classified as undetermined, a component that is difficult to analyze. The Other component only covers 7% of the time. Moreover, this component comprised of several activities. Therefore, Undetermined and Other will be left out of scope in further analysis. This leaves driving, (un)loading, pausing, resting, and waiting to be analyzed. These components together cover nearly 80% of the time which is a substantial share.

Then, the start and end of a trip were defined in order to enable trip analysis. The start of a trip is defined as the start of the first interval on a day with a distance larger than 0. The end of a trip is defined as the end of the last interval on a day with a distance larger than 0. This resulted in 7161 trips. For each trip, aggregated information can be derived from earlier extractions. Trip information includes date, total distance (in km), total duration (in hrs), average speed (in km/hr), stop time (in hrs), and drive time (in hrs). The definition of a trip ensures that one trip only has one date. Total distance is the summation of interval distances over all intervals that are part of the trip. Similarly, total duration is the summation of interval times. Average speed can be derived by dividing the total distance by the total duration. The classification of intervals as either stopping or driving interval is used to calculate the average driving speed. This is different from average speed: stop time is included in the calculation of average speed, but not in the calculation of average driving speed.

The trip information was examined to check for errors in data. Errors in the data can lead to unreliable conclusions about the trips. Therefore, trips that contain one or more of the following characteristics were eliminated for analysis:

- TruckNumber = 51
- Total distance is less than or equal to 0
- Drive time is less than or equal to 0
- Average speed is less than or equal to 0 or above 100 km/h
- At least one interval has a duration of more than 1 hr but covers a positive distance of less than 50 km.

The first criterion is used because validation at Jan de Rijk learned that TruckNumber 51 is a car instead of a truck. The second and third criteria are clear indicators of erroneous trip data. The lower limit of the fourth criterion prevents impossible measures to be included in the analysis. The upper limit of this criterion is set at 100 km/h since trucks have a limiter that enables them to drive around 90 km/h at maximum. A margin of 10 km/h is built in for downward slopes and inaccuracy of the limiter due to variability in tire pressure. The last criterion is used because each interval is classified as either driving or stopping interval. Intervals of considerable length can give a distorted view if the distance covered in that interval is not large enough to justify the assumption that the truck was driving during the whole interval. Therefore, a threshold value was chosen to exclude long intervals about which no solid claims (i.e. classification as either stopping or driving interval) can be made.

After elimination, 6440 out of the 7161 constructed trips remain for analysis.

3.2 Data analysis

The data dump contains more than 2 million logged truck event instances of almost 400 trucks. The data was gathered during approximately one week in each of the following months: March 2014, June 2014, and July 2014.

Driving

Around 6500 acceptable trips were constructed from these data. As stated in the previous paragraph, a trip starts at the first interval on a day in which a truck covers distance and ends with the last interval on that same day in which distance is covered. The trips are used to get an overview of the most important trip characteristics. The average driving speed of these trips is 66.12 km/h. The distribution of average driving speeds over the 6440 trips looks similar to a normal distribution with $\mu = 70\ km/h$ and $\sigma = 10\ km/h$. Both distributions can be found in Figure 4.

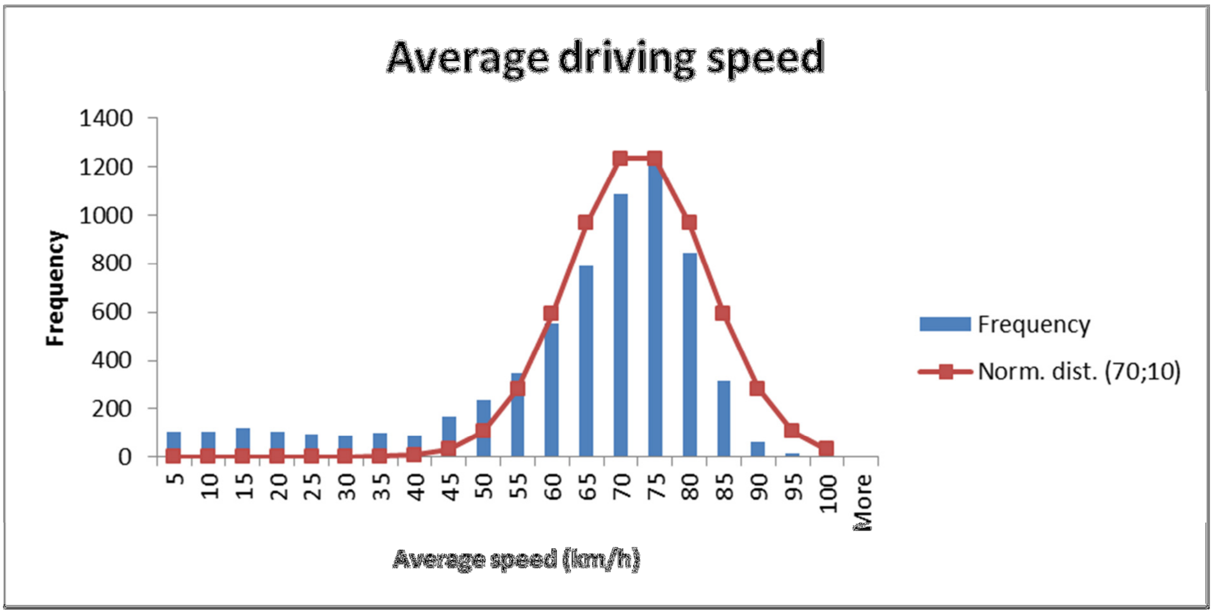

Figure 4 - Average driving speed

Nearly 60% of the total duration was classified as stop time and thus 40% as drive time. The average distance of a trip is 389 km, which corresponds with the international character of this data dump. The average duration of a trip is 14.56 hours, which is obviously dependent on the choice for the transition of days as boundary for a trip. However, the analysis of average speed and activities is not dependent on the definition of trip duration and thus can the choice for these boundaries be justified.

Stopping events will be analyzed from the perspective of the activities themselves rather than the trip perspective that was used above for a general analysis.

(Un)loading

The data dump contains 8152 loading events and 8276 unloading events. The duration of these events varies from 0 to 22.2 hours. An upper and lower limit is used to exclude the outliers that are believed to be unrealistic. The 95th percentile will be used as an upper limit. Working with 5-minute time buckets, for loading this means the upper limit will be 2 hours and 50 minutes. For unloading the upper limit is 2 hours and 20 minutes. The lower limit should approach the minimum time that is needed for (un)loading. This limit is set on 10 minutes for both loading and unloading. This results in 5195 loading events with an average duration of 60.0 minutes and a standard deviation of 59.0

minutes. For unloading, the result is 5348 events with an average duration of 50.3 minutes and a standard deviation of 48.3 minutes. The distribution of the duration of loading is comparable to an exponential distribution with $\lambda = 0.8$. The distribution of unloading duration is similar to an exponential distribution with $\lambda = 1.05$. Both distributions for loading and unloading events can be found in Figure 5 and Figure 6 respectively.

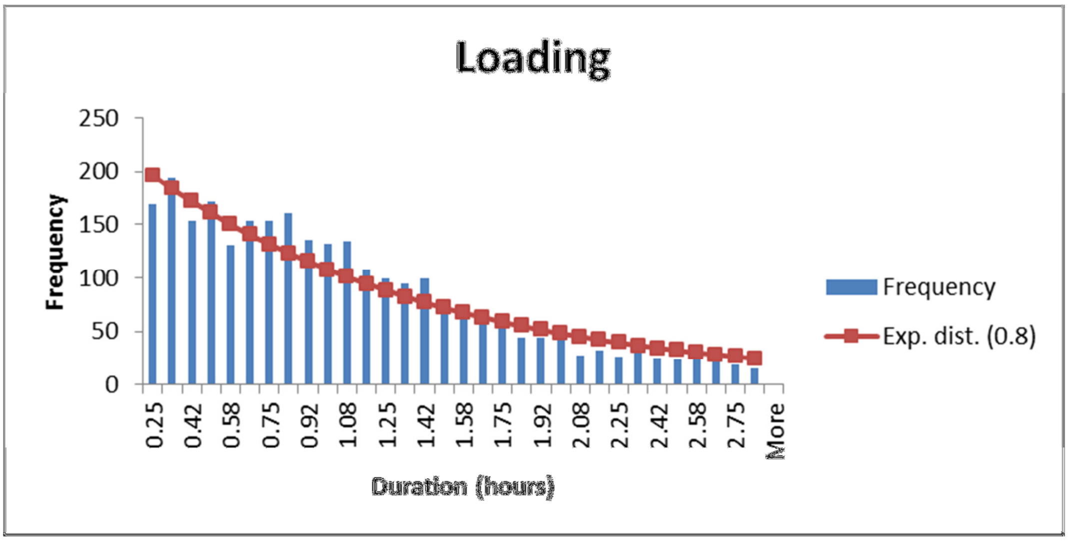

Figure 5 - Loading duration

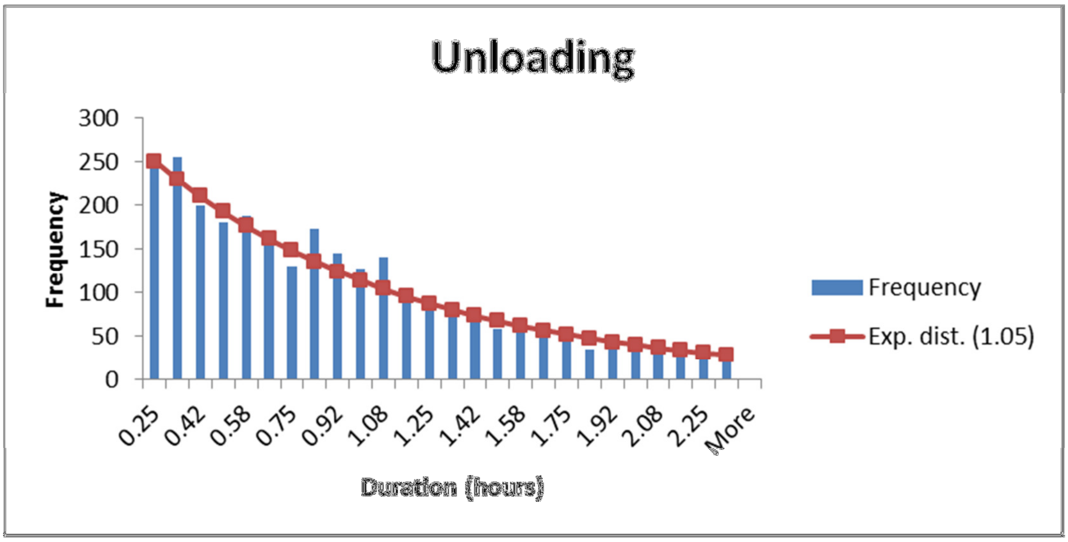

Figure 6 - Unloading duration

The distributions both show a general trend downwards; every shift to the right, to longer event duration, results in fewer measures. For both loading and unloading the standard deviations are high compared to the mean. This suggests that distinctions between different categories of one or more variables for the prediction of (un)loading duration could lead to better results than just using the average duration. The locations of the (un)loading events are matched to a map and can be found in Appendix B.

