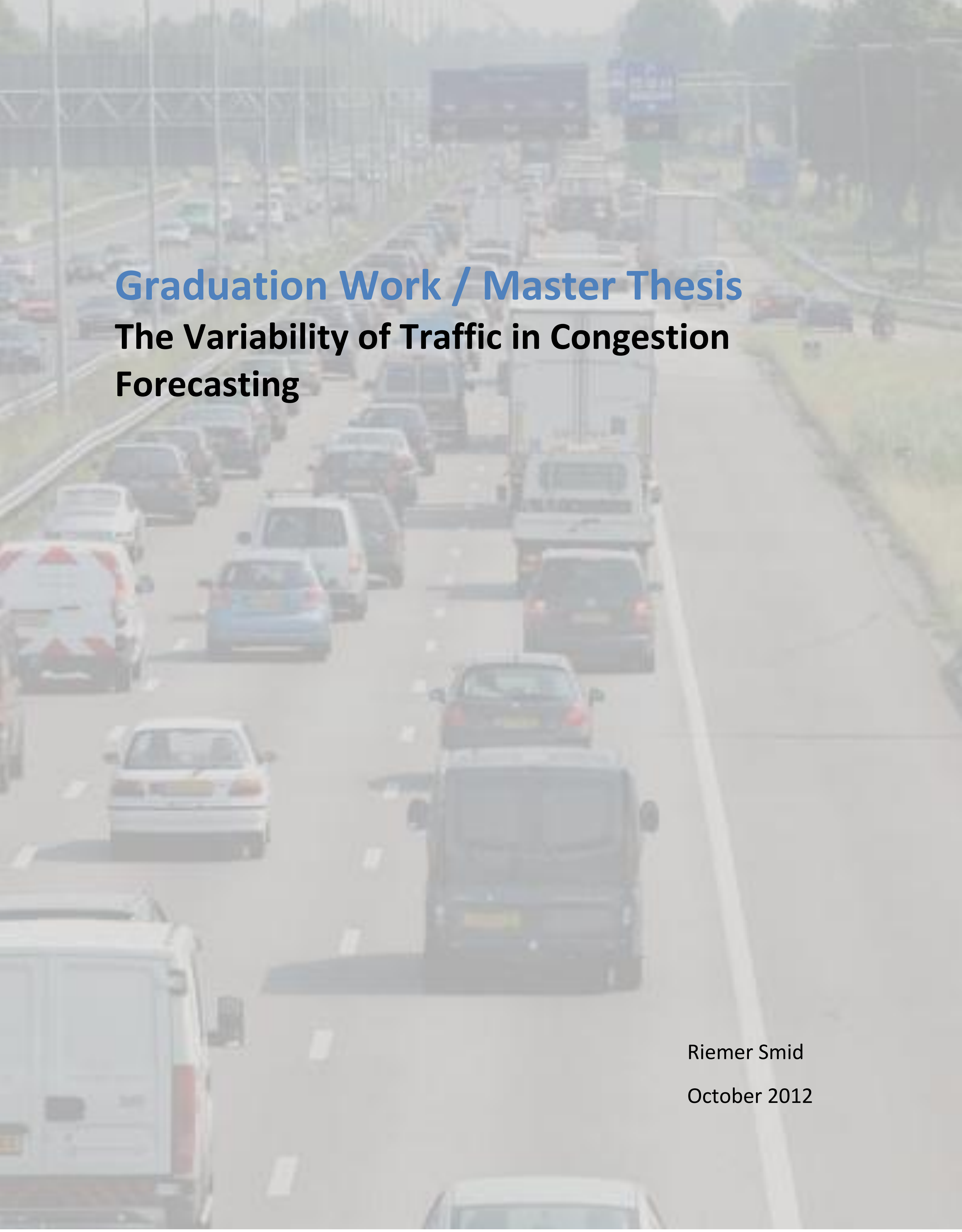

Graduation Work / Master Thesis

The Variability of Traffic in Congestion Forecasting

Riemer Smid

October 2012

Faculteit Civiele Techniek & Geowetenschappen

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The Variability of Traffic in Congestion Forecasting

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MSc Thesis Civil Engineering
Delft University of Technology

Colophon

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Preface

This thesis is the result of the research carried out for my graduation project. It marks the end of my studies in Civil Engineering at the Delft University of Technology. Because of my interest in the traffic system, I took the specialization track in Transport & Planning. Predicting traffic conditions on a motorway corridor is key in this graduation project. The research was conducted in conjunction with Witteveen+Bos Raadgevende ingenieurs B.V. The graduation project was performed at their office in The Hague.

During the process of this graduation project, a number of people have supported or assisted me. First I would like to thank my graduation committee for their input and feedback. From the University, these were chairman Serge Hoogendoorn, my daily supervisor Hans van Lint, thesis coordinator Paul Wiggenraad and external supervisor Pieter van Gelder. From Witteveen+Bos, this was my daily supervisor Jan Willem Goemans. Furthermore, I would like to thank Simeon Calvert, who occasionally took the time to assist me.

I would also like to thank my colleagues at Witteveen+Bos, Ester Falkena-Stegers and the interns. Witteveen+Bos offered a very nice workplace and with help of aforementioned colleagues, a very nice working atmosphere.

Last but not least, I would like to thank my parents and my girlfriend Dieuwertje for their overall support during the research and also for their support throughout my entire study period.

Riemer Smid
The Hague, October 2012

Summary

Congestion on the Dutch motorway network is an actual problem, which originated over the past decades. Over the past few years, the extent of congestion is decreasing, though still very significant. Road authorities therefore show interest in traffic congestion forecasting. In this way they can inform road users or undertake other strategic actions. This thesis is therefore dedicated to the variability of traffic in congestion forecasting.

The main objective is to develop a methodology operationalized in a model, which is able to predict congestion on motorways without knowledge of the actual traffic conditions. The model takes the variability of traffic into account and is substantiated with a solid theoretical framework relating the predictability of factors and their effects to traffic supply and demand.

To fulfill this objective, a literature research has been conducted on traffic flow theory, factors and effects influencing traffic demand and traffic supply, model approaches and probabilistic methods. The identified influence factors are listed below:

- regular pattern of variation in human travel behavior over the day, over the days of the week and over the periods of the year;
- public holidays / vacation periods;
- events;
- weather conditions;
- road works;
- incidents;
- variations in vehicle population;
- variations in driver population;
- luminance;
- ‘intrinsic’ variations in driving behavior and in human travel behavior.

Using the acquired knowledge a research methodology is developed. The model approach makes use of the basic principles of traffic flow theory based on the conservation of vehicles and first order traffic flow theory. To take the variability of influence factors into account, an intelligent sampling technique is used: Latin Hypercube Sampling.

Before the model is constructed, the predictabilities and the effects of the various influence factors on traffic demand and traffic supply are described and explained through a theoretical framework. Some of them are always predictable (e.g. public holidays, luminance), while the predictability of others depend on data (e.g. road works or weather conditions). Incidents are considered not very predictable. The occurrence and therefore the effects of the identified influence factors can be continuously present or only on certain moments in time. They can also be on every cell of the motorway corridor or only on a selection of cells of the motorway corridor.

The developed model makes use of traffic demand profiles and traffic supply

variables. These are processed by a first order traffic model using a Godunov scheme. Traffic is numerically sent through the model subject to the defined boundary conditions. When the flow exceeds the capacity, congestion sets in and propagates backwards in space according to the first order traffic theory. From the modeled data, travel times and other performance indicators can be derived. A trajectory method is used to calculate the actual travel times.

Before the model processes the traffic demand profile and traffic supply variables, these are corrected for the identified influence factors. The occurrence of these influence factors can be defined manually. However, to be able to incorporate the variability of traffic, a sampling component is added to the model. In this way the occurrence of the influence factors can be determined through a probability function. After multiple runs, the output indicators are collected.

The model is calibrated and evaluated using data from the A27 motorway between Hooipolder and Gorinchem. The data was recorded over the year 2011. First the calibration of the traffic supply variables is performed. The calibration results showed a good likeness to the recorded travel times. Congestion in the model also sets in at similar moments in time and space as in the recorded data. Next the intrinsic variability of traffic is calibrated, the recorded travel time distribution over the year 2011 was very well approximated by the model.

The research shows that the developed methodology is suitable for predicting travel times or other performance indicators. Producing traffic demand profiles is achievable, however the effects of some influence factors (road works, weather conditions) are not trivial. The estimation of the traffic supply variables from data showed to be a tougher task.

The model results show relatively large uncertainties in the travel times as congestion was probable to set in (i.e. peak periods). When the traffic demand and traffic supply are close to each other, the probability on congestion increases. However, the difference in travel times when congestion sets in, compared to travel times where congestion remains absent, is relatively large. Hence, the large uncertainties in the peak periods. This implies that, even though the occurrence and effects of the identified influence factors are very accurately available, uncertainties in travel times can still be significant.

Using the developed methodology, it is important to have reliable data sources regarding the identified influence factors. Especially for the influence factors that have significant effects on the traffic conditions (road works, adverse weather conditions, events), the availability of accurate data is highly needed. Predictions made with help of unreliable or incomplete data is deemed to be inaccurate.

The case study results also lead to some recommendations. For operational use of the methodology, further analysis of the possibilities for extension of the model to larger networks (e.g. the Dutch motorway network) is recommended. The effects of the identified influence factors can then not be only adopted from theory.

The prediction of the traffic conditions produced by the model shows less certainty as traffic demand and traffic supply values are close to each other, even though the influence factors are fully predictable and accounted for. Further research on this topic is also advised.

Samenvatting

Filevorming op het Nederlands snelwegennetwerk is een zeer actueel probleem. De omvang van congestie neemt de laatste jaren af, maar is nog steeds aanzienlijk. Om deze reden tonen wegbeheerders interesse in het voorspellen van files. Op deze manier kunnen zij de weggebruiker informeren, of andere strategische maatregelen toepassen. Dit onderzoek is dan ook gewijd aan de variabiliteit van het verkeer bij het voorspellen van files.

Het onderzoeksdoel is het ontwikkelen van een methodologie verwerkt in een model, dat in staat is om files op snelwegen te voorspellen zonder kennis van de actuele verkeerssituatie. De variabiliteit van verkeer wordt daarbij in acht genomen. Het model is onderbouwd met een theoretisch raamwerk dat de voorspelbaarheid van factoren en hun effecten aan verkeersvraag en verkeersaanbod relateert.

Om aan deze doelstelling te voldoen is een literatuuronderzoek uitgevoerd. Hierbij zijn de verkeersstroomtheorie, factoren en effecten die van invloed zijn op de verkeersvraag en het verkeersaanbod, modelaanpak en probabilistische methoden uitgebreid aan bod gekomen. De geïdentificeerde invloedsfactoren zijn hieronder opgesomd:

- patroon van variatie in het menselijk verplaatsingsgedrag over de dag, de dagen van de week en de periodes van het jaar;
- feestdagen / vakantie periodes
- evenementen;
- weersomstandigheden;
- wegwerkzaamheden;
- incidenten;
- variaties in het wagenpark;
- variaties in type bestuurders;
- lichtsterkte;
- ‘intrinsieke’ variaties in het rijgedrag en in het menselijk verplaatsingsgedrag.

Met behulp van de opgedane kennis is een onderzoeksmethode ontwikkeld. De modelaanpak maakt gebruik van de basisprincipes van verkeersstroomtheorie, gebaseerd op het behoud van voertuigen en eerste orde verkeersstroomtheorie. Om met de variabiliteit aan invloedsfactoren rekening te houden, is een intelligente lotingstechniek gebruikt: Latin Hypercube Sampling.

Voordat het model gebouwd kan worden, worden de voorspelbaarheid en de effecten op de verkeersvraag en het verkeersaanbod van de verschillende invloedsfactoren beschreven en toegelicht met behulp van een theoretisch raamwerk. Een aantal zijn altijd voorspelbaar (feestdagen, lichtsterkte), terwijl de voorspelbaarheid van anderen afhangt van data (wegwerkzaamheden, weersomstandigheden). Incidenten worden beschouwd als niet erg voorspelbaar. Het vóórkomen en daardoor de effecten van de geïdentificeerde invloedsfactoren kunnen continu aanwezig zijn of op bepaalde momenten. Ook kunnen ze aanwezig zijn op elke cel van het traject, of op een selectie van cellen van het traject.

Het ontwikkelde model gebruikt verkeersvraag profielen en verkeersaanbod variabelen. Deze worden verwerkt door een eerste orde verkeersmodel met behulp van een Godunov schema. Het verkeer wordt op een numerieke wijze door het model gestuurd, onderworpen aan de gedefinieerde randvoorwaarden. Wanneer de verkeersstroom de capaciteit overschrijdt, ontstaat congestie die terugslaat volgens eerste orde verkeersstroomtheorie. Reistijden en andere indicatoren worden vervolgens afgeleid van de gemodelleerde gegevens. Voor het berekenen van de reistijden is een trajectorie methode gebruikt.

Voordat het model de verkeersvraag profielen en verkeersaanbod variabelen verwerkt, worden deze gecorrigeerd voor de geïdentificeerde invloedsfactoren. Het vóórkomen van deze factoren kan handmatig worden gedefinieerd. Echter, om de variabiliteit van verkeer mee te nemen, is een lotingscomponent toegevoegd aan het model. Op deze manier kan het vóórkomen van de invloedsfactoren bepaald worden aan de hand van een kansverdeling.