Waiting

The data dump contains 2896 waiting events with a duration between 0 and 21 hours. To account for outliers, the method that was used for (un)loading will also be used here. This results in a lower limit of 10 minutes and an upper limit of 3 hours and 5 minutes for waiting. For the 2281 waiting events that remain, the average waiting time is 55.5 minutes with a standard deviation of 50.3

minutes. This distribution looks similar to an exponential distribution with $\lambda = 1.25$. Both distributions are shown in Figure 7.

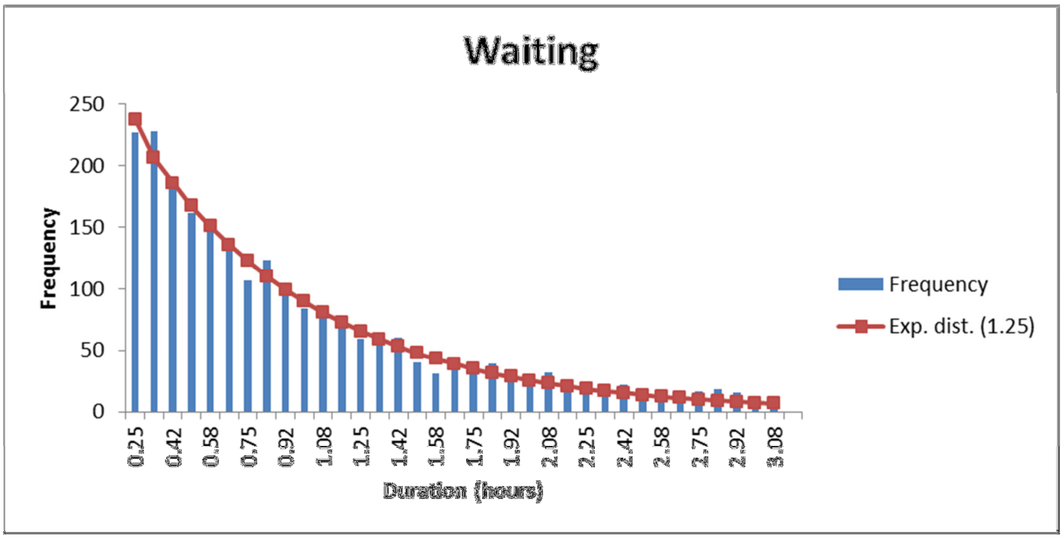

Figure 7 - Waiting duration

Roughly half of the measures has a duration between 10 and 40 minutes; the other half lies between 40 minutes and 3 hours and 5 minutes. Map matched waiting locations can be found in Appendix B.

Pause & Resting

Pause is associated with short periods, typically under an hour, and is meant as a break in between tasks. Resting generally lasts for a longer period, at least 10 hours, and is meant as a rest period in between working days. The number of pause event declined from 3083 to 2756 by taking 10 minutes as lower time bound and 1 hour and 35 minutes, the 95th percentile, as upper time bound. An average pause has a duration of 22.1 minutes. For resting, the data dump included 2246 events which was brought back to 1943 by using 10 minutes as lower bound and 18 hours (95th percentile) as upper bound. A period of resting has an average duration of 10.1 hours. Figure 8 and Figure 9 show the graphs of respectively pause and resting duration.

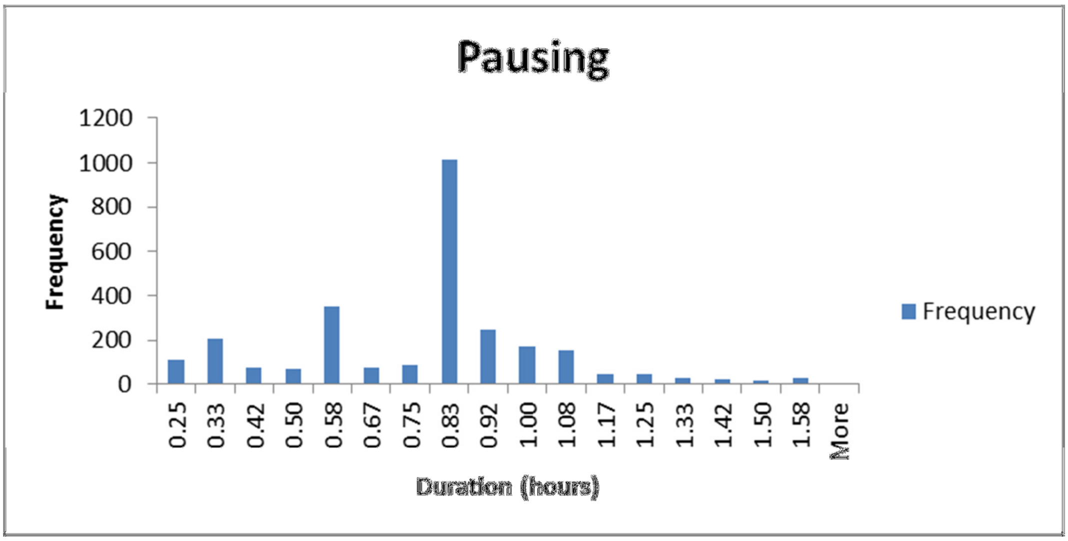

Figure 8 - Pause duration

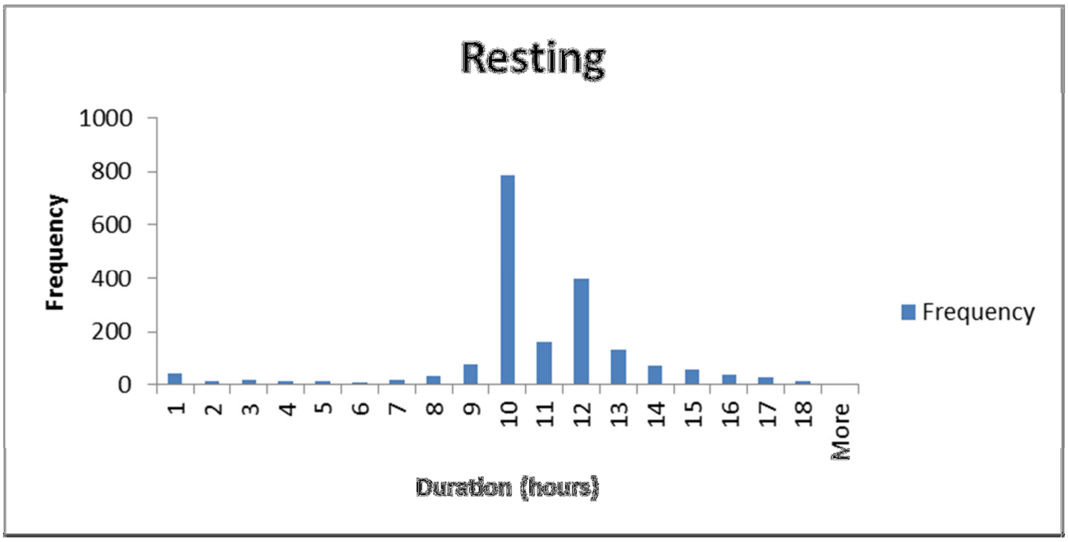

Figure 9 - Resting duration

Both graphs show clusters of measures around the average duration of the activity. Pausing has peaks at 20, 35, and 50 minutes. Resting shows peaks at 10 and 12 hours. Both pausing and resting are subject to regulations. These regulations prescribe a pause of 45 minutes after 4.5 hours of driving. The largest peak for pausing is at 50 minutes, which is slightly longer than the prescribed 45 minutes. The smaller peaks at 20 and 35 minutes can be explained by the fact that drivers are allowed to split 45 minutes of pause into two shorter pauses of 15 and 30 minutes respectively. For resting, regulations prescribe a minimum of 11 hours which can be shortened to at least nine hours maximally three times in two weeks. The frequency of the peak at 10 hours seems high compared to what the regulations prescribe. However, the duration of resting is from truck perspective which is not necessarily equal to driver perspective. When a truck is driven by driver x on Monday and by driver y on Tuesday, the resting duration cannot be coupled to a specific driver. This means that the distribution of resting duration can give a distorted view on driver resting times. For pausing, the truck perspective does not influence the interpretation of the distribution since a driver will continue driving the same truck after a pause.

Map matched pause and resting locations can be found in Appendix B. The regulations that pausing and resting are subject to, can be found in Appendix C.

The prepared and analyzed data will be used for the development of a prediction model as explained in chapter 4.

4. Model

An integrated model is designed to enable prediction of the duration of variable truck travel time components. The components driving, loading, unloading, pausing, and resting are predicted by this model. Prediction of those times will be approached in different ways. Driving duration will be predicted using historical GPS probe data gathered by TomTom. These GPS data enable time-and location-dependent speed predictions. Loading and unloading duration will be predicted with a linear regression model. Pausing and resting duration are subject to regulations as mentioned in 'Rij- en rusttijden vrachtauto'. Logistics companies have to conform to these regulations. Therefore, the prediction of pausing and resting duration will be based on these regulations.

The analysis of waiting duration shows that these are difficult to predict both in duration and appearance. Waiting times are often unexpected and underlying causes are most likely not, or only partly, represented by the obtained data. However, current planning methods do not take waiting time into account. This means excluding waiting duration from the prediction model will not cause any harm. Therefore, waiting duration will be left out of scope for the prediction model.

The outcomes of the prediction model will be compared to the rules of thumb that are currently used at Jan de Rijk. For (un)loading duration, the rule of thumb states that an (un)loading event has a duration of one hour. For driving duration, a combination of distance and speed is used as rule of thumb: the distance is predicted with Pythagoras' proposition and an average speed of 69 km/h is used. The rule of thumb for pausing and resting is based on the regulations as mentioned before. The rules of thumb will be checked with the prediction model and reality in order to show the potential improvement that can be gained by implementing the integrated prediction model.

4.1 Predicting (un)loading duration

The distribution of loading and unloading durations that can be found in section 3.3 shows a relatively large dispersion of these durations. This could be an indicator for using distinct categories in predicting (un)loading duration rather than a standard time, which is used now. Jan de Rijk uses a prediction of one hour as rule of thumb for both loading and unloading duration. Linear regression models for the prediction of both loading and unloading duration will be built. The results of these models will be compared with the results of the rule of thumb and with reality. This will give an indication whether linear regression enables better prediction of (un)loading durations than the use of a rule of thumb.

In order to build a linear regression model, an outcome and its possible predictors are needed. In this case, the outcome is (un)loading duration. Possible predictors of this outcome that are represented by the available data can be used as input for the regression model. Possible predictors:

- Day of (un)loading
- Time of (un)loading
- Location of (un)loading
- Amount of freight to (un)load

These predictors could possibly influence the duration of (un)loading activities and will be used as input for the prediction model.

In practice this means that day will be categorized as day of the week: Monday, Tuesday, Wednesday, Thursday, Friday, Saturday or Sunday. Time will be categorized as part of the day: night (0-6h), morning (6-12h), afternoon (12-18h), or evening (18-0h). The data represents location by city and street. The number of loading meters represents the amount of freight. One loading meter is equivalent for the amount of freight that takes the space of one meter over the full width of the trailer (2.55 meter).

The information mentioned above can be extracted from the prepared data, except the amount of freight. The amount of freight, i.e. the number of loading meters, to (un)load is stored in another table on shipments. This table also includes information about the type of freight. However, due to the bad quality of time-related data, the (un)loading events from this shipment table cannot be matched to the (un)loading events from the table that was constructed in paragraph 3.1. Therefore, a different approach was chosen to enable inclusion of the amount of freight as a possible predictor in the linear regression model:

Each line in the shipment table contains a ‘From location’, a ‘To location’, and a certain number of loading meters. The ‘From location’ represents the city where loading the corresponding number of loading meters took place. The ‘To location’ similarly shows where the freight was unloaded. The amount of loading meters for loading on a certain location was averaged. The same was done for unloading. This resulted in an estimation of the number of loading meters that was (un)loaded in each city. These estimations shall be used as possible predictor ‘Amount of freight to (un)load’ in the regression models. For practical reasons, such as the amount of dummy variables to work with, the linear regression models will be restricted to prediction in the Netherlands. Map matched load locations (stars) and unload locations (dots) in the Netherlands can be found in Figure 10. It should be noted that some locations serve as both load and unload locations and thus are marked by both a star and a dot.

Figure 10 - Loading & unloading locations NL

The rule of thumb that is used by Jan de Rijk states that an hour should be planned for both loading and unloading. From the 5195 loading events that fell between the established limits as set in section 3.3, 2200 are situated in the Netherlands. Using the rule of thumb for these loading events resulted in an average deviation from the real duration of 29.74 minutes. For unloading, there were 5348 events between the set limits from which 1917 are located in the Netherlands. The rule of thumb gives an average deviation from the real unloading duration of 25.12 minutes.

In order to develop a prediction model, the data for both loading and unloading events was prepared. Dummy variables were created for weekday, part of the day, street, and city. Given the large amount of dummy variables, regression based on forward selection is preferred to regression based on backward elimination. Therefore, linear regression with forward selection was used as method to construct different prediction models. This means that an iterative process is used to include the most significant predictor in the model each time the process is repeated.

For both loading and unloading, linear regression was executed with several combinations of predictors as model input. Due to the amount of possible predictors, a large number of combinations can be made. It is chosen to present all single predictors and only the combinations that resulted in at least 5% reduction of the deviation from the rule of thumb in Table 2. The full model is also given for comparison. The predictors are abbreviated as follows:

- WD = Weekday
- TD = Time of the Day
- CI = City
- ST = Street
- LM = Loading Meters

Table 2 - Rule of thumb and linear regression compared to reality

	Loading			Unloading		
Predictor input	*Deviation from real duration (minutes)*	*Reduction relative to rule of thumb (%)*	R^2	*Deviation from real duration (minutes)*	*Reduction relative to rule of thumb (%)*	R^2
Rule of thumb	29.67	-	-	25.08	-	-
WD/TD/CI/ST/LM	26.54	10.5%	.162	21.74	13.3%	.107
WD	29.53	0.5%	.010	23.35	6.9%	.005
TD	29.70	-0.1%	.004	23.29	7.1%	.007
CI	27.30	8.0%	.117	22.27	11.2%	.068
CI/LM	27.40	7.6%	.121	,,	,,	,,
ST	27.00	9.0%	.149	21.74	13.3%	.110
ST/LM	26.93	9.2%	.149	,,	,,	,,
LM	29.37	1.0%	.018	23.28	7.2%	.008

Table 2 shows that for loading the maximum reduction of deviation from reality that can be obtained lies around 10%. For unloading this number is somewhat higher: around 13%. The value of R^2 shows which part of variation can be explained by the produced models. For loading the maximum lies around 16% and for unloading around 11%. This means that relatively little variance is explained by these models. In other words, a large part of the variance remains unexplained; data do not account for a large part of the variance. This could indicate the presence of factors that have a large influence on the duration of (un)loading but are not represented by the data that were used. One can think about the exact amount of loading meters, since only estimates are available for the model. Furthermore, drivers may have to queue behind other drivers that want to (un)load on that same location. Or drivers need to wait for the right equipment to enable (un)loading the truck. In addition, the human factor could play a role here. Different drivers and/or customers may have different levels of efficiency, which can cause variability in (un)loading duration.

A trade-off was made between the fitting of the models and the suitability for practical use. Loading Meters is highly correlated to Street and City because of the way loading meters were estimated. Naturally, Street and City also have a high correlation. Due to multi-collinearity between different groups of predictors (e.g. streets and cities) it is recommendable to use only one group of predictors if possible. The reduction of deviation from reality should be taken into account by making a choice for the predictor(s) to include in the final model. For this data set, Street is the most detailed level of information about a client location. Assuming that two clients are never located in the same street, predictor Street would have a one-to-one relation with the client that is served with the concerning (un)loading event. This would be suitable for practical use. The predictor 'Customer Location' would be more ideal since that would cover separate customer location whereas Street could occasionally cover more customers that are located in the same street. However, Customer Location as predictor is not available hence could not be chosen. Street is the best available approximation of Customer Location. The trade-off resulted in the choice for the variable Street as predictor for both loading and unloading duration.

The output of linear regression in a formula has this general form:

$$Y = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \cdots + \beta_n * X_n$$

With
$Y = dependent\ variable$
$\beta_{0,1,\ldots,n} = coefficient$
$X_{1,2,\ldots,n} = explanatory\ variable$

In this case, dependent variable Y would be the duration of (un)loading in hours. The explanatory variables $X_{1,2,\ldots,n}$ are dummy variables (i.e. instances) of the predictor Street. The β coefficients are given as output of the linear regression process.

For loading, the regression formula using Street as predictor is as follows:

$$\begin{aligned} Loading\ duration \\ &= 0{,}866 + 0{,}431 * Pelikaanweg - 0{,}482 * Prooyelaan - 0{,}387 * RingCentrum \\ &+ 1{,}176 * Babberischeweg - 0{,}577 * Havennummer72018100 - 0{,}57 \\ &* Missouriweg - 0{,}33 * MiddelBroekweg + 1{,}362 * LogisticBoulevard \\ &+ 0{,}191 * Anchoragelaan + 0{,}207 * Exportplein + 0{,}348 * Heibloemseweg \\ &+ 0{,}287 * Ganderweg + 0{,}321 * Gesworenhoekseweg + 1{,}608 * Duitslandweg \\ &+ 1{,}578 * Express - 0{,}386 * Magnolia + 0{,}198 * Leemstraat + 0{,}919 \\ &* Papland + 0{,}746 * TtTunnelweg + 1{,}237 * Kranenberg + 0{,}867 \\ &* Protonweg - 0{,}522 * Poortcamp + 0{,}67 * Rijerscheweg + 0{,}326 \\ &* Oirloseweg + 0{,}294 * RandwegOost \end{aligned}$$

The formula for unloading with Street as predictor is as follows:

$$Unloading\ duration\ = \\ = 0{,}75 - 0{,}429 * Havennummer72018100 + 0{,}495 * VanLeeuwenhoekstraat + 0{,}423 * \ Heibloemseweg\ - 0{,}238 * \ RingCentrum\ + 0{,}184 * Anchoragelaan\ + 0{,}2 * \ Exportplein\ + 1{,}23 * \ Havennummer22502490 + 0{,}205 * \ Vrijhavenplein\ + 1{,}39 * Onderweg\ + 1{,}369 * \ Nieuwesluisweg + 0{,}125 * \ +0{,}218 * \ Pelikaanweg\ + 1{,}336 * Bellstraat + 1{,}269 * Weteringseweg + 1{,}185 * AbelTasmanstraat + 0{,}592 * Dongenseweg - 0{,}552 * Moervaart + 0{,}535 * Marshallweg + 1{,}039 * Columbusweg + 0{,}149 * Cessnalaan - 0{,}263 * OudeVijfhuizerweg$$

Significance of those variables can be found in Appendix D.

Bear in mind that the explanatory variables, the street names in this case, are dummy variables and can therefore only have the value 0 or 1. Furthermore, for both formulas applies that Street is the only predictor hence at most one of the street dummies in the formula can have the value of 1, the others will be 0. It is also possible that all street dummies have the value 0. This means the (un)loading event takes place in a street that was not found to have a significant influence on (un)loading duration. In such cases, the prediction of (un)loading duration will only enclose the constant: 0.866 hr, or 52 minutes for loading, and 0.75 hr, or 45 minutes for unloading.

It should be noted that the usability of these regression model is dependent on changes over time. For example, if a new customer is acquired, a new street should be added to the model which means the regression has to be executed again. In addition, (un)loading durations at certain streets could change substantially over time. Therefore, it is desirable to have automatic updates of the regression models once every couple of months and after adding or deleting customers from the system. Once the regression is executed and will be automatically updated, the models are easy to use.

With these models, the average deviation from reality is reduced from 29.67 to 27.00 minutes for loading, a reduction of 9.0%. For unloading, the average deviation from reality is reduced from 25.08 to 21.74 minutes, which is a reduction of 13.3%. Both reductions were tested with a two-sample t-test assuming equal variances. The outcomes of the t-test were significant with $P(T \leq t, one\ tail) = 2.5 * 10^{-5}$ for loading and $P(T \leq t, one\ tail) = 5.18 * 10^{-10}$ for unloading respectively. More information about the results of both the rule of thumb and the linear regression prediction models compared to reality can be found in Table 3. In this table, 'Planned too tight' refers to a planned (un)loading duration that is too short compared to reality, whereas 'Planned too loose' refers to a planned (un)loading duration that is too long compared to reality.