Het model is gekalibreerd en geëvalueerd aan de hand van gegevens van de A27 tussen Hooipolder en Gorinchem. De data is verzameld over het jaar 2011. De kalibratie van de verkeersaanbod variabelen is als eerste uitgevoerd. De kalibratie resultaten toonden een goede gelijkenis met de meet data. Ook ontstond congestie op dezelfde plekken en tijdstippen. Vervolgens werd de intrinsieke variabiliteit van het verkeer gekalibreerd. De gemeten reistijdverdeling over het jaar 2011 kwam zeer goed overeen met de gemodelleerde reistijdverdeling.

Het onderzoek toont aan dat de ontwikkelde methode geschikt is het voorspellen van reistijden of andere indicatoren. Het creëren van de verkeersvraag profielen is haalbaar. De effecten van sommige invloedsfactoren zijn echter niet altijd triviaal. Het bepalen van de verkeersaanbod variabelen bleek een lastiger karwei te zijn.

Wanneer de kans op file aanzienlijk was (piekperioden), tonen de modelresultaten relatief grote onzekerheden in de reistijdverdeling. Wanneer de verkeersvraag en het verkeersaanbod dicht bij elkaar komen, wordt deze kans groter. Het verschil in reistijd in een situatie met file, vergeleken met een situatie zonder file is echter aanzienlijk. Hierdoor kunnen de groter onzekerheden in de reistijdverdeling in die piekperioden verklaard worden. Dit impliceert dat de onzekerheid in de voorspelde reistijden significant kan zijn, ondanks dat het vóórkomen en de effecten van de invloedsfactoren zeer nauwkeurig beschikbaar zijn. Bij het gebruik van de ontwikkelde methodiek, is het essentieel dat de gegevensbronnen betreffende de invloedsfactoren, betrouwbaar zijn. Vooral voor de invloedsfactoren die grote gevolgen hebben voor de verkeersafwikkeling is de beschikbaarheid van accurate gegevens noodzakelijk.

De case studieresultaten leiden ook tot een aantal aanbevelingen. Voor operationeel gebruik van de methodologie, is het aanbevolen de mogelijkheden tot uitbreiding van het model tot grotere netwerken (het Nederlandse snelwegennet) te analyseren. De effecten van de invloedsfactoren kunnen dan ook niet alleen worden aangenomen vanuit theorie.
De voorspellingen geproduceerd door het model blijken meer onzekerheid te bevatten wanneer verkeersvraag en verkeersaanbod dichter bij elkaar komen, zelfs als volledig rekening wordt gehouden met de invloedsfactoren. Aanvullend onderzoek op deze bevinding is aanbevolen.

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1 Introduction

In this chapter the subject of this research will be introduced. First some background information will be given, next the problem definition will be discussed. After this the research objective will be formulated, followed by the research questions. Also the research relevance and approach will be discussed. This chapter will conclude with the thesis outline.

1.1 Background

In the past a number of studies have been done to gain more insight in predicting traffic congestion. A lot of factors influence the predictability of congestion. Of course there is the stochastic characteristic of traffic itself. But also factors like weather conditions, maintenance works on roads, incidents, events and traffic management and control have impact on whether there will be congestion on a certain road stretch or not. (Jong, Pieters et al.)

Although it is known that these factors never have the exact same effect on traffic, still a single value for road capacity or traffic intensity is most often used in traffic models.

Witteveen+Bos is currently developing a congestion forecasting model commissioned by Rijkswaterstaat. In this model, an average expectation of the traffic state is calculated using historical data. This is directly based on the average registered congestion per road stretch. A distinction is made between daytime, day and month. This basic prognosis is complemented by different scenarios. Using a simple queuing model, the effects of weather, events and road works on capacity and intensity lead to a congestion prediction (Witteveen+Bos, 2011).

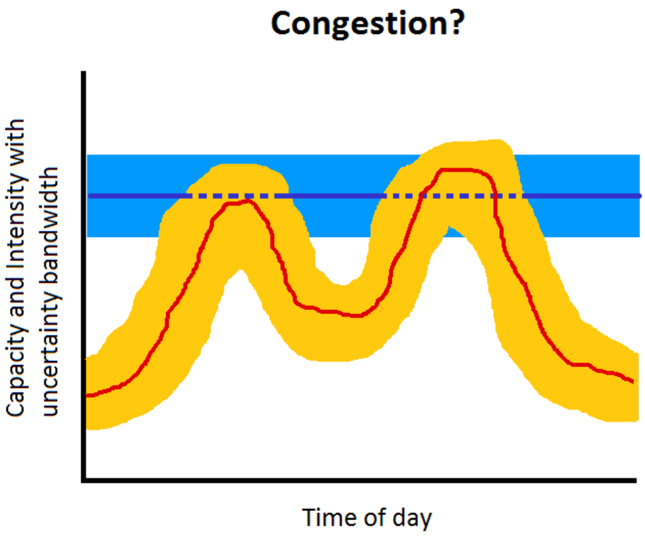
In this model already a number of factors and their effects influencing traffic congestion are used. But maybe even more factors could be included. Also in this model, single values for capacities and intensities are calculated. In this master thesis a model will be created in which distributions for these input values are proposed.

1.2 Problem definition

Research in variability of traffic is mainly focused on the effects of certain factors on traffic. Studies seeking for factors explaining traffic phenomena include (Chrobok, Kaumann et al., 2004), (Chung, Ohtani et al., 2006), (Miete, 2011), (Cohen and Southworth, 1999), (Calvert, 2009), (Noland and Polak, 2002), (Miete, 2011), (Agarwal, Maze et al., 2005).

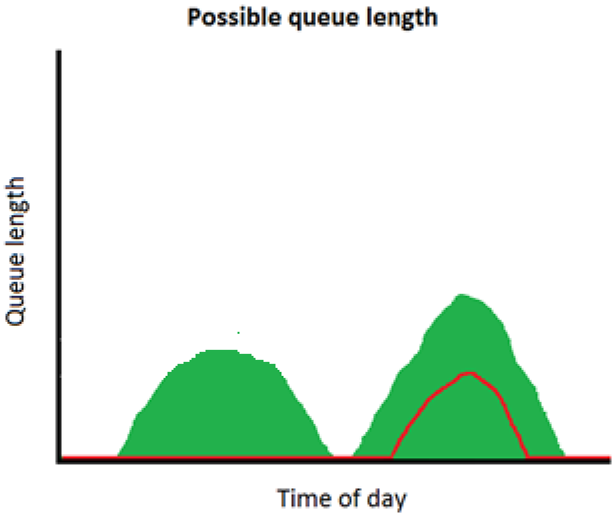
However, their focus was not on the predictability of these factors. This research focusses on how traffic can be predicted using traffic demand and traffic supply distributions. In Figure 1-1 a possible bandwidth for both the capacity (blue) and the intensity (orange) on a certain day are given. An important question in this research is how to translate this to a congestion prediction.

***Figure 1-1:** Capacity and intensity with uncertainty bandwidth*



The queue length corresponding to the graph in Figure 1-1 is approximated by another sketch in Figure 1-2. The red line indicates the queue length at the representative situation (thick red and blue line in Figure 1-1). The green area shows all possible queue lengths. The outline of the area for example shows the queue length at maximum intensity and minimum capacity. At maximum capacity and minimum intensity no congestion would occur. It would be interesting to know for this thesis to quantify these distributions.

***Figure 1-2:** Possible queue length on a certain road stretch*



The predictability of congestion in traffic forecasting depends on a number of factors, each with its own predictability, effects and predictability of these effects. This variability is not incorporated in capacity or intensity inputs in today's traffic models. It would be useful to gain more insight in how this variability could be implemented using capacity and intensity distributions instead of one single input value.

1.3 Research objective

The main objective of this thesis, based on the problem definition is as follows:

> The main objective is to develop a methodology operationalized in a model, which is able to predict congestion on motorways without knowledge of the actual traffic conditions. The model takes the variability of traffic into account and is substantiated with a solid theoretical framework relating the predictability of factors and their effects to traffic supply and demand.

Taking the main objective into account, the result of this research is:

- This report explaining the details of the model methodology and results, including a theoretical framework relating influence factors to traffic demand and supply and a clear overview of the effects of incorporating the variability of traffic in the model.
- A software tool based on the developed theoretical framework, which is able to predict congestion taking the variability of traffic into account explicitly.

1.4 Research questions

To fulfill the research objective three main research questions have been formulated. First a solid theoretical framework relating the predictability of factors and their effects to traffic supply and demand has to be made. The following question deals with this:

[Research question 1] *To what extent can the different components of the variability in traffic be predicted?*

In order to answer this question, the following sub questions are considered:

[Sub question 1.1]	What factors play a role in predicting traffic congestion?
[Sub question 1.2]	What effects do these factors have on traffic congestion?
[Sub question 1.3]	How do these factors relate qualitatively to traffic supply and traffic demand?
[Sub question 1.4]	To what extent are these factors and their effects predictable?
[Sub question 1.5]	How do these factors relate quantitatively to traffic supply and traffic demand?

The questions above will primarily be answered from a literature study and will provide the foundation for the thesis. After determining the factors and effects influencing traffic, a method has to be found to incorporate the variability of traffic in a model:

[Research question 2] *How can the variability of traffic be incorporated in a congestion prediction model?*

In order to answer this question, the following sub questions are considered:

[Sub question 2.1]	How can a variability of factors lead to a capacity and intensity distribution?
[Sub question 2.2]	How can these distributions be implemented in a model?
[Sub question 2.3]	How can capacity and intensity distributions lead to a congestion probability distribution?

The answers on these questions will be produced during the development of a model. This is also the main part of the thesis. When a model has been developed, the results have to be evaluated:

[Research question 3] *What are the effects of incorporating the variability of traffic on congestion predictions?*

In order to answer this question, the following sub questions are considered:

[Sub question 3.1]	Compared to congestion predictions without taking variability account; to what extent does the proposed model provide us with better, more accurate or more complete predictions?
[Sub question 3.2]	How does output probability distribution look like (in comparison to classical model outcomes)?

These questions will be answered in the last part of the thesis. After the model has been developed the effects of incorporating the variability of traffic on congestion predictions can be evaluated.

1.5 Research relevance

This explains paragraph the scientific and the practical relevance of this research.

On a scientific level this research contributes to a deeper understanding in the predictabilities and effects of influence factors on the traffic conditions. A lot of research has been done in the past to see how certain factors influence capacity, travel times or travel time uncertainty. These factors lead to uncertainties in capacity and intensity. However, in most traffic models, input values of for example the capacity consist of one single number. Including the uncertainties of these factors would lead to capacity or intensity distributions. From a scientific point of view it would be relevant to know if the proposed methodology is able to produce accurate predictions and also how the discussed distributions would look like and how they influence congestion predictions.

To this end, the predictabilities and effects of influence factors are collected and applied in a model. To deal with the intrinsic variations in driving behavior, a new approach is conceived. The way in which the variability is modeled, is also innovatory; an intelligent sampling technique is used.

On a practical level, this research also holds relevance. With the availability of this theoretical framework it would be possible for Witteveen+Bos to verify and maybe extent their current traffic congestion forecasting model. The methodology behind a model using capacity and intensity distributions to predict congestion could also be implemented in their model.

1.6 Research approach

The approach to retrieve the research objective and answer the research questions is described here.

First a comprehensive literature study is conducted **(Chapter 2)**. To understand traffic flow processes, basic traffic flow theory is explained here. Next the factors and effects influencing traffic demand and traffic supply are identified and discussed. Also the model approach and the estimation of traffic demand and supply is presented here. Probabilistic methods that can be used to incorporate variability conclude this chapter.

The specific approach and methodology used in the research and the development of the model are explained in **Chapter 3**. This also includes the selected model, the used data sources and the evaluation method.

Chapter 4 contains the theoretical framework used to create the model. An overview of the influence factors illustrating their relations is presented here. Next the predictabilities and effects of the various influence factors are described and quantified.

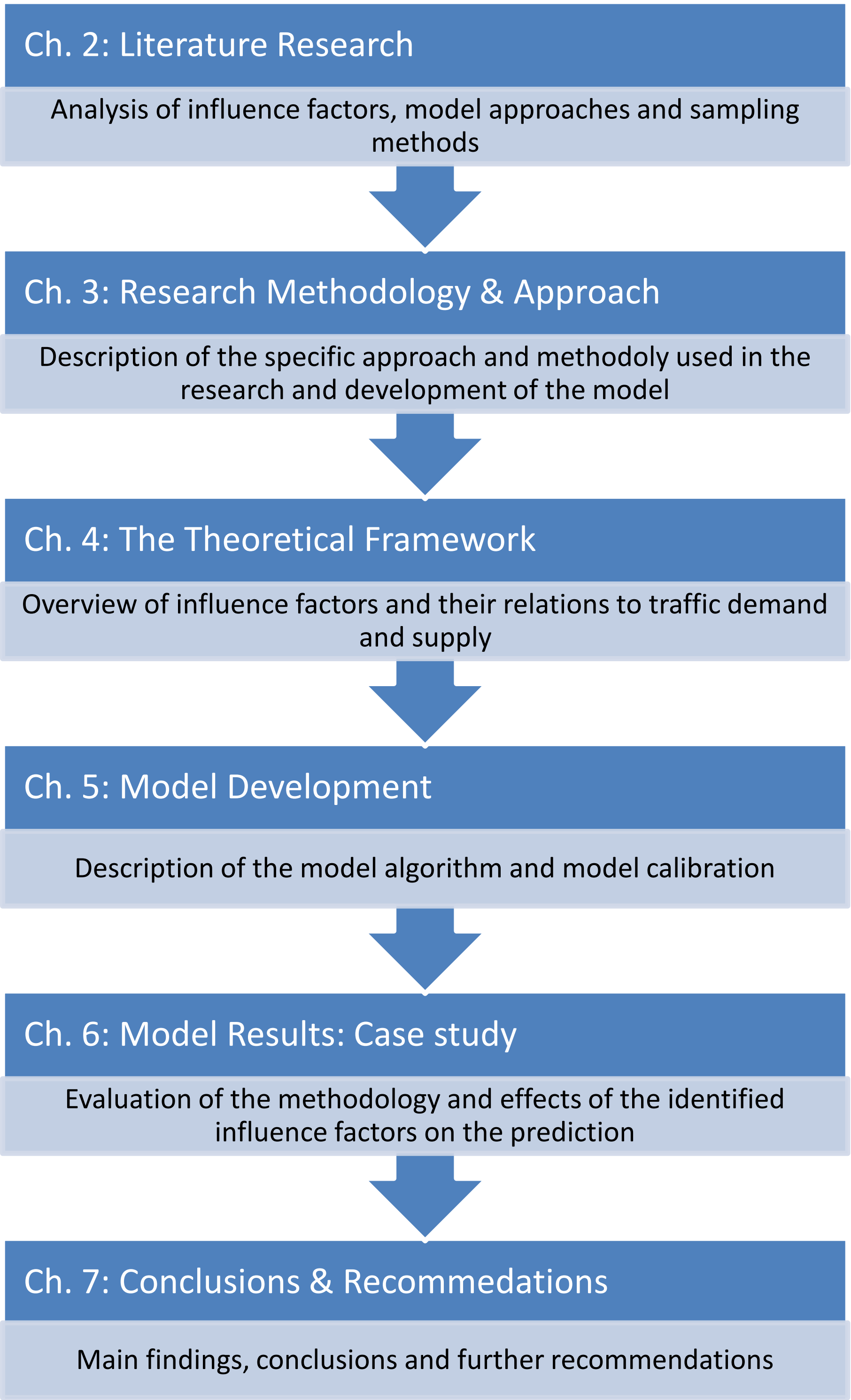
After the theoretical framework has been completed, the model was developed. **Chapter 5** describes the model algorithm and the model calibration. Using historical traffic data in combination with the quantified influence factors on traffic demand and supply, the prediction can be produced.

Finally the model approach and the influence factors are evaluated using a case study. Here the effects of the different influence factors are tested. The model results can be found in **Chapter 6**.

The main findings, final conclusions and further recommendations are presented in **Chapter 7**.

1.7 Thesis outline

The structure of this report follows that of the research as it was performed. Figure 1-3 shows a graphical overview of the report structure.



Ch. 2: Literature Research

Analysis of influence factors, model approaches and sampling methods

Ch. 3: Research Methodology & Approach

Description of the specific approach and methodoly used in the research and development of the model

Ch. 4: The Theoretical Framework

Overview of influence factors and their relations to traffic demand and supply

Ch. 5: Model Development

Description of the model algorithm and model calibration

Ch. 6: Model Results: Case study

Evaluation of the methodology and effects of the identified influence factors on the prediction

Ch. 7: Conclusions & Recommedations

Main findings, conclusions and further recommendations

Figure 1-3: *The structure of the thesis*

2 Literature Research

Before the congestion prediction model taking the variability of traffic into account can be developed, a literature survey has been conducted. First general traffic flow theory on which the traffic model will be based is explained. Next the factors influencing traffic supply and demand will be discussed. Then some model approaches are proposed. The last paragraph of this chapter contains methods for taking into account the variability in the forecast i.e. sampling methods.

2.1 Traffic flow theory

To be able to predict congestion on motorways, a deeper understanding of traffic flow theory is needed. This paragraph gives an explanation of this theory and how this will be used to predict congestion. The main source used for describing the theory is a publication by Hoogendoorn (2007).

2.1.1 Demand-supply approach

Traffic flow is governed by the interaction between traffic demand and traffic supply. Traffic demand is the amount of traffic wanting to traverse a road, while the traffic supply represents the road capacity. As long as the demand is lower than the supply (or capacity), traffic can flow without congestion. However, at the point that the demand exceeds the capacity the traffic flow will break down. This forms the basis of traffic flow theory, but several other phenomena occur. These will be discussed in the next paragraphs.

2.1.2 Traffic Flow Variables

In traffic flow theory a distinction is made between microscopic and macroscopic traffic flow. Microscopic traffic flow theory focuses on the characteristics of individual vehicles. Microscopic traffic models consider the individual vehicles and their interaction with the surrounding infrastructure and other vehicles. Macroscopic traffic flow theory focuses on a large number of vehicles simultaneously. Consequently, macroscopic traffic models consider the collective behavior of multiple vehicles.

Figure 2-1 shows a location-time diagram for vehicle trajectories for one-way traffic. On the vertical axis the location of the vehicle is shown, while the time is shown on the horizontal axis. From the trajectories individual speeds and accelerations can be determined. The speed of a vehicle is the tangent in a point of the trajectory; $v_i = dx_i/dt$. The acceleration of a vehicle is defined by $a_i = d^2x_i/dt^2$. This graphically means the following:

- steeply increasing or decreasing lines denote a accelerating or decelerating vehicle;
- horizontal lines denote a stopped vehicle;
- straight lines denote a vehicle with constant speed, the shallower the line, the slower the vehicle is moving.

Figure 2-1: *Location-time diagram for vehicle trajectories (Hoogendoorn, 2007)*

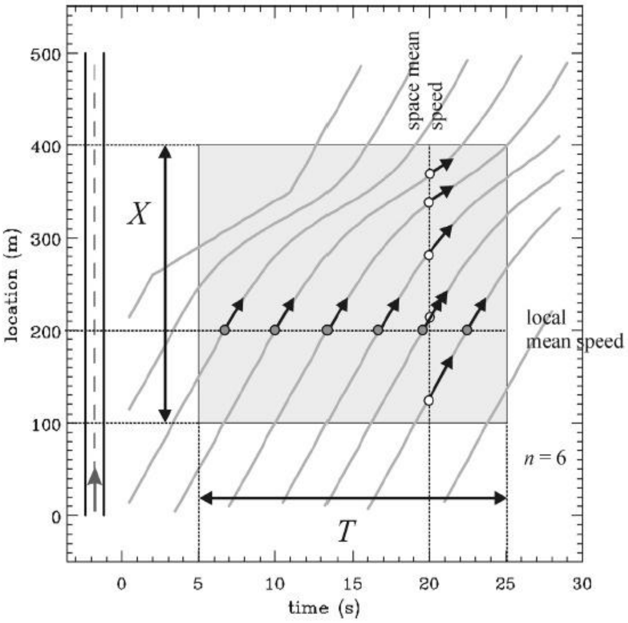


Figure 2-1 also shows the difference between space (or instantaneous) mean speed and local (or time) mean speed. The space mean speed is the average speed of all vehicles on a *section of a road* on a certain *time instance*. The local mean speed is the average speed of all vehicles over a *period of time* at a *certain location*. The mean speeds are expressed as follows:

Equation 2-1

$$u_L = \frac{1}{n}\sum_{i=1}^{n} v_i$$

Equation 2-2

$$u_M = \frac{1}{m}\sum_{j=1}^{m} v_j$$

Where: u_L = Local mean speed
n = vehicles passed cross-section x in time period T
u_M = Space mean speed (index m refers to moment)
m = vehicles on road section X on time instance t

For macroscopic traffic theory, the space mean speed is most commonly used, as it has a direct relation to other fundamental quantities. However often it is the time mean speed that is more readily available, therefore care should be taken when analyzing mean speed data.

In addition to the space mean speed (u), there are two other main parameters in macroscopic traffic theory. These parameters are flow (q) and density (k).

Flow is defined as the number of vehicles that pass a certain place on a road divided by the time over which the count takes place. This results in an intensity of traffic, a quantity that is often used to describe how busy a road is. The flow is expressed by the following equation:

Equation 2-3

$$q = \frac{n}{T}$$

Where:
n = number of vehicles
T = period of time

The density is defined as the number of vehicles occupying a section of a road divided by the length of this section. This indicates how crowded a certain road section is. Usually indirect estimations of density are made, because it is often complicated or expensive to determine the density directly. The reason for this is that the density is an instantaneous quantity and therefore cannot be easily measured from a single location. The density is expressed by the following equation:

Equation 2-4

$$k = \frac{n}{X}$$

Where:
n = number of vehicles
X = road section

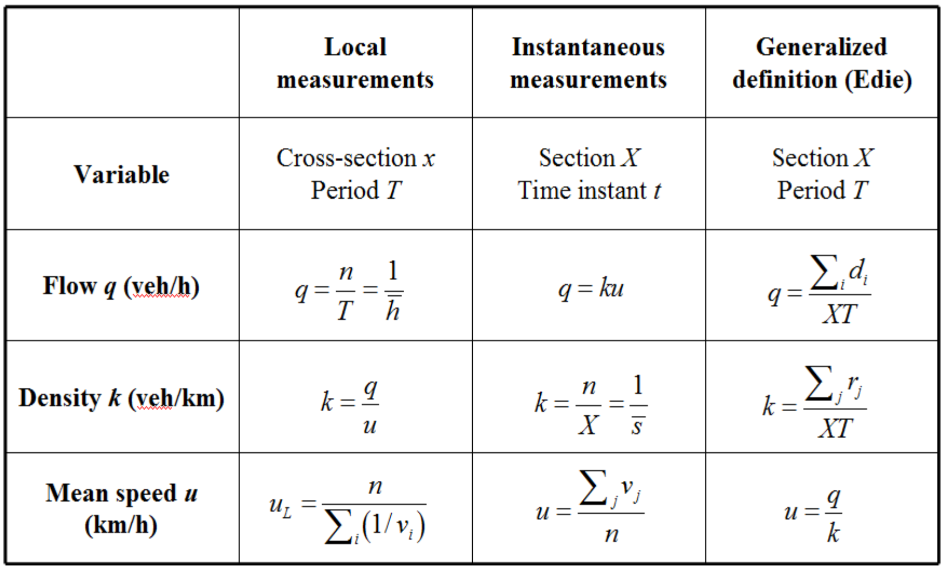
Between these three main parameters a relation exists known as the continuity relation, which is expressed by the following equation:

Equation 2-5

$$q = k \cdot u$$

Figure 2-2 gives an overview of al aforementioned traffic flow variables.

Figure 2-2: *Overview of variables (Hoogendoorn, 2007)*



	Local measurements	**Instantaneous measurements**	**Generalized definition (Edie)**
Variable	Cross-section x Period T	Section X Time instant t	Section X Period T
Flow q (veh/h)	$q=\frac{n}{T}=\frac{1}{\bar{h}}$	$q=ku$	$q=\frac{\sum_i d_i}{XT}$
Density k (veh/km)	$k=\frac{q}{u}$	$k=\frac{n}{X}=\frac{1}{\bar{s}}$	$k=\frac{\sum_j r_j}{XT}$
Mean speed u (km/h)	$u_L=\frac{n}{\sum_i(1/v_i)}$	$u=\frac{\sum_j v_j}{n}$	$u=\frac{q}{k}$

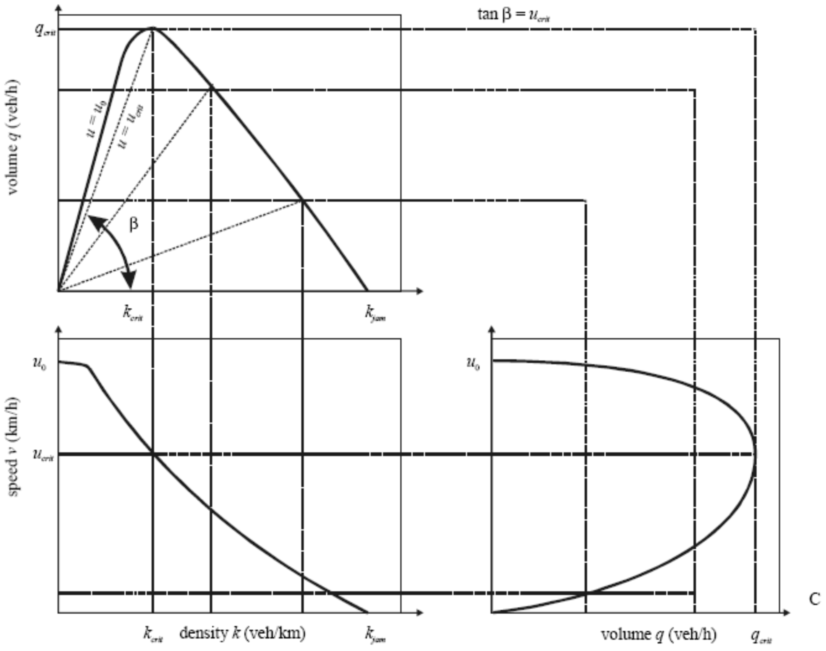
2.1.3 *Fundamental diagrams*

In traffic flow theory the relations between the macroscopic characteristics of flow are called fundamental diagrams. These diagrams are proven to be generic for traffic flow and are an essential part of traffic flow theory. Each diagram shows the relation between two of the three main parameters, namely:

- intensity - density
- speed - density
- speed - intensity

However, it is important to understand that these three relations represent the same information: from one relation one can deduce the other two, see Figure 2-3 (Hoogendoorn, 2007).