Table 3 - Comparison (un)loading duration with reality

	Planned too tight		**Planned too loose**		**Overall**	
Method	*# cases*	*Average deviation from reality*	*# cases*	*Average deviation from reality*	*# cases*	*Average deviation from reality*
For loading						
Rule of thumb	952	-35 min.	1239	+26 min.	2200	30 min.
Prediction model	920	-32 min.	1280	+23 min.	2200	27 min.
For unloading						
Rule of thumb	654	-25 min.	1256	+25 min.	1917	25 min.
Prediction model	857	-24 min.	1060	+20 min.	1917	22 min.

4.2 Predicting driving duration

In this paragraph, historical probe data of TomTom will be used to predict driving times. Afterwards, the results of this method will be compared to the result of a rule of thumb and reality.

TomTom has access to a vast amount of historical GPS data. These data can serve to predict driving times on different routes and times. The road network is split up in multiple segments with a length varying from several meters to a kilometre. For each of these road segments, historical GPS data from the most recent two years is compiled per day of the week and matched to a so-called speed profile. A speed profile shows the average speed on each time of the day relative to the free flow speed. Free flow speed is the average speed that is driven at a certain road segment between roughly 0h and 6h; usually the quietest hours on the roads which allow you to drive without having to break for other road users. A speed profile serves as a mold for the perceived behaviour on a certain road segment and day of the week. Because of data requirements, a limited set of around 200 different speed profiles is used. The historical data from each road segment and each day of the week are matched to the best fitting speed profile. An example of a speed profile can be found in Figure 11.

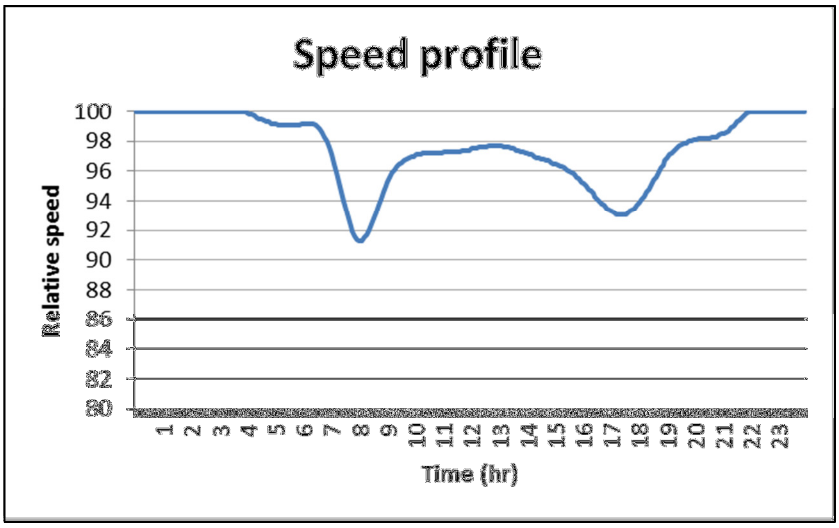

Figure 11 - Example of speed profile

This speed profile shows dips in average speed around 8h and around 17h30: morning and afternoon peak hours. The morning peak hour is heavier than the afternoon peak hour with a speed drop of almost 9% compared to a speed decrease of 5% relative to the free flow speed. This could indicate a clustering of commuters that all drive to their offices around 8h. The homeward journeys seem to be more spread between 16h and 19h.

Once all road segments are matched to a speed profile for every weekday, this information can be used to predict driving times and thus ETA. For each road segment that will be used, the length, free flow speed, and relative speed at the moment of riding the segment can be used to deduce the expected time that is needed to pass the road segment. An example: on Monday at 20h one passes a road segment that was matched for Mondays to the speed profile in Figure 11 with a free flow speed of 60 km/h. Using the figure, one can derive that the expected speed at 20h is 98% of the free flow speed, so $0{,}98 * 60 = 58.8\ km/h$. Assuming the road segment has a length of 750 meter. The expected time in which the road segment will be passed is $\frac{0.750}{58.5} = 0.0128\ hr = 45.9\ sec$. Repeating this for all road segments that are included in a route will lead to the expected driving time that is needed for that route. Adding this driving time to the departure time of the trip gives the ETA of that trip.

The historical GPS data that are used to match road segments to speed profiles come from different types of vehicles. Passenger cars are well represented here, while trucks only make up for 8 to 10% of these historical data. In terms of speed, trucks show other behavior on the road than passenger cars. For example, trucks are limited to a speed of around 90 km/h on flat roads and trucks accelerate and decelerate slower than passenger cars do. Therefore, the outcome of the matching of speed profiles is adapted to make them usable for trucks. The adaption comprises a speed reduction of 5 to 10% and cutting of speeds above the maximum allowed speed for trucks.

Now, these matched and adapted speed profiles will be used to predict driving times for trucks. In order to enable comparison with reality, the trips that were constructed with data from the data dump are used. The weekday, departure time, and GPS coordinates of a trip are used to calculate the expected driving time based on the adapted speed profiles as discussed before. All GPS coordinates that were passed by the truck were put on a map and connected to each other on time sequence. This gives a fairly accurate description of the route that was travelled. Now, an algorithm tries to match this route to roads that are known to be accessible by trucks. Recurring problems were found at the start and end of a large part of the routes. This is likely caused by the mismatch between GPS coordinates and accessible roads for trucks around some of the (un)loading locations such as airports. To enable better matching to the real route, 20 kilometers was cut off on the start and end of each trip. This reduced the number of trips to check from 6440, the initial number of acceptable trips, to 5430. The trips that were eliminated were simply shorter than 40 kilometers. The route matching procedure resulted in 4979 successful cases and thus 451 fails. A successful case in this respect means that the algorithm succeeded in finding a route for trucks. However, the degree to which these constructed routes matched the actual driven route varies enormously. An example of a good match is shown in Figure 12, the real route, and Figure 13, the matched route. This example shows only a minor difference in route length: 2.6 km difference on a total route length of 621 km, which equals 0.4% deviation.

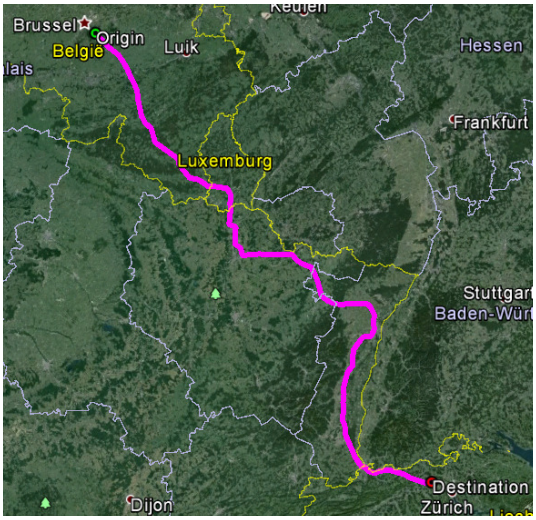

Figure 12 - Example of driven route

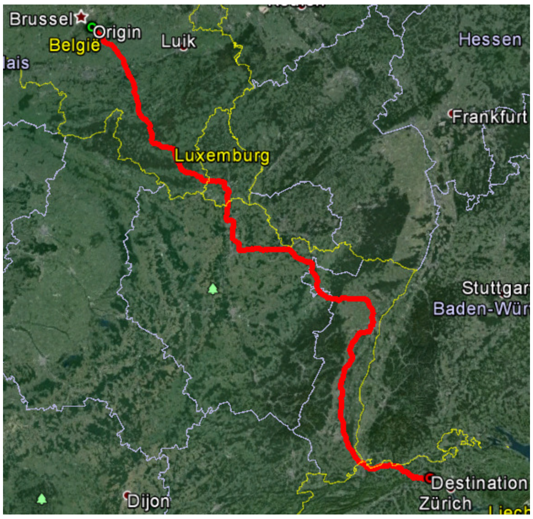

Figure 13 - Example of matched route

The distance of the constructed route was checked against two criteria. First, a maximum difference in route length was set to reduce the chance that a matched route significantly differs from the real route that was driven. Random inspection learns that a difference of maximally 5% generally results in a good fitting of the real travelled route and the constructed route. Therefore, routes with a difference between real route length and constructed route length of bigger than 5% were eliminated. This left 1553 routes to be checked against the second criterion. The second criterion compares the length of the constructed route to the distance that was covered by driving intervals. This means that stopping intervals, i.e. during loading, unloading, waiting, resting or pause, in which distance was covered, are excluded from the total route length. This is done because these intervals were not included in the total driving time as explained in section 3.3. This leaves 71 routes for validation of the prediction of driving times with speed profiles. Since the results of the model need to be compared to the results of the rule of thumb, these results need to be produced as well. The rule of thumb calculates expected driving time based on speed and distance in the following way:

- Average speed is 69 km/h
- Distance to travel is calculated using Pythagoras' proposition between the latitude and longitude of two points: start location and (un)loading location 1, (un)loading location 1 and 2, … , (un)loading location n and end location.

Due to empty coordinates in the data dump, i.e. latitude and longitude are both represented as '0,000', one trip did not give results for the rule of thumb. However, 70 trips were left for comparison. For these trips, the results of the rule of thumb showed an average deviation from real driving time of 55.2 minutes. For the method that uses time-dependent speed profile information, this was 44.0 minutes. This is a reduction of deviation from reality of 20.3%. More detailed information on this can be found in Table 4.

Table 4 - Comparison driving time predictions with reality

	Planned too tight		**Planned too loose**		
Method	*# cases*	*Average deviation from reality*	*# cases*	*Average deviation from reality*	*Average deviation (absolute)*
Rule of thumb	55	-63 min.	15	+28 min.	55 min.
Prediction model	19	-32 min.	51	+49 min.	44 min.

This shows that the rule of thumb tends to produce planned driving times that are too tight compared to reality (i.e. the truck arrives later than planned). This could result in problems such as tardiness in delivery or pick up and overtime for drivers. The prediction model that bases its predictions on the information from speed profiles and adjustments for trucks succeeds to deliver a more balanced planned driving time which results in a lower average absolute deviation from reality.

4.3 Predicting pausing and resting duration

Prediction of pausing and resting times is subject to the legally defined 'Rij- en rusttijden vrachtauto'. This means that planning of these periods is done conform to these regulations. Truck drivers are deemed to act in line with the regulations with respect to pausing and resting times.