Figure 2-3: *Fundamental diagrams and their interrelations (Hoogendoorn, 2007)*

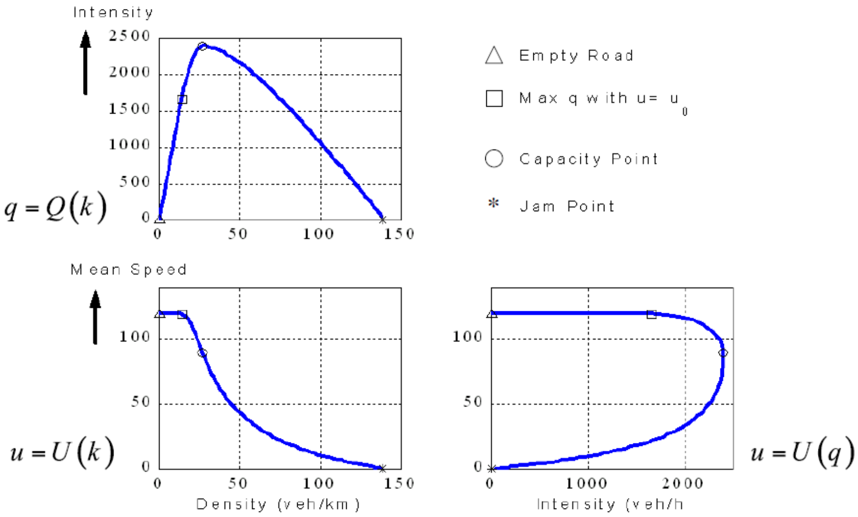

$\tan\beta = u_{crit}$
q_{crit}
volume q (veh/h)
$u = u_0$
$u = u_{crit}$
β
k_{crit}
k_{jam}
u_0
u_{crit}
speed v (km/h)
k_{crit}
density k (veh/km)
k_{jam}
u_0
volume q (veh/h)
q_{crit}
C

In Figure 2-4 the special points of the fundamental diagrams are indicated. The special points of the diagram are:

- (mean) Free speed u0; this is the mean speed if q=0 and k=0; it equals the slope of the function q(k) in the origin;
- Capacity q_c; this is the maximal intensity, sometimes called critical intensity;
- Capacity density or critical density k_c; i.e. the density if $q=q_c$;
- Capacity speed u_c; i.e. the mean speed if $q=q_c$;
- Jam density k_j; i.e. the density if u=0 and q=0.

Note that u(q) is a two-valued function, i.e. at one value of q there are two possible values for u and k. Note also that capacity is not a special point of the function u(k).

***Figure 2-4:** Special points of the fundamental diagrams (Hoogendoorn, 2007)*



The fundamental diagram clearly shows the difference between the free flow and the congested branch. Free flow is observed when the vehicle density is small, interactions between vehicles are then negligible. Vehicles can then move at their desired speeds (subject to traffic rules). When the density increases and approaches the critical density, vehicle interaction cannot be neglected anymore and the probability of congestion occurrence increases.
At the point where flow, density and speed are critical, traffic breaks down and congestion will occur (Capacity point in Figure 2-4). In theory this capacity point is only one value, but in practice it is not.

Capacity drop

It appears that the capacity just before the on-set of congestion is larger than the capacity after the on-set of congestion. This means that the maximum flow rate observed just before the on-set of congestion (from free flow to congested) is larger than the maximum flow rate of cars leaving a queue (from congested to free flow). This phenomenon is called the capacity drop. This capacity drop is in the range of 1 to 15 percent (Hoogendoorn, 2007). A queue will consequently only dissolve if the traffic demand is lower than the queue discharge flow rate. Figure 2-5 shows the three forms of fundamental diagrams (in another order than before) with a capacity drop.

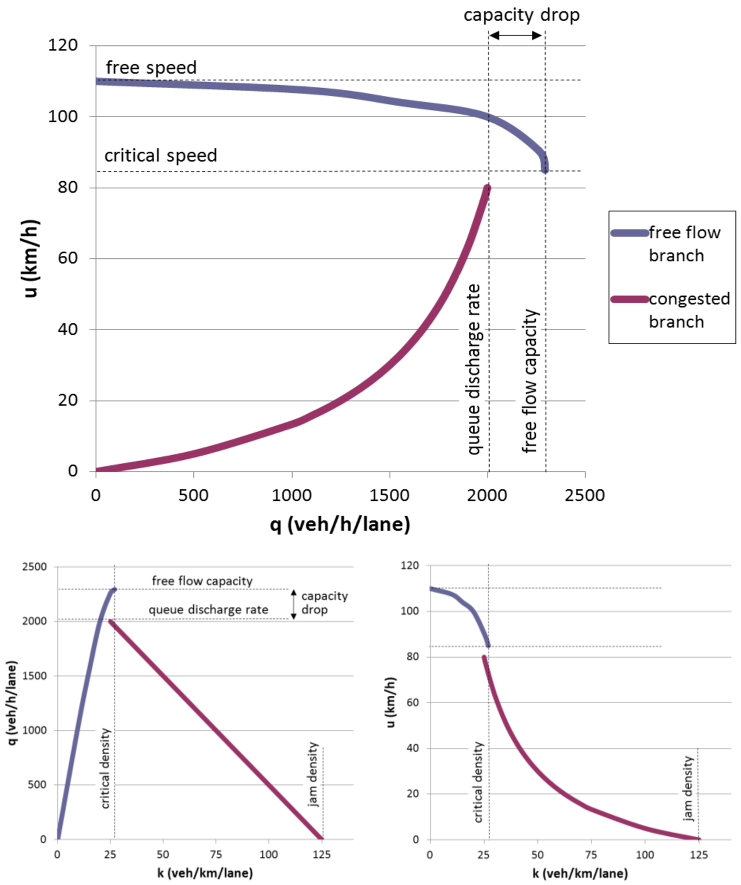


Figure 2-5:
Fundamental diagrams with a capacity drop (Miete, 2011)

Models of the fundamental diagram

A lot of models for the diagram are available from literature. In this section some will be discussed.

- Fundamental diagram of Greenshields

This is one of the oldest models of traffic flow theory. It is based on the assumption that mean speed decreases linearly with density. The model is expressed by the following formulas:

Equation 2-6

$$u(k) = u_0\left(1 - \frac{k}{k_j}\right)$$

Where: u_0 = free speed
k_j = jam density

From the continuity equation easily follows:

Equation 2-7

$$q(k) = ku_0\left(1 - \frac{k}{k_j}\right) = ku_0 - \frac{k^2u_0}{k_j}$$

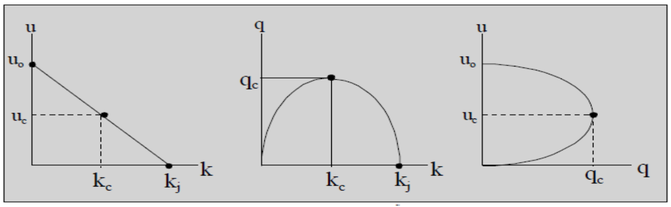


Figure 2-6: *Greenshields' fundamental diagram (Hoogendoorn, 2007)*

- Fundamental diagram of Smulders

In developing a dynamic macroscopic model for traffic flow on motorways, Smulders introduced the diagram in Figure 2-7. This fundamental diagram is parabolic in the free flow part and linear in the congested part.

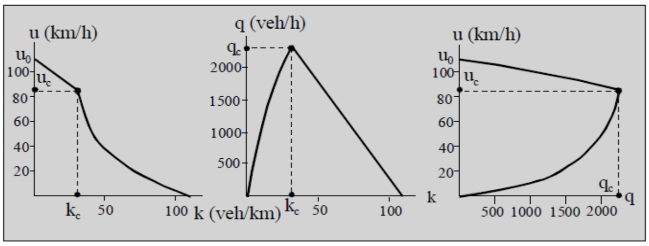


Figure 2-7: *Smulders' fundamental diagram (Hoogendoorn, 2007)*

This fundamental diagram is expressed in the following equation:

Equation 2-8

$$u(k) = \begin{cases} u_0(1 - {}^{k}/_{k_j}) & for\ k < k_c \\ \gamma\left({}^{1}/_{k} - {}^{1}/_{k_j}\right) & for\ k > k_c \end{cases}$$

Main parameters here are u_0, k_c, k_j and γ. From the requirement that u(k) is continuous at $k=k_c$ follows that $\gamma = u_0k_c$.

- Fundamental diagram of De Romph

De Romph has generalized Smulder's diagram to:

Equation 2-9

$$u(k) = \begin{cases} u_0(1 - \alpha k) & for\ k < k_c \\ \gamma\left({}^{1}/_{k} - {}^{1}/_{k_j}\right)^{\beta} & for\ k > k_c \end{cases}$$

Here there are six parameters: u_0, k_c, k_j, α, β and γ. The number of parameters can be reduced to five due to the required continuity at $k=k_c$. From this, it follows that $\gamma = u_0 (1 - \alpha k_c) / (1/k_c - 1/k_j) \beta$. Parameters α and β can and have been estimated for different elements of the motorway by data analysis.

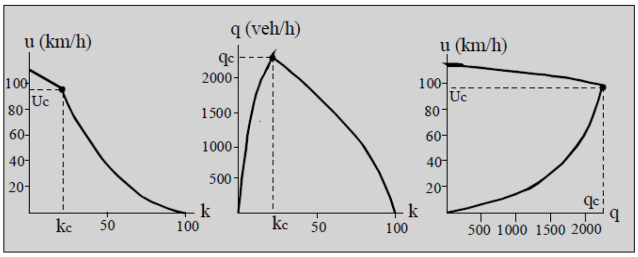


Figure 2-8: *De Romphs' fundamental diagram (Hoogendoorn, 2007)*

- Fundamental diagram of Daganzo

When developing a new traffic model a simple fundamental diagram that represents the essential properties of traffic flow correctly is needed. The fundamental diagram of Greenshields is an example of this, but Daganzo has introduced an alternative in which the function Q(k) is represented by two straight lines. The model has three parameters: u_0, k_c and k_j and is formulated as follows:

Equation 2-10

$$u(k) = \begin{cases} u_0 & for\ k < k_c \\ \gamma\left({}^{1}/_{k} - {}^{1}/_{k_j}\right) & for\ k > k_c \end{cases}$$

From the continuity relation follows that:

Equation 2-11

$$q(k) = \begin{cases} u_0 k & for\ k < k_c \\ \gamma k\left({}^{1}/_{k} - {}^{1}/_{k_j}\right) & for\ k > k_c \end{cases}$$

From the requirement that u(k) is continuous at $k=k_c$ follows that $\gamma = u_0 / (1/k_c - 1/k_j)$.

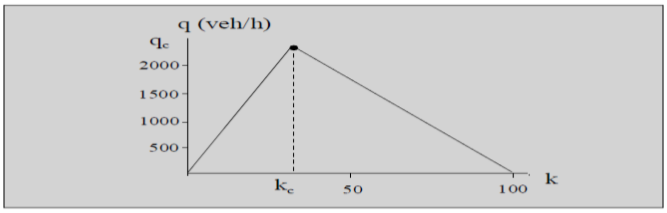


***Figure 2-9:** Daganzo's fundamental diagram (Hoogendoorn, 2007)*

- Fundamental diagram with a capacity drop

Figure 2-10 shows a fundamental diagram with a discontinuity. For predicting congestion on a road stretch a method for dealing with this capacity drop is needed.

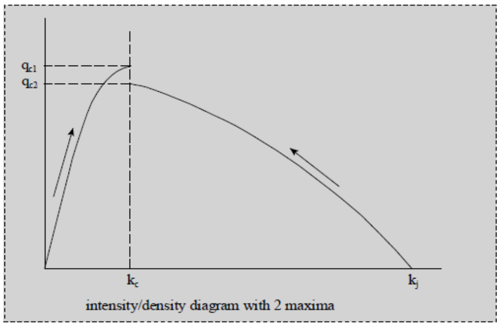


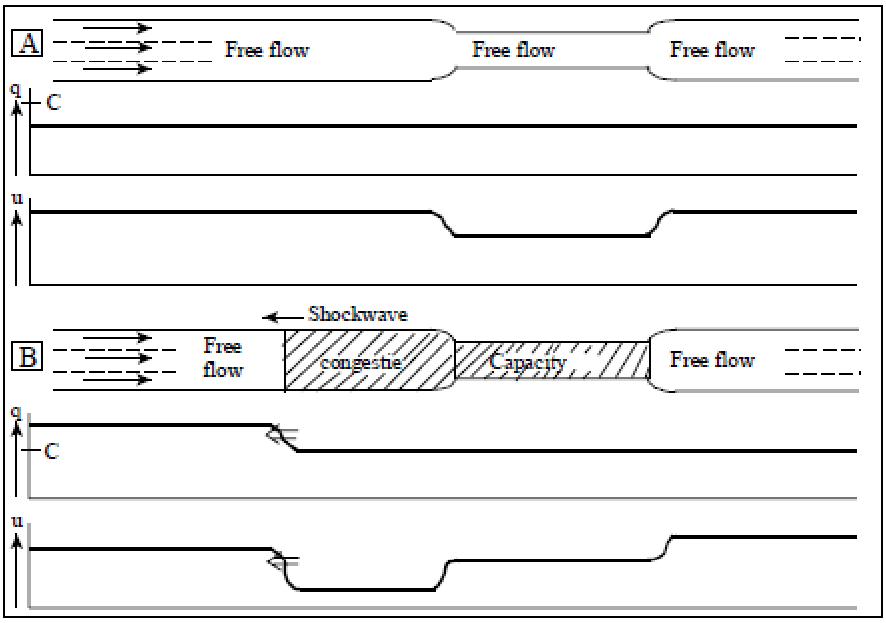
***Figure 2-10:** Fundamental diagram with a discontinuity (Hoogendoorn, 2007)*

2.1.4 *Onset of congestion and queuing*

To explain the phenomena that take place during the onset of congestion can be explained using Figure 2-11. A bottleneck situation is shown here. At this bottleneck the capacity is lower than on the rest of the road stretch. As long as the demand flow is less than the capacity flow, the traffic flow conditions can be determined using the fundamental diagram. In situation A there is no oversaturation. On the entire road, free flow conditions exist. In the bottleneck, a small delay may be incurred due to the higher densities.