Based on the regulations, the following rules are used to plan pausing and resting times:

- After 4.5 hours of driving, a pause of 45 minutes is planned.
- After nine hours of driving on a certain day, 11 hours of rest are planned. Maximally twice a week driving can be extended to ten hours before planning 11 hours of rest. Maximally three times per two weeks, daily rest can be shortened to a minimum of nine hours.
- Plan at least 45 hours of uninterrupted rest for a driver on weekly basis.
- Weekly driving time may not exceed 56 hours.
- Biweekly driving time may not exceed 90 hours.

Since pausing and resting times are subject to regulations that are also leading for Jan de Rijk, the current way of planning these will be maintained.

The developed prediction model will be tested with a proof of concept as described in chapter 5.

5. Proof of Concept

The theoretical potential of the integrated prediction model was calculated and described in chapter 4. This chapter will describe a proof of concept comparing the results of a planning made by Jan de Rijk with the results of a planning made by the prediction model.

5.1 Jan de Rijk

The set of trips that was used for verification of the prediction model for driving times in chapter 4.1 is used as a pool to select trips for the proof of concept. First, trips for which all (un)loading points are located in the Netherlands are selected. This is done because the prediction model for (un)loading times from chapter 4.2 only includes locations in the Netherlands. There are six trips for which all (un)loading locations are situated in the Netherlands. Another four trips, without (un)loading events, were randomly selected to total the number of cases to ten. For each of these ten trips, the following information was given as input for the proof of concept:

- Day and time of start
- Start location
- (Un)loading and/or pausing locations if any
- End location

A planner from Jan de Rijk was asked to use this information to plan the ten trips with the regular planning method. This is a combination of rules of thumb and Smartour, a planning system from the company PTV. The planner from Jan de Rijk used the following method:

1. Driving time is first predicted based on the Pythagoras distance between two locations and an average speed of 69 km/h. This prediction is indicated in the planning system. At the moment of planning, a request is sent to the PTV server. The feedback on this request is the prediction of distance and driving time from the PTV system. As soon as this feedback is available, the prediction in the planning system will be updated.
2. (Un)loading duration is predicted with another rule of thumb. This rule of thumb differs per business unit. For national distribution, (un)loading location and amount of loading meters influence the planned (un)loading duration. For international distribution, where the data dump originates from, the rule of thumb prescribes to plan one hour for both loading and unloading, independent of location and amount of loading meters.
3. Pausing and resting times are planned based on the rules that are prescribed by the regulations Rij- en rusttijden vrachtauto as discussed earlier in this report.

The prediction model described in chapter 4 was used to plan the same trips. Afterwards, both schedules are compared to reality. The input and output of this proof of concept can be found in Appendix E.

Ten (un)loading events were present in the data set. The duration predictions of these events were compared. For these events, the planning method of Jan de Rijk showed an average deviation from real (un)loading duration of 38.4 minutes. The planning method as described in chapter 4.2 shows an average deviation from reality of 29.6 minutes. This is an improvement of almost 23%. This information is represented in Table 5, where 'JdR and 'Model' represent the rule of thumb from Jan de Rijk' and the prediction model respectively.

Table 5 - Comparison (un)loading durations

Location	Activity	Duration: Reality	Duration: JdR	Duration: Model	Absolute deviation (minutes): JdR vs. Reality	Absolute deviation (minutes): Model vs. Reality
Van Leeuwenhoekstraat, Oostrum (NL)	Unload	1hr09	1hr	1hr15	9.0	5.7
Rue de l’Aéroport, Grâce-Hollogne (BE)	Load	3hr33	1hr	0hr52	153.0	161.1
Klappolder, Bleiswijk (NL)	Unload	0hr25	1hr	0hr45	35.2	20.2
Pelikaanweg, Schiphol (NL)	Load	1hr20	1hr	1hr18	20.3	2.5
Anchoragelaan, Schiphol (NL)	Load	2hr03	1hr	1hr05	62.5	57.9
Middel Broekweg, Honselersdijk (NL)	Load	0hr37	1hr	0hr32	22.9	4.9
Prooyelaan, Honselersdijk (NL)	Load	0hr22	1hr	0hr23	38.0	1.0
Exportplein, Schiphol (NL)	Load	1hr20	1hr	1hr04	20.3	15.9
Folkstoneweg, Schiphol (NL)	Load	0hr47	1hr	0hr52	13.0	4.9
Ring Centrum, Aalsmeer (NL)	Load	0hr51	1hr	0hr29	9.4	21.8
					38.4 (avg.)	29.6 (avg.)

A two-sample t-test on the absolute deviations shown in Table 5 assuming equal variances gives the following outcome: $P(T \leq t, one\ tail) = 0.339$. This means that the difference of 23% cannot be considered significant. Since the planning rules for (un)loading duration are equal to the rule of thumb that is used in paragraph 4.2. The difference between prediction based on the rule of thumb and the prediction model was proven to be significant in paragraph 4.2. Therefore, saving calculations will be based on the results of that paragraph. The results will be extrapolated to yearly basis.

The data dump contains 8152 loading and 8276 unloading events in a period of 24 days:

$$\frac{8{,}152}{24} * 365 = 124{,}000\ loading\ events\ per\ year$$

$$\frac{8{,}276}{24} * 365 = 125{,}000\ unloading\ events\ per\ year$$

Using the model from chapter 4.2 leads to a deviation reduction of 9% for loading and 13.3% for unloading:

$$124{,}000 * 0.09 + 125{,}000 * 0.133 = 27{,}900\ hours\ less\ deviation\ per\ year$$

An average truck driver costs Jan de Rijk around €20 per hour:

$$27{,}900 * €20 = €558{,}000\ salary\ savings\ per\ year$$

In other words, using the prediction model for prediction of (un)loading times instead of the rule of thumb from Jan de Rijk could save up to half a million per year. The reason for this is that the model gives a better estimation of the amount of time that is needed which will reduce the overtime and undertime (i.e. working fewer hours than contracted for) that has to be paid to drivers.

For comparison of driving time predictions, some side notes should be made first. Not all start and end locations from the trips to plan were available in the planning system. If a location was not present in the planning system, the planner chose a location that was close to the given location. This results in a deviation in trip distance which should be corrected to enable comparison between the two planning methods. This correction is done by calculating the difference between real and predicted distance and adding, or subtracting in case the predicted distance is larger than the real distance, the amount of time it takes to cover that distance with the average speed according to the planning system. However, comparing the output of both planning models (i.e. planning by Jan de Rijk and with the prediction model) on driving times remains complicated since routes and locations do not match completely. Cutting out the trips that were too divergent from reality, leaves the predicted driving times of seven trips to compare. This comparison shows an average deviation from reality of 22.2 minutes for the model used at Jan de Rijk and 21.2 minutes for the model from chapter 4.1, an improvement of around 4.5%. This information can be found in Table 6, where 'RoT', 'PTV' and 'Model' represent the rule of thumb from Jan de Rijk, the planning system of Jan de Rijk, and the prediction model respectively. The outcomes of the rule of thumb are added to give an idea of how the prediction of distance and driving time change between the preliminary prediction of the rule of thumb and the prediction of the PTV planning system as explained in step 1 of the planning method earlier in this paragraph. Furthermore, the driving times of Jan de Rijk's planning system are corrected to account for the difference in distance due to research limitations as explained before.

Table 6 - Comparison driving times

	Distance (km)				Driving time				Absolute deviation (minutes)		
Trip	Real	RoT	PTV	Model	Real	RoT	PTV	Model	RoT-Reality	PTV-Reality	Model-Reality
1	310	250	285	310	4hr10	3hr38	4hr34	4hr15	32.8	24.1	4.9
2	332	228	270	331	5hr14	3hr18	5hr46	5hr33	116.0	31.5	18.6
4	520	433	508	522	7hr01	6hr17	7hr28	7hr45	43.6	27.4	44.9
5	419	352	445	420	5hr47	5hr06	5hr38	6hr09	40.8	8.6	22.3
8	554	430	565	555	6hr43	6hr14	7hr22	7hr07	29.0	39.1	24.1
9	362	300	327	361	4hr38	4hr21	4hr51	5hr06	17.0	13.3	27.9
10	415	253	268	417	6hr30	3hr40	6hr19	6hr36	169.8	11.7	6.0
									79.4 (avg.)	22.2 (avg.)	21.2 (avg.)

It may be clear that the amount of cases is too small to make hard claims about the performances of these models compared to reality. A two-sample t-test assuming equal variances on the absolute deviations of 'PTV' and 'Model' compared to reality gave $P(T \leq t, one\ tail) = 0.442$ as outcome, which means the differences cannot be considered significant. Further investigation of this element of the prediction model on a larger scale could result in significant differences and is thus desirable.

In addition, the routes that were given by Jan de Rijk's planning system were simulated with a TomTom truck navigation device in order to enable comparison between the two prediction methods. This gave nine routes. On these nine routes, the TomTom device predicts distances that are on average 0.6% longer than those of Jan de Rijk. Therefore, it seems plausible that both systems calculate approximately the same route. On the other hand, the driving times predicted by the TomTom device are all shorter, on average 7.6%, than those of the planning system at Jan de Rijk. This is an interesting finding that strengthens the need to investigate this on a larger scale. Underlying numbers can be found in Table 7, where 'JdR' and 'TomTom Pro 5150' represent the planning system at Jan de Rijk and the TomTom truck navigation device respectively.

Table 7 - Comparison driving times planning system and TomTom truck navigation

	Distance (km)		Difference (%)	Driving time (hrs)		Difference (%)
#	*JdR*	*TomTom Pro 5150*	*TomTom compared to JdR*	*JdR*	*TomTom pro 5150*	*TomTom compared to JdR*
1	285	274	-4.0 %	3.95	3.52	-12.3 %
2	270	263	-2.7 %	4.55	3.72	-22.4 %
3	234	245	+4.5 %	3.40	3.28	-3.6 %
4	508	512	+0.8 %	7.30	7.08	-3.1 %
5	445	451	+1.3 %	6.08	6.00	-1.4 %
6	507	509	+0.4 %	7.58	7.08	-7.1 %
8	565	596	+5.2 %	8.28	8.07	-2.7 %
9	327	334	+2.1 %	4.48	4.25	-5.5 %
10	268	262	-2.3 %	4.00	3.63	-10.1 %
			+0.6 % (avg)			-7.6 % (avg)

Further calculations shall be based on a driving time deviation reduction of 4.5%. The reduction in deviation from reality as found in chapter 4.1 shall also be discussed. This will give an idea of the possible gains in an environment where rules of thumb are used instead of planning systems.