Situation B shows the road stretch under oversaturated conditions. The demand exceeds the capacity in the bottleneck and vehicles will experience delay. In the bottleneck however capacity flow is observed, while the queue starts just upstream of the bottleneck.

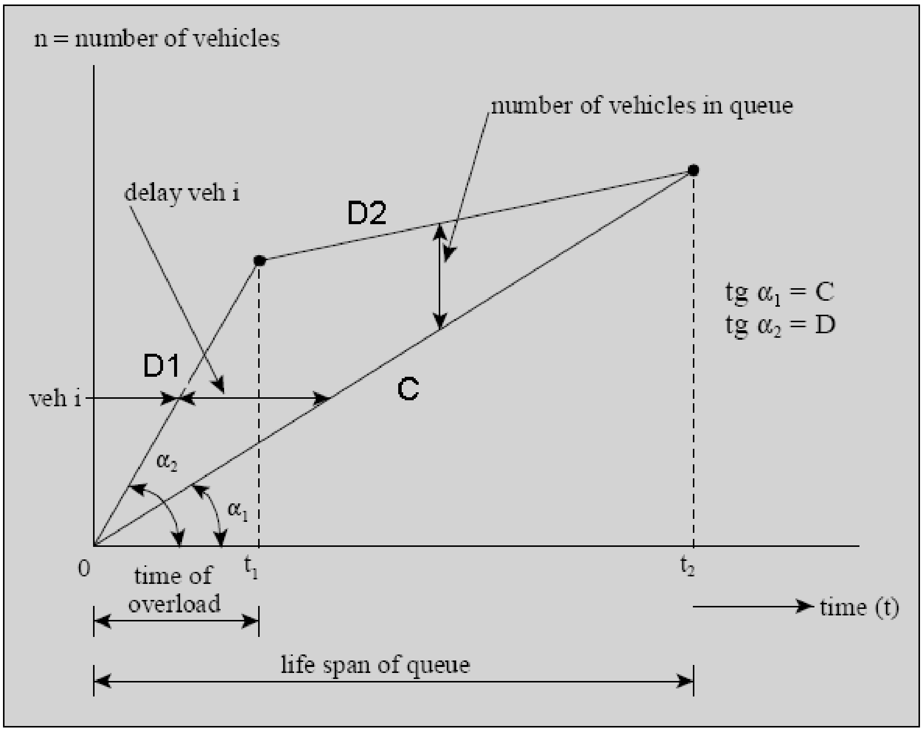
Figure 2-11: *Traffic flow at bottleneck (Hoogendoorn, 2007):*
a) Bottleneck capacity > flow
b) Bottleneck capacity < flow



2.1.5 *Traffic queuing & shockwave theory*

The resulting queues and delays from congestion can be calculated using different methods. The deterministic queuing model is commonly used as it can give a correct and accurate delay due to a queue (Hoogendoorn, 2007). Shockwave theory is also commonly applied to explain traffic queuing phenomena. Figure 2-12 explains the deterministic queuing model. In this graph the cumulative number of vehicles is on the vertical axis and time on the horizontal axis. The ‘arrival’ curve is a line with demand D as slope. The ‘departure’ curve has the capacity C as *maximum* slope. When the slope of the ‘arrival’ curve exceeds the slope of the ‘departure’ curve, queuing will occur. The distance between the arrival curve and the departure curve at a given moment (the vertical distance) equals the length of the queue (expressed in number of vehicles). The distance between the arrival curve and the departure curve for a given arriving vehicle (the horizontal distance) equals the time the vehicle spends in the queue. In Figure 2-12 the slope line D1 clearly is clearly larger than the slope of line C, a queue will start to grow along the time axis. At a certain moment the demand decreases (transition from line D1 to line D2). At this moment the queue has reached its maximum length and will start to dissolve. It should be duly noted that congestion does not end when the demand becomes smaller than the supply. The congestion is finished, when both curves intersect. The total delay equals the area between the arrival and departure curve.

***Figure 2-12:** Graphical depiction of queuing in time (Hoogendoorn, 2007)*

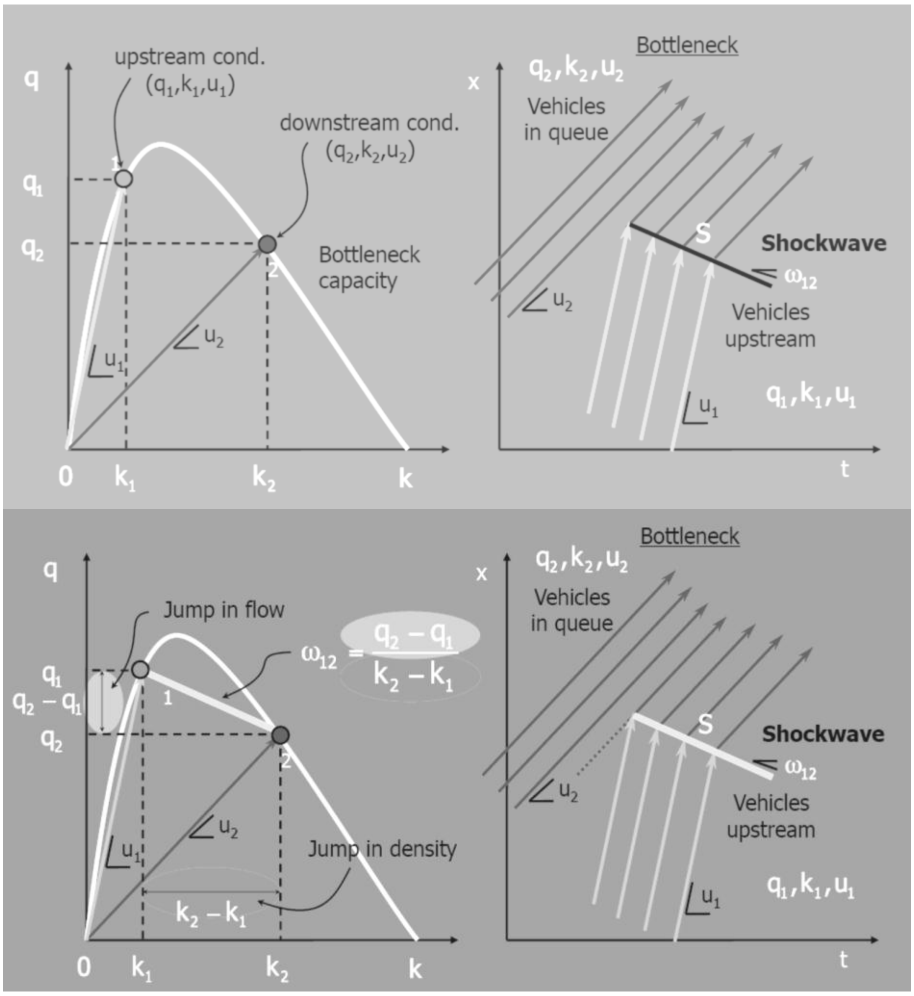


The main drawback of this method is that it queues vehicles vertically. This means that the queue is measured from a single point and will not propagate from this location, the amount of space taken by the queue is not taken explicitly.

Other methods to calculate queues and delays make use of shockwave theory. Multiple consecutive sections are used to model traffic flow, sections pass traffic flow and queue information to the next section. In this way vehicles are to a certain extent, depending on the section length, not queued vertically anymore. Methods using shockwave theory are especially useful when modeling network situations.

Figure 2-13 shows a graphical representation of first order traffic theory. With this theory it is possible to model shockwaves. This is done by making use of a simplified fundamental diagram. The shockwaves can be derived from the fundamental diagram and will move at a rate corresponding to the lines from the fundamental diagram. In the bottom part of Figure 2-13 the shockwave speed is graphically derived. From the graph it is clear that the shockwave speed equals the jump in flow divided by the jump in density. This speed is almost always recorded between 15 and 20 km/h in an upstream direction, meaning that congestion propagates upstream.

Figure 2-13: *Graphical representation of first order traffic theory (Hoogendoorn, 2007)*


q
upstream cond.
(q_1,k_1,u_1)
downstream cond.
(q_2,k_2,u_2)
q_1
q_2
1
2
Bottleneck capacity
u_1
u_2
0
k_1
k_2
k
x
Bottleneck
q_2,k_2,u_2
Vehicles in queue
S
Shockwave
ω_{12}
Vehicles upstream
q_1,k_1,u_1
t
q
Jump in flow
$\omega_{12} = \frac{q_2 - q_1}{k_2 - k_1}$
q_1
$q_2 - q_1$
q_2
Jump in density
$k_2 - k_1$
0
k_1
k_2
k
x
Bottleneck
q_2,k_2,u_2
Vehicles in queue
S
Shockwave
ω_{12}
Vehicles upstream
u_2
u_1
q_1,k_1,u_1
t

The conservation of vehicle equation (Equation 2-12) is used to describe dynamic phenomena in traffic flow. Conservation of vehicles means that no vehicles are created or lost. So if on a specific roadway section more vehicles are entering than leaving, then the number of vehicles in this section should increase. Combining this with the continuity equation (Equation 2-13) and the fundamental relation (Equation 2-14), a representation of traffic using capacity and flow data can be modeled. The fundamental relation is a mathematical formulation of a fundamental diagram.

A method which has been widely used is the LWR (Lighthill-Whitham-Richards) method. This method makes use of flows that influence both upstream and downstream conditions. The model is generally solved by the Godunov scheme. The scheme iteratively determines the allowed flows for each space and time step as well as the traffic density for each section by solving the corresponding Riemann problems making use of the equations from the LWR-model (Calvert, 2009).

Equation 2-12

$$\frac{\delta k(x,t)}{\delta t} + \frac{\delta q(x,t)}{\delta x} = 0$$

Equation 2-13

$$q(x,t) = k(x,t) \cdot v(x,t)$$

Equation 2-14

$$q(x,t) = Q_E(k(x,t))$$

Where:
k = density
q = flow
v = average speed
Q_E = fundamental diagram
x = space step
t = time step

2.1.6 *Conclusions*

This paragraph explained basic traffic flow theory and the position it has in congestion forecasting. It showed that traffic states are depicted from the interaction between traffic supply and demand.

The difference between microscopic and macroscopic traffic flow has been explained. Microscopic traffic flow theory focuses on the characteristics of individual vehicles. Macroscopic traffic flow theory focuses on a large number of vehicles simultaneously.

The main parameters – speed, flow and density – combined in the continuity equations, as well as the fundamental diagrams form a powerful basis for traffic flow theory. These parameters and diagrams form the basis of traffic flow theory and will be needed to predict future traffic conditions with traffic demand and supply as a basis.

Also some mathematical models for the fundamental diagram have been proposed. A simple mathematical model for the fundamental diagram is needed to predict congestion. Furthermore a phenomenon called the capacity drop has been identified and needs to be dealt with.

The location of the onset of congestion has been discussed as well. Congestion usually sets on just upstream the bottleneck and not in the bottleneck. The capacity drop could also ensure that congestion might not start at a location further downstream. This effect has to be taken into account.

Aside from the onset of congestion, also the manner in which congestion propagates has been discussed. Two methods for dealing with this were proposed. A basic queuing method is generally easy to implement, but leaves out the dynamics of congestion. First order shockwave theory does have the capability to deal with the movement of congestion in space and time and could therefore be very adequate in addition to basic queuing modeling.

2.2 Factors and effects influencing traffic demand and traffic supply

To be able to predict congestion on the basis of multiple influence factors, insight should be gained on factors influencing traffic conditions. To this end, the factors and a categorization of these factors will be presented here. With this, the information needed can be determined per factor.

2.2.1 Introduction

For both the temporal variability in traffic demand and the temporal variability in traffic supply a large number of causes can be discerned.

The following sources of variability are identified for the *traffic supply* by Miete (2011):

- weather conditions
- luminance
- incidents
- road works
- traffic control actions
- variations in vehicle population
- variations in driver population
- ‘intrinsic’ variations in human behavior
- strike actions / demonstrations
- emergencies

For *traffic demand*, he distinguished the following sources:

- regular pattern of variation in human travel behavior over the day
- regular pattern of variation in human travel behavior over the days of the week
- regular pattern of variation in human travel behavior over the periods of the year
- public holidays
- events
- weather conditions
- road works
- strike actions / demonstrations
- emergencies
- other variations in human travel behavior (i.e. those not explained by the aforementioned factors)

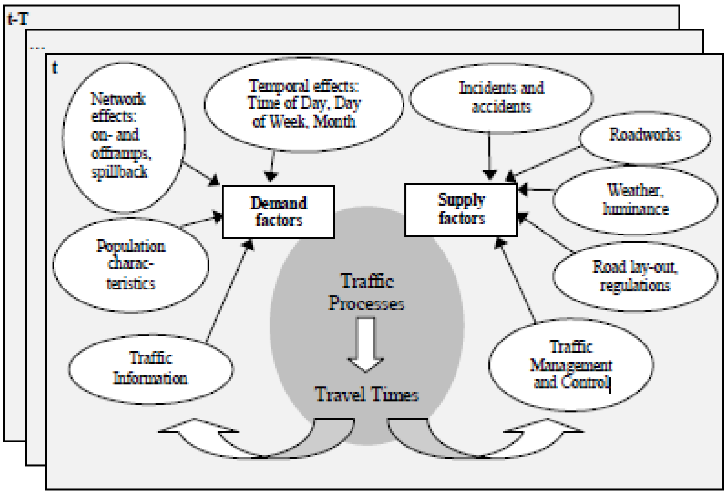
Two other factors influencing the traffic demands are:

- travel behavioral changes in response to traffic information
- travel behavioral changes in response to one’s recent travel experiences

The latter can however not really be considered sources of variations, because they only exist due to actual sources of variations in traffic demand and supply. Without variations, traffic conditions would be fully predictable anyway. Note that although not considered actual sources of variations, these factors can be included in identified sources of variations. Strike actions, demonstrations and emergencies will not be considered in this thesis due their low frequencies of occurrence.