The data dump contains 7145 truck trips in a period of 24 days:

$$\frac{7{,}145}{24} * 365 = 109{,}000 \; trips \; per \; year$$

The average driving time per trip is 5.9 hours:

$$109{,}000 * 5.9 = 640{,}000 \; driving \; hours \; per \; year$$

Using the results from the proof of concept a deviation reduction of approximately 4.5% can be achieved:

$$640{,}000 * 0.045 = 28{,}800 \; hours \; less \; deviation \; per \; year$$

Expressed in costs:

$$28{,}800 * €20 = €576{,}000 \; salary \; savings \; per \; year$$

Or, using the results from chapter 4.1 based on a rule of thumb that uses Pythagoras’ proposition to predict distance and an average speed of 69 km/h. In that case the deviation reduction on trip basis is 20.3%:

$$109{,}000 * 0.203 = 22{,}000 \; hours \; less \; deviation \; per \; year$$

Expressed in money:

$$22{,}000 * €20 = €440{,}000 \; salary \; savings \; per \; year$$

Using the prediction model from section 4.2 could lead to savings of around half a million per year compared to using the planning system or rules of thumb form Jan de Rijk.

It must be noted that the found numbers depend to a large extent on the cases that are used since the sample only comprises ten cases. Unfortunately, the current dependency on manual labor and system experience hampers the extension of this trial to a substantial amount of cases. The ten trips that were used are not completely representative for the whole pool of cases. The trips with (un)loading events are largely situated in the Netherlands since the prediction model is only enabled for prediction of (un)loading durations in the Netherlands.

The amounts in this chapter are a quantified indication of the yearly salary savings that could be achieved when adapting the prediction model as presented in chapter 4.

5.2 Planner interviews

Interviews with planners from ten different logistics companies gave more insight in the methods that are currently used in this sector and the daily challenges these organizations have to tackle. The companies that participated in these interviews are: Jan de Rijk Logistics, Kotra Coldstores Yerseke BV, Kotra van Maanen, Nabek BV, Van Rooijen Logistiek, Spar, Van Uden, H. Veldhuizen Transport, Versteijnen Logistics, and Van Wieren Special BV. These companies are diverse in terms of size, type of cargo, and use of planning standards.

For the prediction of driving times, four of the ten interviewed companies solely rely on their experience. Two of these companies build in slack for driving during rush hour: 15 and 30 minutes respectively. Another company builds in 1-2 hours standard slack for international trips. Two other interviewed companies use rules of thumb for calculating distance and combine those with an average speed to predict driving times. One of these companies uses Pythagoras' proposition for distance and an average speed depending on the trips length: 60 km/h for trips shorter than 100 km and 55 km/h for trips longer than 100 km. The other company uses GoogleMaps to calculate distance and an average speed of 80 km/h. Three of the interviewed companies use a planning system to predict driving times: PTV Smartour, Winroute, and Ortec are mentioned. Lastly, one company predicts driving times with experience for regional trips and with PTV Intertour, a predecessor of PTV Smartour, for longer trips.

The prediction of (un)loading duration is also approached in different ways. Four of the interviewed companies base their predictions on experience. Rules of thumb in this respect look like '(un)loading a full truck takes 1 to 2.5 hours', 'unloading at private customers takes around 2 hours' or '(un)loading takes 1 hour'. The other six companies have simple heuristics to predict (un)loading durations. Three of these companies use a standard process time of 10 minutes that is increased with 2 minutes per container, or 1 minute per pallet, to (un)load. The other three companies use heuristics that distinguish different types or amounts of cargo and assigns standard times for these. The rules that they use are: 'loading takes 5 minutes per loading meter', ' (un)loading up to 4 units takes 15-30 minutes, half to full truck load takes an hour', and 'loading takes 15-30 minutes for A-units and 30-45 minutes for B-units'.

An overview of the prediction methods as mentioned above can be found in Appendix F.

Several other interesting findings from the interviews will be briefly discussed below:

A large number of factors influence total travel time. One can think of unexpected road issues such as a traffic jam, accident, closed road, or a flat tire. The duration of (un)loading is influenced by several factors. For example, the driver may need to queue behind other trucks or suppliers that also want to (un)load at that location or the driver must wait for the equipment that is needed to (un)load his cargo. Next to that, there are different customer 'rituals' that can influence (un)loading duration such as long lunch pauses in certain countries and early closing times of harbors. The relationship between a logistics company and a customer can differ concerning formality and balance of power. Some customers do not give priority to drivers that are waiting to (un)load. Therefore, some logistics companies let customers pay if they delay the (un)loading process too much. There are also more informal relationships between customers and logistics companies/drivers. A driver that gets along with a customer could realize a shorter (un)loading duration because they are anticipated to each other or a longer (un)loading duration because they like to chat and drink coffee with each other. The human aspect is considered to be important. It is claimed that drivers with more experience on the job or in a certain area are able to complete all tasks considerably faster than other drivers.

The large amount of influencing factors probably contributes to the focus on real time problem handling rather than planning optimization. Planners point out the usefulness of real time traffic information about traffic jams, accidents, road closures, and updates of the expected time of arrival. In addition, there seems to be demand for route planning systems and maps that are adapted to truck dimensions and mark zones with restricted access. One planner expressed the need for information about route speed rather than a standard average speed. It should be noted that a better planning can help in overcoming or handling some of these problems upfront. An improved planning will reduce the amount of problems that will be encountered during execution.

Two interviewed planners mentioned that they plan trips with outdated systems or software. Furthermore, KPIs are often not used; only two of the interviewed companies check their planning with reality in quantitative way. However, planners attempt to absorb feedback from driver and customers in order to improve future performance.

6. Conclusion & Recommendations

This chapter presents the conclusions that are drawn from the results of this research. Furthermore, recommendations arising from the conclusions are discussed. Finally, interesting topics for future research are given.

6.1 Conclusion

The planner interviews gave the impression that the logistics sector does not fully utilize the current possibilities to predict truck travel time components. Table 8 gives an overview of how the interviewed companies predict driving and (un)loading durations. A more detailed version of this table can be found in Appendix F.

Table 8 - Prediction methods

Interviewed companies		**Driving duration**	*Experience*	*Rule of thumb*	*Planning system*	*Average speed (km/h)*	*Slack (hrs)*	**(Un)loading duration**	*Experience*	*Rule of thumb*
	1		X			-	-		X	
	2		X			-	0.25			X
	3		X			-	0.5			X
	4		X			86-93	1-2		X	
	5		X		X	-	-			X
	6			X		80	-			X
	7			X		55-60			X	
	8				X	55-70	-			X
	9				X	70	-		X	
	10				X	-	-			X

Planners often rely on their experience to predict travel time components. This is not necessarily incorrect, but does have several consequences. First of all, it makes planning subjective. The disadvantage of this is that subjectivity could, with fixed input, lead to variety in output whereas ideally an optimized solution would be used. Next to that, it will be very hard for a new, unexperienced planner to perform its job because of this subjective and often implicit knowledge. Nevertheless, the emphasis is slowly shifting from people and experience to planning systems in the logistics sector. It is very complicated to incorporate all the implicit knowledge (e.g. which driver is acquainted with a certain area or customer and which driver is not) of planners into a system. In practice, it is not feasible to include all experience and external factors in a prediction model. However, it is beneficial to include external factors in a prediction model where possible since that will improve predictions made by the model.

In a case study it was proven that there certainly is potential in the use of historical data for the prediction of truck travel times. The prediction model reduced the average deviation of planned time compared to reality with 9% for loading events, 13.3% for unloading events, and 20.3% for driving times. In other words, replacing the rules of thumb that were used in the case study with a regression model for prediction of (un)loading duration and speed profile information for prediction of driving duration results in a more reliable planning. A more reliable planning has several advantages. It enables logistics companies to give customers a more precise expected time of arrival the day before delivery or pick-up. This can be considered an improvement of the service towards customers. On a higher level, better predictions of travel time components enables planners to make better decisions about how to group delivery and pick-up locations together in trips and about whether or not to include an extra location on a certain day. In addition, a more reliable planning gives a better overview of the expected driver working hours. Since the working time regulations for drivers are very strict, it is desirable to have a reliable overview of the expected working hours. This will lead to less undertime and overtime (i.e. working less respectively more hours than contracted for), which are both undesired since they lead to extra, often unnecessary, costs. An extrapolation of the results to yearly basis shows that up to approximately one million euros a year could be saved by using the prediction model for (un)loading and driving duration.

Concerning generalizability of the advantages of the proposed prediction model as explained in detail in chapter 4 and 5, the following claims can be made:

- The rule of thumb for driving duration used in the case study, a combination of Pythagoras' proposition and an average speed, is quite advanced compared to the experience-based predictions that were mentioned in five of the planner interviews. Since the prediction model for driving duration performs better than the Pythagoras rule of thumb, it is plausible that the prediction of driving duration using speed profiles also performs better than the predictions based on experience that are used in half of the interviewed companies.
- Since the prediction model for (un)loading duration performs better than the 1 hour rule of thumb, it is expected that the prediction model will also perform better compared to other rules of thumb that use a standard duration for (un)loading.
- The data that were used for the prediction model originate from international trips with relatively few (un)loading events per trip. It should be noted that expected improvements by the prediction model not only depend on the current prediction methods, but also on the type of trips. The number of (un)loading events per trip and the distribution of time over activities can influence the improvements that are achieved by the prediction model.

6.2 Recommendations

The results of this research are promising in terms of the potential for improving distribution planning with the use of historical data. This research can be used as a business case for companies that use similar or simplified versions of, rules of thumb that are used by Jan de Rijk.

In practice, the prediction model for (un)loading duration could be coupled to the existing truck product from TomToms Telematics business unit, called Webfleet. This product enables logging of (un)loading times and locations and can therefore be used to generate input for the regression model with which (un)loading duration can be predicted for a particular logistics company. Prediction of (un)loading duration can be sold as an add-on for existing Webfleet users and can be used to attract new Webfleet clients. In practice the client would need to ask its planners and drivers to log information about each loading: amount, location of (un)loading, and start/end of (un)loading activity. Logging this information for a certain period would generate input for the regression model. Afterwards, the output of the regression model can be used by the client to predict (un)loading duration more precisely and incorporate this prediction in their distribution planning (e.g. as parameters in the planning system they are currently using). It is advisable to automate the generation of these regression models since it takes a lot of time to execute this process manually. Furthermore, it is advisable to have some pilots in which the deviation reduction for rules of thumb other than the one from Jan de Rijk could be tested as well.