Figure 2-14 shows a general overview of factors that influence travel time in a schematic way.

Figure 2-14: *General (not exhaustive) overview of factors that influence travel time (Van Lint, 2004)*


t-T
...
t
Network effects: on- and offramps, spillback
Temporal effects: Time of Day, Day of Week, Month
Incidents and accidents
Roadworks
Demand factors
Supply factors
Weather, luminance
Population charac-teristics
Traffic Processes
Road lay-out, regulations
Traffic Information
Travel Times
Traffic Management and Control

In addition to the factors mentioned above, network effects might be a source of variability as well. When only considering a section of a road, the traffic conditions can be influenced by traffic conditions on other locations in the network. These network effects will be discussed in a separate subparagraph.

2.2.2 Classification

The sources of variability can be classified in different ways. The following classifications have been considered by Miete (2011):

- regular (or systematic) versus irregular;
- continuous (though variable) versus only during well-defined spaces of time ('events' or 'disturbances');
- network wide versus locally versus in between the network level and the local level.

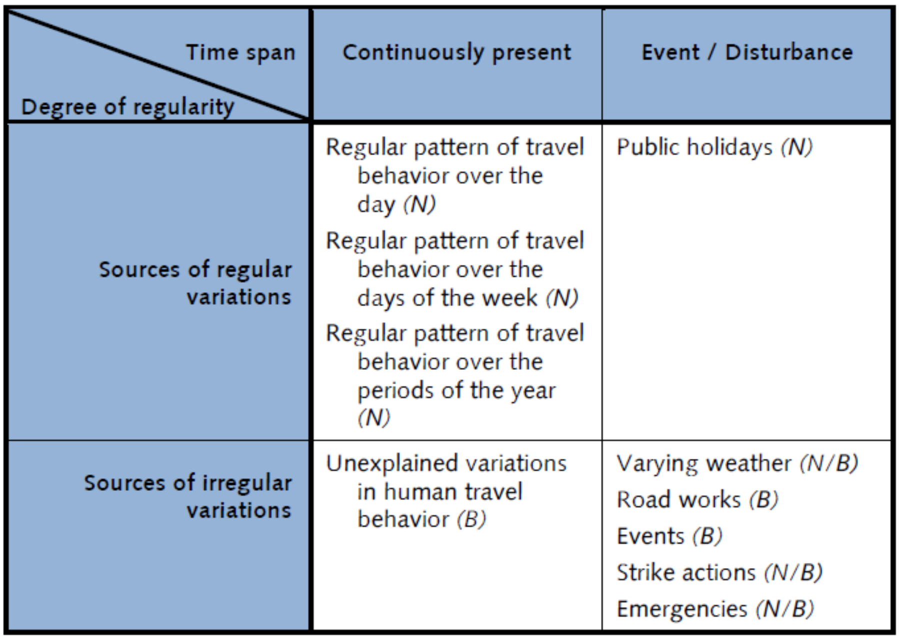
The sources mentioned before are assigned to these classes for both the demand (Figure 2-15) as for the supply (Figure 2-16). Rows and columns represent the first two classes, while the third class is indicated by symbols.

There are a number of notes that should be kept in mind for this classification (Miete, 2011):

- If the traffic demand and/or supply are affected at an above-local level, this not necessarily means that the effect is homogeneous in magnitude. An example here is the demand effect of the summer vacation period. On some routes daily traffic might be lower (less commuting traffic), while there might also be routes on which the traffic demand is larger (more recreational traffic)
- A substantial part of the sources of variability can take place at different spatial levels. For example adverse weather conditions might be local in nature, cover

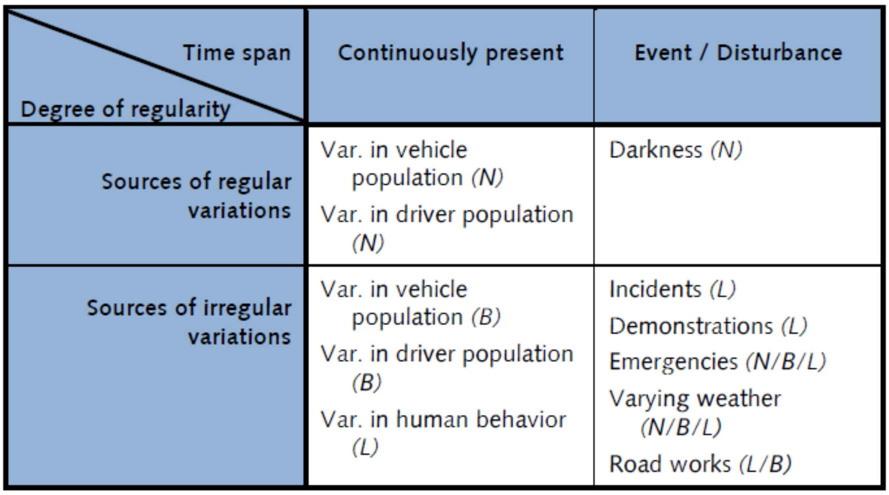
the whole network, or somewhere in between. It is also possible that the primary effect on traffic demand or supply is local in nature, but the consequence for the traffic conditions might have a much larger spatial scope.

- Inevitable, in some cases the assignment to categories is debatable to some extent. The variation in weather conditions for example is assigned to the class ‘events/disturbances’, while in reality variations in weather conditions are practically continuously present. However, adverse weather conditions can be distinguished reasonably well from ‘normal’ weather conditions. Another example is the assignment of ‘events’ to the category ‘irregular’. Some events might be organized every year again and rather belong to the category ‘regular’.
- The influence factors ‘variations in vehicle population’ and ‘variations in driver population’ are assigned to both the categories ‘sources of regular variations’ and ‘sources of irregular variations’. This is because of the fact that these sources of variations to a large extent can be described by regular patterns over time (representing their systematic parts), but still with a part of the variations remaining unexplained (representing their random/irregular parts).
- In the supply classification, the influence factor ‘traffic control actions’ is omitted. This is because of the fact that it cannot really be assigned to one of the categories. Some traffic control actions influence the supply conditions on a continuous basis, while others are active only during specific periods of time. Furthermore, some types of traffic control are regular in nature, while others act in a traffic responsive (and thus partially irregular) way.
- The category of irregular events/disturbances can be further divided into circumstances that are planned (road works and events) and circumstances that are unplanned (incidents and emergencies). Strike actions, demonstrations and varying weather conditions cannot be unambiguously assigned to one of these two categories.



Time span Degree of regularity	Continuously present	Event / Disturbance
Sources of regular variations	Regular pattern of travel behavior over the day *(N)* Regular pattern of travel behavior over the days of the week *(N)* Regular pattern of travel behavior over the periods of the year *(N)*	Public holidays *(N)*
Sources of irregular variations	Unexplained variations in human travel behavior *(B)*	Varying weather *(N/B)* Road works *(B)* Events *(B)* Strike actions *(N/B)* Emergencies *(N/B)*

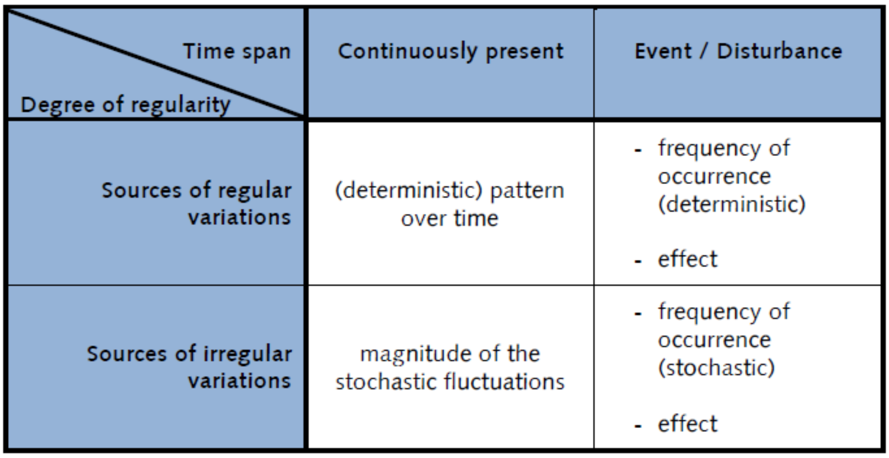
Figure 2-15: *Classification of the various sources of variations in the traffic* *__demand__* *according to time span (horizontal), degree of regularity (vertical) and spatial scope (N=network-wide, L=local, B=’in between’) of their effects (Miete, 2011)*



Time span / Degree of regularity	Continuously present	Event / Disturbance
Sources of regular variations	Var. in vehicle population *(N)* Var. in driver population *(N)*	Darkness *(N)*
Sources of irregular variations	Var. in vehicle population *(B)* Var. in driver population *(B)* Var. in human behavior *(L)*	Incidents *(L)* Demonstrations *(L)* Emergencies *(N/B/L)* Varying weather *(N/B/L)* Road works *(L/B)*

Figure 2-16: *Classification of the various sources of variations in the traffic supply according to time span (horizontal), degree of regularity (vertical) and spatial scope (N=network-wide, L=local, B='in between') of their effects (Miete, 2011)*

For each category different aspects need to be clear in order to be able to be processed in a model. The important aspects to be considered for the different categories are shown in Figure 2-17.



Time span / Degree of regularity	Continuously present	Event / Disturbance
Sources of regular variations	(deterministic) pattern over time	- frequency of occurrence (deterministic) - effect
Sources of irregular variations	magnitude of the stochastic fluctuations	- frequency of occurrence (stochastic) - effect

Figure 2-17: *Relevant aspects for the different categories of sources of variability in traffic demand and supply (Miete, 2011)*

Note that 'effect' refers to its impact on traffic demand or supply and not to the final impact on the traffic conditions. This final impact will be referred to as a 'consequence'. Figure 2-18 shows the terminology used in this thesis.

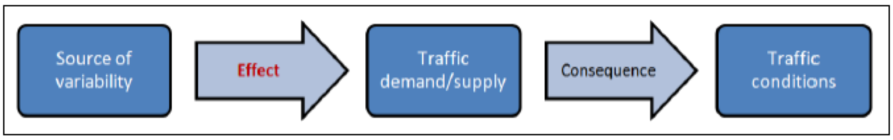
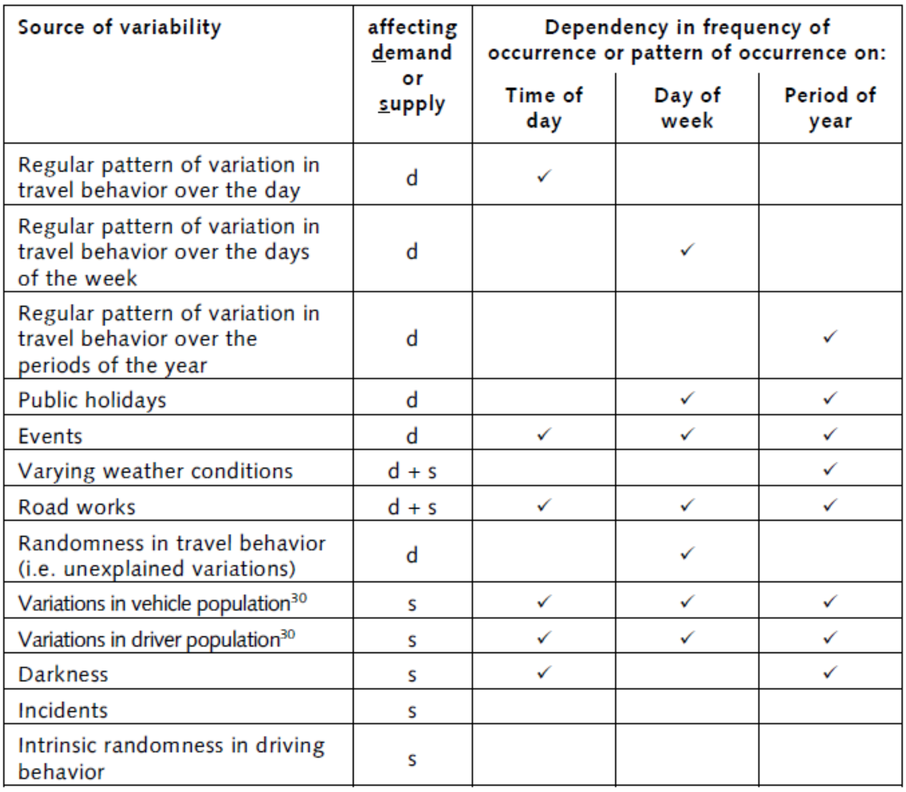


Figure 2-18: *Distinction between effect and consequence (Miete, 2011)*

2.2.3 *Interdependencies between the influence factors*

The aforementioned factors do not only influence traffic demand or supply, but also affect each other. These interdependencies have also been dealt with extensively by Miete (2011). In this paragraph the interdependencies will be discussed rather shortly. Awareness of these interdependencies is important for processing the influence factors in congestion predictions. First the common time-dependency of the sources of variability are discussed. Different sources might not have a causal relationship, but can be linked together due to a common time-dependency. Figure 2-19 shows the dependencies in the frequency of occurrence (or patterns of occurrence) of all sources of variability on the factor 'time'. A distinction between 'time of day', 'day of week' and 'period of year' has been made.