For the prediction of driving times, the practical integration of the prediction model based on speed profiles is more complicated. The method that was used to predict truck driving times for this research is not user-friendly. From a practical point of view, it is therefore recommendable to develop tooling for truck driving time prediction. Furthermore, a distinction between two types of logistics companies should be made: the ones who use a planning system (e.g. from PTV) and the ones who do not. For the companies that already use a planning system, it would be interesting to have a more extensive case study that compares the driving time predictions of their planning systems to those of TomTom. Therefore, it is recommended to extend the comparison of driving time predictions from PTV and TomTom with more cases. For companies that do not use a planning system to predict driving times, a separate tool for driving time predictions could be developed and offered. It should be noted that overall it is more appealing for logistics companies to purchase an integrated planning system rather than a separate tool that only covers a part of the planning process. Therefore, it is advisable to choose for the path that uses established planning systems and tries to improve their parameters and underlying calculations as mentioned earlier in this paragraph

6.3 Future Research

This research gives several clues for possible future research. From an academic point of view, it would be interesting to examine (un)loading duration from the perspective of (un)loading locations. It could be possible to partially predict (un)loading durations based on location, independent of which logistics company is (un)loading at that location. Investigating GPS probe data from trucks on (un)loading locations could be a first step for this type of research.

In a more practical context it could be interesting to investigate the possible improvements that could be realized by using TomTom’s truck routing algorithm for planning rather than the algorithms that are used by existing planning software packages.

Another practical direction could be to investigate whether drivers get enough rest as prescribed by the regulations on working, pausing and resting. It could be useful to add a feature to the existing truck navigation device that suggests pausing and resting locations based on these regulations and the route that will be travelled. In this way, daily execution can be optimized further.

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Appendix A – Data dump

Table 9 - Tables and variables in data dump

Table	*Variable*	*Explanation*	*Data type*
Trucklogevent	Id	Identifier for trucklogevent	Integer
	Latitude	Part of GPS coordinate	Decimal (WGS-84)
	Longitude	Part of GPS coordinate	Decimal (WGS-84)
	Heading	Direction of truck in degrees	Integer
	Mileage	Traveled distance in meters	Integer
	Speed	Speed at certain moment in km/h	Integer
	Time	Date and time of measure	dd-mm-yyyy, hh:mm:ss
	Type	Activity as declared by driver[1]	Integer
	TruckNumber	Identifier for truck	Integer (length ≥ 4)
Trucklogevent-property	PropertyKey	Property of activity type	String (length ≥ 3)
	PropertyValue	Value of property	Character
	TruckLogEventId	Identifier for trucklogevent	Integer
Addressmatch	City	Part of address	String
	Country	Part of address	String (length 2)
	Street	Part of address	String
	Zipcode	Part of address	Character (length ≥ 4)
	Latitude	Part of GPS coordinate	Decimal (WGS-84)
	Longitude	Part of GPS coordinate	Decimal (WGS-84)
	TruckLogEventId	Identifier for trucklogevent	Integer
Activitiets-rosettastone	EncryptedName	Property value of activity	String
	HumanIntelligibleName	Explanation of encryptedname	String
Jplexsdata	TruckNr	Identifier for truck	Integer (length ≥ 4)
	PlannedLoadingStart	Planned time to start loading	yyyy-mm-dd, hh:mm:ss
	PlannedLoadingEnd	Planned time to finish loading	yyyy-mm-dd, hh:mm:ss
	PlannedUnloadingStart	Planned time to start unloading	yyyy-mm-dd, hh:mm:ss
	PlannedUnloadingEnd	Planned time to finish unloading	yyyy-mm-dd, hh:mm:ss
	ExpectedLoadingStart	Expected time to start loading	yyyy-mm-dd, hh:mm:ss
	ExpectedLoadingEnd	Expected time to finish loading	yyyy-mm-dd, hh:mm:ss
	ExpectedUnloadingStart	Expected time to start unloading	yyyy-mm-dd, hh:mm:ss
	ExpectedUnloadingEnd	Expected time to finish unloading	yyyy-mm-dd, hh:mm:ss
	ActualLoadingStart	Actual time loading started	yyyy-mm-dd, hh:mm:ss
	ActualLoadingEnd	Actual time loading ended	yyyy-mm-dd, hh:mm:ss
	ActualUnloadingStart	Actual time unloading started	yyyy-mm-dd, hh:mm:ss
	ActualUnloadingEnd	Actual time unloading ended	yyyy-mm-dd, hh:mm:ss
	Lm_Shipment	Amount of loading meters to (un)load	Double
	TotalCommodityCode	Referral to commodity type	String(length 4)
	FromLocationCode	Location to pick up cargo	String (length ≥ 3)
	ToLocationCode	Location to drop off cargo	String (length ≥ 3)
	EarliestLoadingStart_ Shipment	Earliest point in time to start loading	yyyy-mm-dd, hh:mm:ss
	EarliestUnloadingStart_ Shipment	Earliest point in time to start unloading	yyyy-mm-dd, hh:mm:ss

The table Trucklogevent was used as base table. Trucklogevent was sorted by TruckNumber and within TruckNumber by Time. The variable Type in Trucklogevent refers to trace types as explained in the Fleet Integrator Guide (Trimble Fleet Integrator Guide, 2012). For this research, a limited number of trace types and accompanying properties are interesting. The trace types of interest are

[1] (Trimble Fleet Integrator Guide, 2012)

the start and end of activities. Other trace types, concerning subjects such as navigation and driver tasks, are not relevant for this research and were therefore ignored. The accompanying properties of interest are Activity Type (ATY) and Actual Length (ALEN). Activity Type shows which activity was carried out (e.g. rest, unload). Actual Length gives the duration of this activity. Other properties, such as fuel usage and driver ID, are irrelevant for this research and therefore left out of scope.

Instances, i.e. rows, from different tables were coupled to each other:

- Instances where TruckLogEventId from Trucklogeventproperty corresponds to Id from Trucklogevent are matched. For matches that concern property ATY or ALEN, PropertyKey and PropertyValue from Trucklogeventproperty are copied to the concerning instance in Trucklogevent. This leads to insight in which activities are executed on a certain moment.
- Instances where EncryptedName from Activitiesrosettastone corresponds to PropertyValue in Trucklogevent are matched. For matches, HumanIntelligibleName from Activitiesrosettastone is copied to the concerning instance in Trucklogevent. This serves as translation for the activities from the previous step (e.g. 1_WA is translated as 'waiting').
- Instances where Latitude and Longitude of Addressmatch correspond to both Latitude and Longitude of Trucklogevent are matched. For matches, City, Country, Street, and Zipcode from Addressmatch are copied to the concerning instance in Trucklogevent. This method is preferred to matching on TruckLogEventId as it leads to more matches. This leads to insight in which locations are visited by the trucks.
- Attempts to couple instances from Jplexsdata to Trucklogevent were terminated because of problems with data quality. Planned, expected, and actual (un)loading start and end times are not reliable since Jplexsdata contains a combination of snapshots with information that is not always updated. Attempts to match actual (un)loading times from Jplexsdata to Trucklogevent times that are associated with (un)loading activities result in mismatches. In addition, instances were found whereby for example PlannedLoadingEnd takes place before PlannedLoadingStart. Consultation with Jan de Rijk confirmed aforementioned irregularities and justifies exclusion of time-related data in Jplexsdata from the research.

Above-mentioned process is represented schematically in Figure 13.

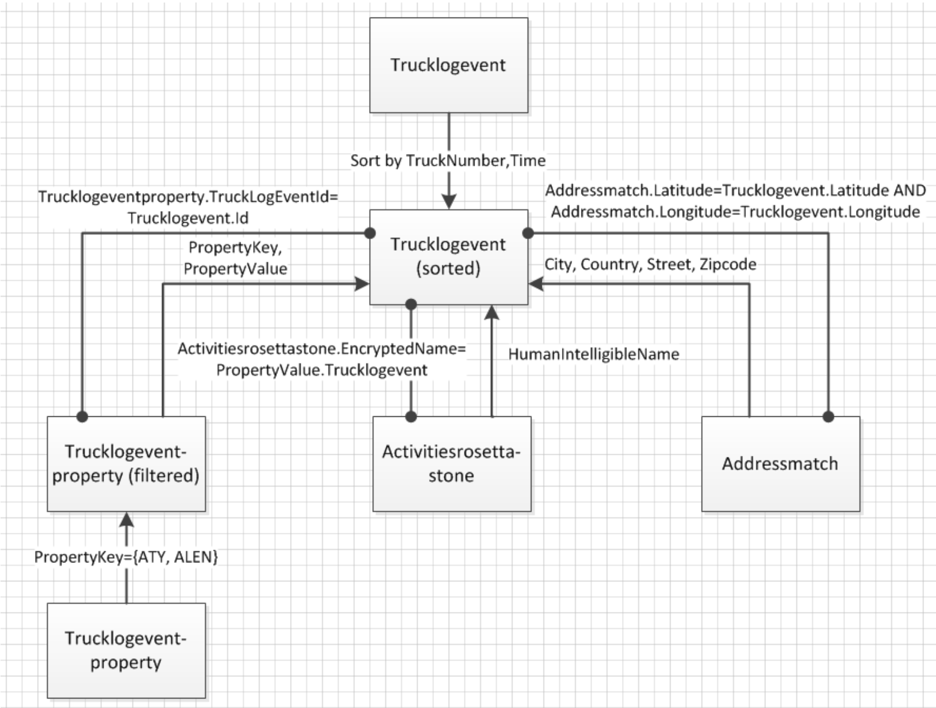

Figure 14 - Data Preparation

Appendix B – Locations of (un)loading, wait, pause, and rest events

Figure 15 - Loading & unloading locations EU

Figure 16 - Waiting locations EU

Figure 17 - Pausing & resting locations EU

Appendix C – Rij- en rusttijden vrachtauto

Rij- en rusttijden vrachtauto en touringcar (Vo. (EG) nr. 561/2006)
(Inspectie Leefomgeving en Transport, 2011)

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), 1e 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

Appendix D – Significance of included predictors

Table 10 - Significance predictors (un)loading duration

Loading	
Predictor	*Significance*
(Constant)	.000
Pelikaanweg	.000
Prooyelaan	.000
RingCentrum	.000
Babberichseweg	.000
Havennummer72018100	.001
Missouriweg	.003
MiddelBroekweg	.010
LogisticBoulevard	.001
Anchoragelaan	.000
Exportplein	.000
Heibloemseweg	.000
Ganderweg	.000
Gesworenhoekseweg	.001
Duitslandweg	.005
Express	.006
Magnolia	.027
Leemstraat	.014
Papland	.024
TtTunnelweg	.025
Kranenberg	.032
Protonweg	.033
Poortcamp	.043
Rijerscheweg	.044
Oirloseweg	.043
RandwegOost	.043

Unloading	
Predictor	*Significance*
(Constant)	.000
Havennummer72018100	.000
VanLeeuwenhoekstraat	.000
Heibloemseweg	.000
RingCentrum	.005
Anchoragelaan	.000
Exportplein	.000
Havennummer22502490	.000
Vrijhavenplein	.000
Onderweg	.003
Nieuwesluisweg	.003
Pelikaanweg	.000
KanaaldijkZuid	.001
Bellstraat	.004
Weteringseweg	.006
AbelTasmanstraat	.010
Dongenseweg	.010
Moervaart	.017
Marshallweg	.021
Columbusweg	.025
Cessnalaan	.031
OudeVijfhuizerweg	.042

Appendix E – Proof of Concept

Table 11 - Input proof of concept

#	Day	Time	Start location	Activity	Location	End location
1	Mon	19:42	Oude Vijfhuizerweg, Schiphol (NL)	-	-	A26/E25, Champ-de-Harre (BE)
2	Thu	01:00	A2, Abcoude (NL)	Unloading	Van Leeuwenhoekstraat, Oostrum (NL)	Amsterdamstraat, Meer (BE)
3	Tue	01:03	E40, Leuven (BE)	Loading	Rue de l'Aéroport, Grâce-Hollogne (BE)	
				Unloading	Klappolder, Bleiswijk (NL)	
				Unloading	Ganderweg, Schiphol (NL)	
				Loading	Pelikaanweg, Schiphol (NL)	Anchoragelaan, Schiphol (NL)
4	Fri	14:43	A4, Rijpwetering (NL)	Loading	Middel Broekweg, Honselersdijk (NL)	
				Loading	Prooyelaan, Honselersdijk (NL)	A31, Pont-à-Mousson (FR)
5	Sat	12:55	Reykjavikweg, Schiphol (NL)	Loading	Exportplein, Schiphol (NL)	Flughafen Frankfurt, Frankfort aan de Main (DE)
6	Wed	00:20	A2, Breukelen (NL)	Loading	Folkstoneweg, Schiphol (NL)	
				Loading	Ring Centrum, Aalsmeer (NL)	A1, Thiers-sur-Thève (FR)
7	Wed	07:05	E35, Mulhouse (FR)	Pausing	A31/E25, Oeutrange (FR)	A1/A19, De Merel (BE)
8	Wed	08:00	Salomon Hirzel-Strasse, Winterthur (DU)	Pausing	A92/E53, Langenpreising (DE)	E552, Wels (DU)
9	Sun	17:32	Flughafen Frankfurt, Frankfort aan de Main (DE)	-	-	E314/N2, Bekkevoort (BE)
10	Thu	05:46	A12, Ede/Arnhem (NL)	Pausing	Amsterdamsestraat, Meer (BE)	A14/E17, Marke (BE)

Table 12 - Planning by Jan de Rijk

#	From location	Activity	Start time	Distance	Duration	To location
1	Fokkerweg, Schiphol (NL)	Driving	19:42	285 km	3hr57	Dieupart 44, Aywaille (BE)
2	Gein Zuid 31, Abcoude (NL)	Driving	01:00	156 km	2hr27	Van Leeuwenhoekstraat, Oostrum (NL)
	Van Leeuwenhoekstraat, Oostrum (NL)	Unloading	03:27	-	1hr00	Van Leeuwenhoekstraat, Oostrum (NL)
	Van Leeuwenhoekstraat, Oostrum (NL)	Driving	04:27	114 km	2hr06	Amsterdamstraat, Meer (BE)
3	Mechelsestraat 125, Leuven (BE)	Driving	01:03	72 km	1hr06	Rue de l'Aéroport, Grâce-Hollogne (BE)
	Rue de l'Aéroport, Grâce-Hollogne (BE)	Loading	02:09	-	1hr00	Rue de l'Aéroport, Grâce-Hollogne (BE)
	Rue de l'Aéroport, Grâce-Hollogne (BE)	Driving	03:09	162 km	2hr18	Amsterdamstraat, Meer (BE)
4	Veenderveld 116, Roelofarendsveen (NL)	Driving	14:43	39 km	0hr43	Middel Broekweg 29, Honselersdijk (NL)
	Middel Broekweg 29, Honselersdijk (NL)	Loading	15:26	-	1hr00	Middel Broekweg 29, Honselersdijk (NL)
	Middel Broekweg 29, Honselersdijk (NL)	Driving	16:26	1 km	0hr03	Nieuweweg 2, Honselersdijk (NL)
	Nieuweweg 2, Honselersdijk (NL)	Loading	16:29	-	1hr00	Nieuweweg 2, Honselersdijk (NL)
	Nieuweweg 2, Honselersdijk (NL)	Driving (+ pausing)	17:29	468 km	6hr32 (+ 0hr45)	Ctre Commercial le b, Pont-à-Mousson (FR)
5	Reykjavikweg 2, Schiphol (NL)	Driving	12:55	9 km	0hr17	Vrijhavenplein, Schiphol (NL)
	Vrijhavenplein, Schiphol (NL)	Loading	13:12	-	1hr00	Vrijhavenplein, Schiphol (NL)
	Vrijhavenplein, Schiphol (NL)	Driving (+ pausing)	14:12	436 km	5hr48 (+0hr45)	Flughafen Frankfurt, Frankfort aan de Main (DE)
6	Keulschevaart 1100, Breukelen (NL)	Driving	00:20	34 km	0hr33	Folkstoneweg 182, Schiphol (NL)
	Folkstoneweg 182, Schiphol (NL)	Loading	00:53	-	1hr00	Folkstoneweg 182, Schiphol (NL)
	Folkstoneweg 182, Schiphol (NL)	Driving	01:53	12 km	0hr17	Legmeerdijk 313, Aalsmeer (NL)
	Legmeerdijk 313, Aalsmeer (NL)	Loading	02:10	-	1hr00	Legmeerdijk 313, Aalsmeer (NL)
	Legmeerdijk 313, Aalsmeer (NL)	Driving (+ pausing)	03:10	461 km	6hr45 (+0hr45)	Bois des Saints Peres, Crepy en Valois (FR)
7	Unable to plan due to unknown locations	-	-	-	-	-
8	Klosterstrasse 20, Winterthur (DU)	Driving	08:00	334 km	4hr49	Alfred Kuhnstrasse 20, Langenbach (DE)

	Alfred Kuhnstrasse 20, Langenbach (DE)	Pausing	12:49	-	0hr45	Alfred Kuhnstrasse 20, Langenbach (DE)
	Alfred Kuhnstrasse 20, Langenbach (DE)	Driving	13:34	231 km	3hr28	Bohmerwaldstrasse, Wels (DU)
9	Cargo City Süd, Frankfort aan de Main (DE)	Driving	17:32	327 km	4hr29	Industrieterrein 2, Diest (BE)
10	Ampèrestraat 36, Ede (NL)	Driving	05:46	122 km	1hr49	Amsterdamstraat, Meer (BE)
	Amsterdamstraat, Meer (BE)	Pausing	07:35	-	0hr45	Amsterdamstraat, Meer (BE)
	Amsterdamstraat, Meer (BE)	Driving	08:20	146 km	2hr11	Michiel Vandewielstraat, Marke (BE)

Table 13 - Comparison (un)loading durations Jan de Rijk and prediction model

			Duration (hrs)			Absolute deviation (hrs)	
#	**Location**	**Activity**	**Real**	**JdR**	**Model**	**JdR-Real**	**Model-Real**
2	Van Leeuwenhoekstraat, Oostrum (NL)	Unload	1.15	1.00	1.25	0.15	0.09
3	Rue de l'Aéroport, Grâce-Hollogne (BE)	Load	3.55	1.00	0.87	2.55	2.68
3	Klappolder, Bleiswijk (NL)	Unload	0.41	1.00	0.75	0.59	0.34
3	Pelikaanweg, Schiphol (NL)	Load	1.34	1.00	1.30	0.34	0.04
3	Anchoragelaan, Schiphol (NL)	Load	2.04	1.00	1.08	1.04	0.96
4	Middel Broekweg, Honselersdijk (NL)	Load	0.62	1.00	0.54	0.38	0.08
4	Prooyelaan, Honselersdijk (NL)	Load	0.37	1.00	0.38	0.63	0.02
5	Exportplein, Schiphol (NL)	Load	1.34	1.00	1.07	0.34	0.27
6	Folkstoneweg, Schiphol (NL)	Load	0.78	1.00	0.87	0.22	0.08
6	Ring Centrum, Aalsmeer (NL)	Load	0.84	1.00	0.48	0.16	0.36
						0.64 (avg)	0.49 (avg)

Table 14 - Comparison driving times Jan de Rijk and prediction model

	Distance (km)			Driving time (hrs)			Absolute deviation (hrs)	
#	Real	JdR	Model	Real	JdR[2]	Model	JdR-Real	Model-Real
1	310	285	310	4.17	4.57	4.25	0.40	0.08
2	332	270	331	5.23	5.76	5.54	0.53	0.31
3	401	234	401	6.22	8.10	9.43	1.89[3]	3.22
4	520	508	522	7.01	7.46	7.76	0.46	0.75
5	419	445	420	5.78	5.64	6.15	0.14	0.37
6	517	507	519	7.43	7.81	8.53	0.38	1.10
7	609	-	607	9.42	-	7.23	-	2.19
8	554	565	555	6.72	7.37	7.12	0.65	0.40
9	362	327	361	4.63	4.85	5.09	0.22	0.46
10	415	268	417	6.50	6.31	6.60	0.19	0.10
							0.37 (avg)	0.35 (avg)

[2] Driving time JdR is corrected to account for the difference in distance caused by research limitations.
[3] Cases in red are deleted because of mismatches as explained in chapter 5.

Appendix F – Prediction methods

Table 15 - Prediction methods (detailed)

#	Driving duration			(Un)loading duration
	Tool	*Average speed*	*Slack*	*Method*
1	Experience	-	-	Experience
2	Experience	-	15 min. during rush hour	10 min. + 1 min. per pallet
3	Experience	-	30 min. during rush hour	15-30 min. for A units, 30-45 min. for B units (full truck load)
4	Experience	86-93 km/h	1-2 hrs for international trips	Experience
5	Experience for regional trips, PTV Intertour for longer trips	-	-	10 min. + 1 min. per pallet, 10-15 min. per unit that is not a pallet
6	GoogleMaps	80 km/h	-	15-30 min. for <4 pallets, 1 hr for half to full truck load
7	Pythagoras	60 km/h for trips <100 km, 55 km/h for trips >100 km		Experience
8	PTV	55 km/h for national trips, 65-70 km/h for international trips	-	5 min. per loading meter for national transport, 1 hr for international transport
9	Ortec	70 km/h	-	Experience
10	Winroute	-	-	Process time + 2 min. per container