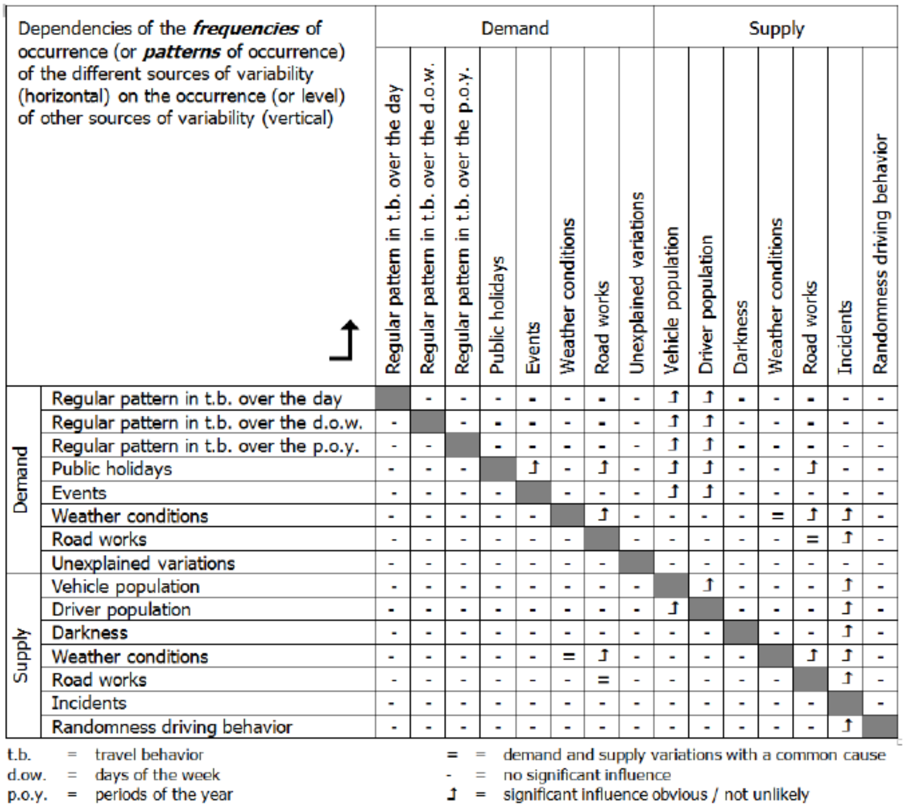


Source of variability	affecting demand or supply	Dependency in frequency of occurrence or pattern of occurrence on:		
		Time of day	Day of week	Period of year
Regular pattern of variation in travel behavior over the day	d	✓		
Regular pattern of variation in travel behavior over the days of the week	d		✓	
Regular pattern of variation in travel behavior over the periods of the year	d			✓
Public holidays	d		✓	✓
Events	d	✓	✓	✓
Varying weather conditions	d + s			✓
Road works	d + s	✓	✓	✓
Randomness in travel behavior (i.e. unexplained variations)	d		✓	
Variations in vehicle population[30]	s	✓	✓	✓
Variations in driver population[30]	s	✓	✓	✓
Darkness	s	✓		✓
Incidents	s			
Intrinsic randomness in driving behavior	s			

Figure 2-19: *Common time-dependency of sources of variability, resulting in mutual interdependencies (Miete, 2011)*

Aside from these common time-dependencies, more causal interdependencies exist as well. Note that the indicated interdependencies are not all equal in strength. Some of them are likely to be much stronger than others. Figure 2-20 shows the dependencies in the *frequencies/patterns* of occurrence of the sources of variability. For example, accidents tend to happen more frequently under bad weather conditions. Figure 2-21 shows the dependencies in the *effects* of the sources of variability. An example here is that a combination of bad weather conditions and darkness has a larger effect on capacity than each of those conditions individually. Therefore the effect of the occurrence of one of these conditions is dependent on the occurrence of the other.

Figure 2-20:
Dependencies of the frequencies/patterns of occurrence of the different sources of variability on the occurrence/level of other sources of variability (Miete, 2011)

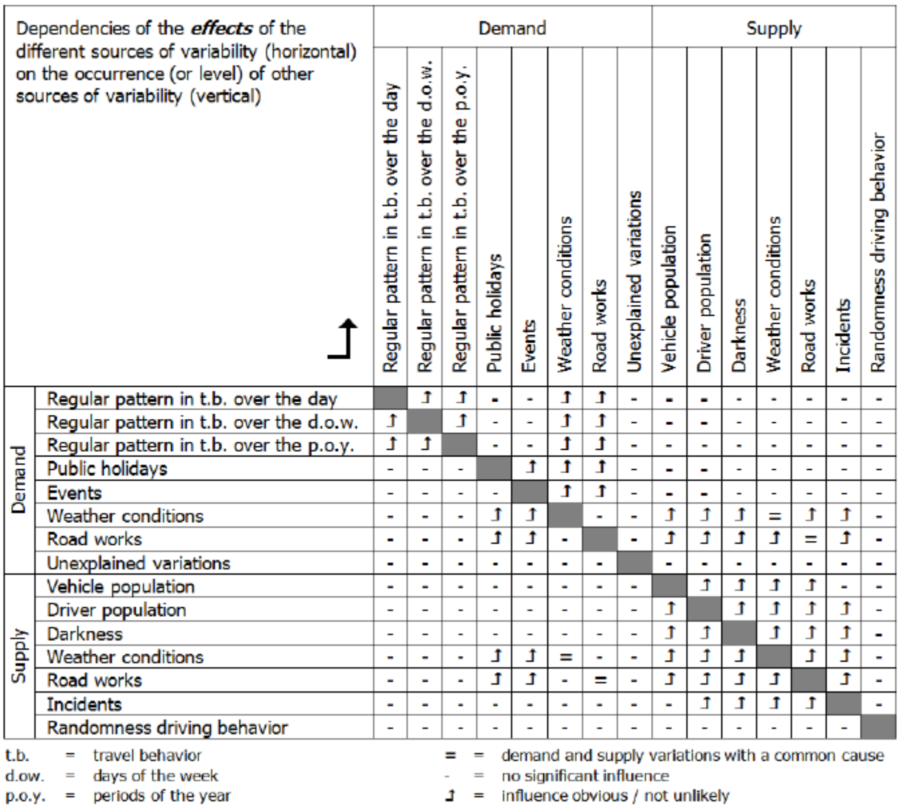


Dependencies of the ***frequencies*** of occurrence (or ***patterns*** of occurrence) of the different sources of variability (horizontal) on the occurrence (or level) of other sources of variability (vertical) ↥		Demand								Supply						
		Regular pattern in t.b. over the day	Regular pattern in t.b. over the d.o.w.	Regular pattern in t.b. over the p.o.y.	Public holidays	Events	Weather conditions	Road works	Unexplained variations	Vehicle population	Driver population	Darkness	Weather conditions	Road works	Incidents	Randomness driving behavior
Demand	Regular pattern in t.b. over the day	▨	-	-	-	-	-	-	-	↥	↥	-	-	-	-	-
	Regular pattern in t.b. over the d.o.w.	-	▨	-	-	-	-	-	-	↥	↥	-	-	-	-	-
	Regular pattern in t.b. over the p.o.y.	-	-	▨	-	-	-	-	-	↥	↥	-	-	-	-	-
	Public holidays	-	-	-	▨	↥	-	↥	-	↥	↥	-	-	↥	-	-
	Events	-	-	-	-	▨	-	-	-	↥	↥	-	-	-	-	-
	Weather conditions	-	-	-	-	-	▨	↥	-	-	-	-	=	↥	↥	-
	Road works	-	-	-	-	-	-	▨	-	-	-	-	-	=	↥	-
	Unexplained variations	-	-	-	-	-	-	-	▨	-	-	-	-	-	-	-
Supply	Vehicle population	-	-	-	-	-	-	-	-	▨	↥	-	-	-	↥	-
	Driver population	-	-	-	-	-	-	-	-	↥	▨	-	-	-	↥	-
	Darkness	-	-	-	-	-	-	-	-	-	-	▨	-	-	↥	-
	Weather conditions	-	-	-	-	-	=	↥	-	-	-	-	▨	↥	↥	-
	Road works	-	-	-	-	-	-	=	-	-	-	-	-	▨	↥	-
	Incidents	-	-	-	-	-	-	-	-	-	-	-	-	-	▨	-
	Randomness driving behavior	-	-	-	-	-	-	-	-	-	-	-	-	-	↥	▨

t.b. = travel behavior
d.ow. = days of the week
p.o.y. = periods of the year

= = demand and supply variations with a common cause
- = no significant influence
↥ = significant influence obvious / not unlikely

Figure 2-21:
Dependencies of the effects of the different sources of variability on the occurrence/level of other sources of variability (Miete, 2011)



Dependencies of the ***effects*** of the different sources of variability (horizontal) on the occurrence (or level) of other sources of variability (vertical) ↥		Demand								Supply						
		Regular pattern in t.b. over the day	Regular pattern in t.b. over the d.o.w.	Regular pattern in t.b. over the p.o.y.	Public holidays	Events	Weather conditions	Road works	Unexplained variations	Vehicle population	Driver population	Darkness	Weather conditions	Road works	Incidents	Randomness driving behavior
Demand	Regular pattern in t.b. over the day	▨	↥	↥	-	-	↥	↥	-	-	-	-	-	-	-	-
	Regular pattern in t.b. over the d.o.w.	↥	▨	↥	-	-	↥	↥	-	-	-	-	-	-	-	-
	Regular pattern in t.b. over the p.o.y.	↥	↥	▨	-	-	↥	↥	-	-	-	-	-	-	-	-
	Public holidays	-	-	-	▨	↥	↥	↥	-	-	-	-	-	-	-	-
	Events	-	-	-	-	▨	↥	↥	-	-	-	-	-	-	-	-
	Weather conditions	-	-	-	↥	↥	▨	-	-	↥	↥	↥	=	↥	↥	-
	Road works	-	-	-	↥	↥	-	▨	-	↥	↥	↥	↥	=	↥	-
	Unexplained variations	-	-	-	-	-	-	-	▨	-	-	-	-	-	-	-
Supply	Vehicle population	-	-	-	-	-	-	-	-	▨	↥	↥	↥	↥	-	-
	Driver population	-	-	-	-	-	-	-	-	↥	▨	↥	↥	↥	↥	-
	Darkness	-	-	-	-	-	-	-	-	↥	↥	▨	↥	↥	↥	-
	Weather conditions	-	-	-	↥	↥	=	-	-	↥	↥	↥	▨	↥	↥	-
	Road works	-	-	-	↥	↥	-	=	-	↥	↥	↥	↥	▨	↥	-
	Incidents	-	-	-	-	-	-	-	-	-	↥	↥	↥	↥	▨	-
	Randomness driving behavior	-	-	-	-	-	-	-	-	-	-	-	-	-	-	▨

t.b. = travel behavior
d.ow. = days of the week
p.o.y. = periods of the year

= = demand and supply variations with a common cause
- = no significant influence
↥ = influence obvious / not unlikely

2.2.4 *Predictabilities of influence factors*

For short term predictions, the predictabilities of the various influence factors need to be determined. For each influence factor the predictability will be discussed. Some of the factors may be about 100% predictable while others will have (much) higher uncertainties. For factors where no information is available at all, historical frequencies of occurrence can be used to determine probability.

1. Patterns in human travel behavior
There are numerous patterns in human travel behavior. In paragraph 2.2.1 three of them are identified: patterns over the day, over the days of the week and over the periods of the year. These patterns can vary for different locations and follow directly from measured flows. Therefore they can be predicted quite well. For both the pattern over the day as for the pattern over the week holds that these can be estimated from historical data for each day of the week.

There is also a variation in human travel behavior over the periods of the year. Vacation periods and public holidays play a large role in this. These periods will be discussed later in this subparagraph. Also seasonal effects are significant for the variations in travel behavior over the periods of the year. The effects of these will be discussed in the next subparagraph.

2. Variations in vehicle and driver population
Both vehicle and driver population influences the traffic conditions. In the vehicle population a clear distinction between passenger cars and freight traffic can be made. In contrast to commuting traffic, freight (and professional) traffic is generally evenly distributed over the time of day. Therefore the percentage of trucks is generally lower in peak periods. However, the predictability of the amount of trucks on the road is again location bound. Often a truck percentage of 15% of the total demand is assumed.

Not only different vehicle types can be found on the road, also different types of drivers can be identified. Of course every person is different, but people can be assigned to different driver classes. Examples of driver classes are experience, age, gender, trip-purpose, skills, risk-taking propensity etc. During the peak periods the vehicle population largely consists of commuters and other road users with profession related destinations. This is typically an experienced group of drivers. Outside the peak periods and especially during weekends, public holidays and vacation periods the share of social and recreational road users is relatively high. This group of drivers is typically less experienced.

3. Weather conditions
On a certain time instance the weather conditions can be predicted for the days of the next week. The KNMI (Koninklijk Nederlands Meteorologisch Instituut) does this continuously. The rain intensity as well as the chance on precipitation can be predicted (KNMI). Also warnings for extreme weather conditions such as fog, heavy wind or wintry precipitation like snow are provided.

When the effects of weather need to be predicted further in the future than for one week, historical averages can be used. Historical data for the years 1981-2010 is provided by KNMI (2011). With these frequencies of occurrence the probability of a certain weather conditions can be estimated for each type of weather condition.

Figure 2-22 shows the average number of days with precipitation. It is clear that the winter and autumn months contain more days with precipitation. However, in summer and autumn, most days with heavy rainfall is measured.

Figure 2-22: *Average monthly number of days with precipitation, based on data from KNMI (2011)*

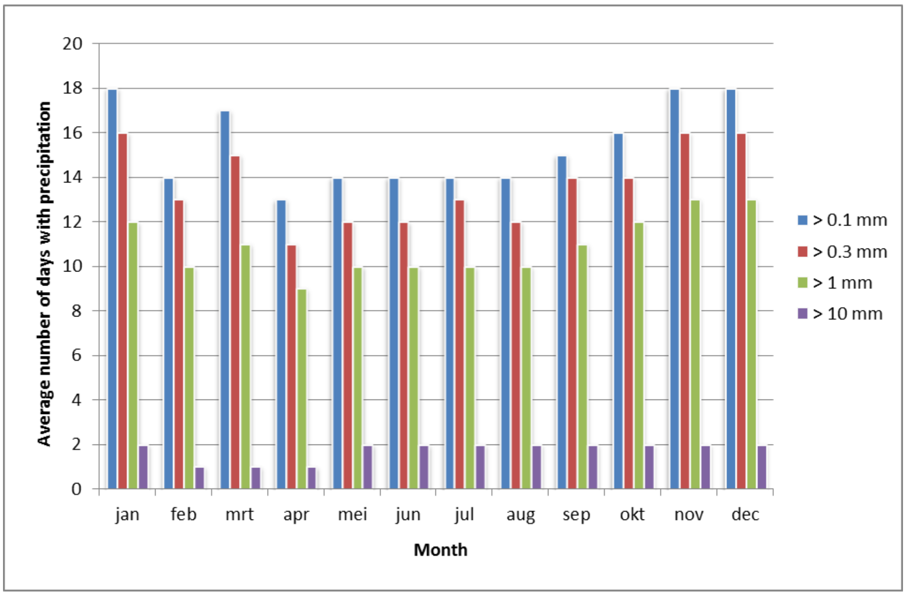


Figure 2-23 shows the average number of days with snow. Figure 2-24 shows the average number of days with fog. Figure 2-25 shows the average number of summery days. Summery days are defined as days with an average temperature over 20°C. With these graphs, the probabilities for weather conditions can be determined for each month. The effects of these weather conditions will be explained in the next subparagraph.

Figure 2-23: *Average monthly number of days with snow, based on data from KNMI (2011)*

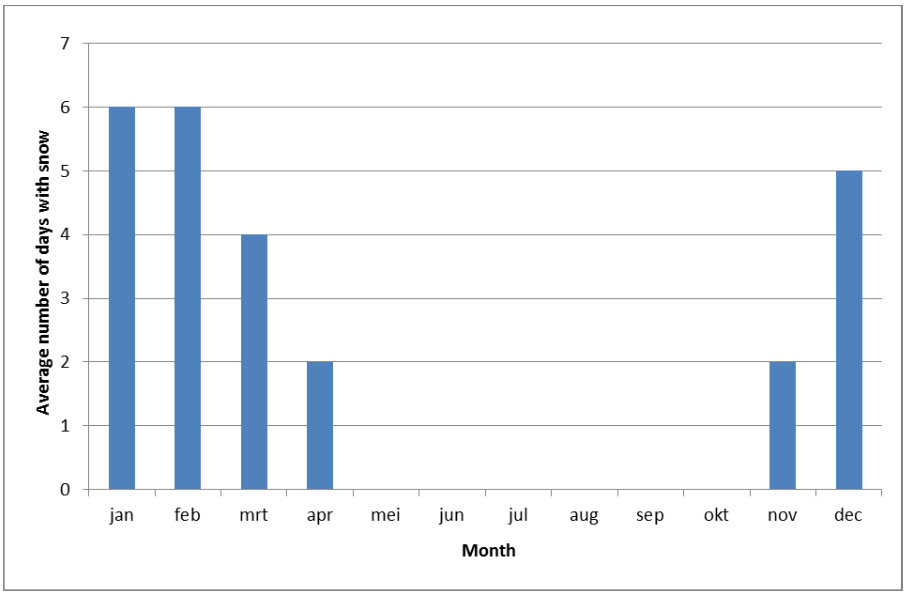


***Figure 2-24:** Average monthly number of days with fog, based on data from KNMI (2011)*

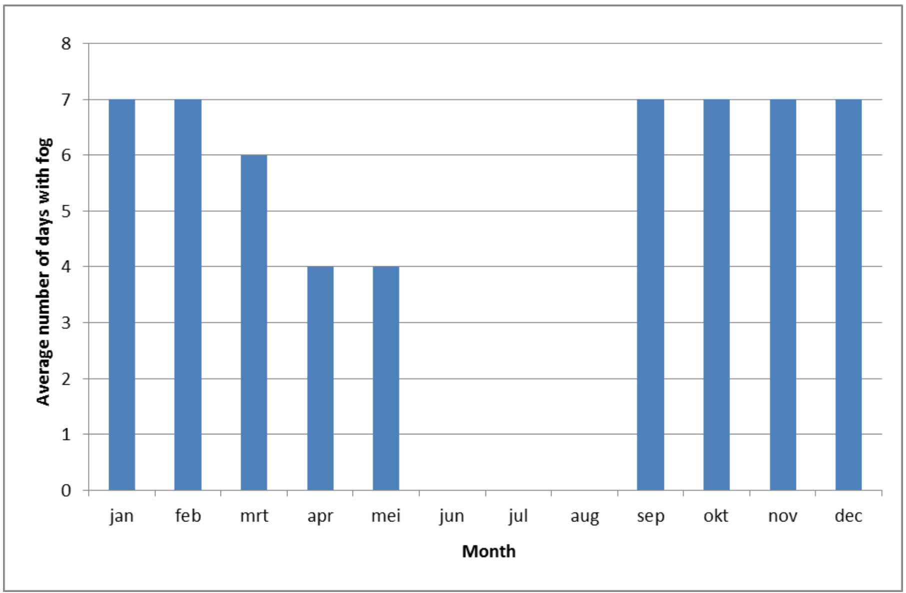


***Figure 2-25:** Average monthly number of summery days, based on data from KNMI (2011)*

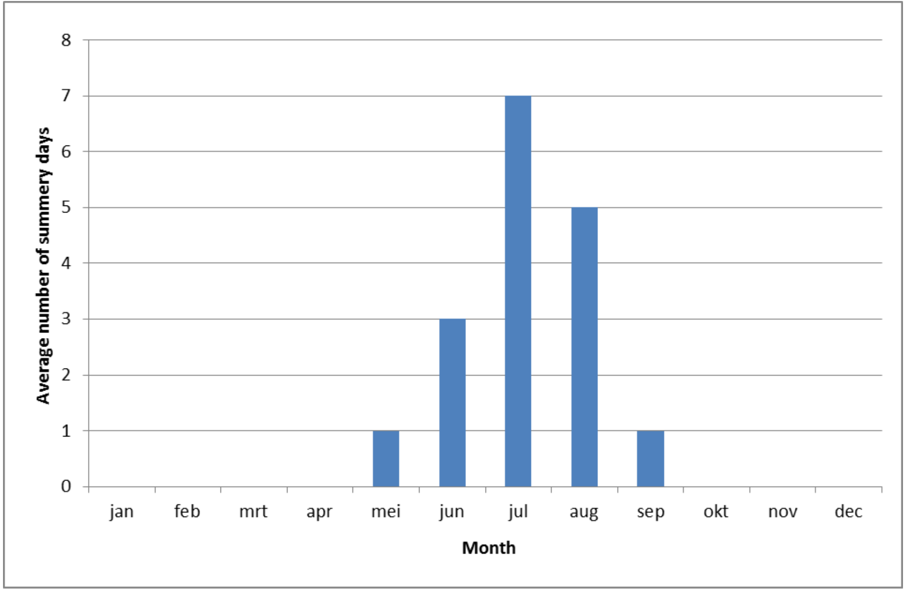
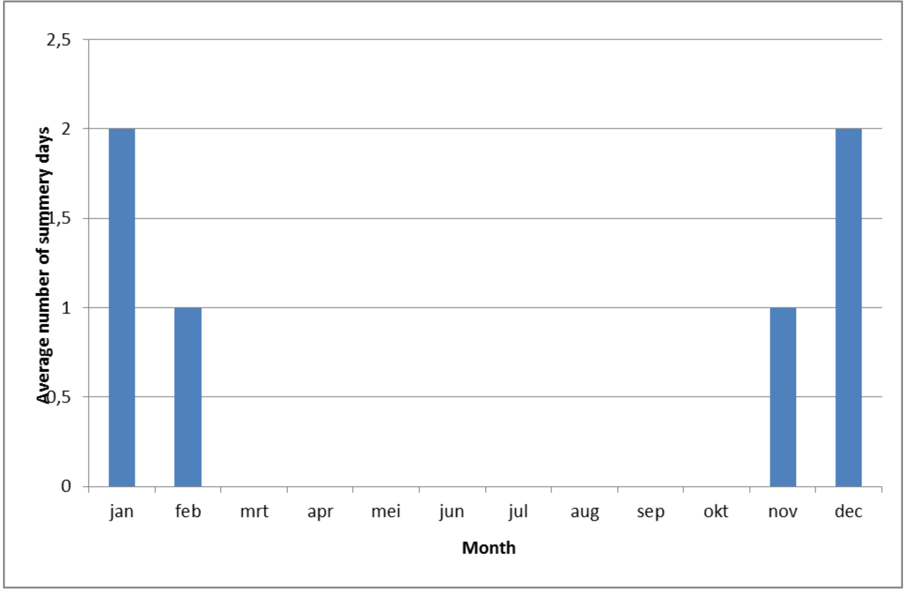


***Figure 2-26:** Average monthly number of days ice forming, based on data from KNMI (2002)*



4. Road works

For the Dutch motorway network, all planned road works are reported by Rijkswaterstaat. In this way, the location, start time and duration of road works is predictable. Most road works are carried out during the evening and night periods to minimize disturbances for road users. However, it is not always possible to avoid carrying out road works in peak periods. Some types of roadwork take long periods of time, while others are unplanned like for example emergency repairs.

To be able to predict the occurrence of road works, historical data could be used. This is especially the case, when no information is available. However, as there is information available about planned road works on a certain road stretch in most cases, these can be very well predicted. Although there might be a chance on unforeseen road works. It is also possible that a certain road work is cancelled. This probability can possibly be determined from historical data, or some assumption has to be made.

5. Events

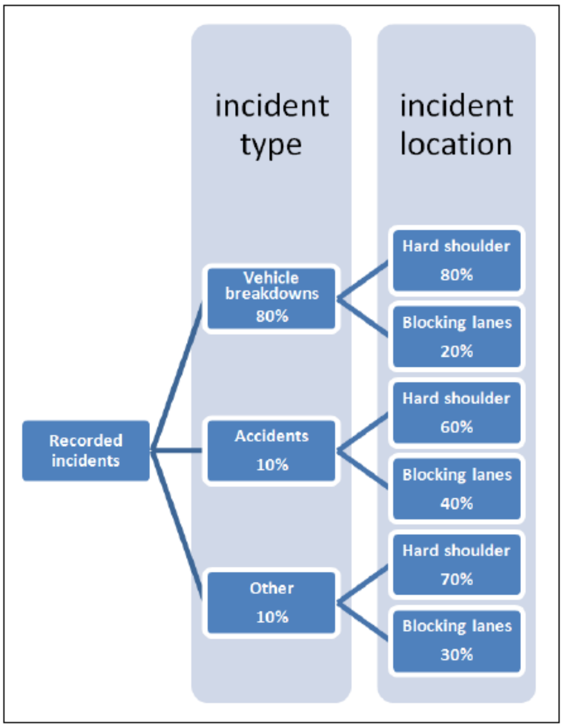
Events are relatively easy to predict, in most cases they are planned in advance. Especially the occurrence of large events are generally well known in advance. Relatively small events might be more difficult to predict, but their effects on traffic supply or demand are equivalently small.
It is also possible that an event is cancelled under certain circumstances. Especially for outdoor events, adverse weather conditions may play a large role in this. Predicting the occurrence of events is also a very location related task and it is therefore rather difficult to say something general about the frequencies of events.

6. Incidents

Incidents are defined as unpredictable short-term events that cause large reduction in available road capacity and vehicle speeds.

Many types of incidents can occur, but in this thesis only two kinds of road incidents are considered: vehicle breakdowns and accidents. Vehicle breakdowns are most common and usually only block the hard shoulder, while the effects of accidents are usually much larger in magnitude. Figure 2-27 shows the relative frequencies of occurrence of incident categories used by Miete (2011).

Figure 2-27: *Relative frequencies of occurrence of incident categories (Farradyne, 2000)*



This figure clearly shows that accidents occur less frequent than vehicle breakdowns, but have a higher probability of blocking lanes. Obviously, the predictability of traffic incidents is very limited and dependent on numerous factors. Paragraph 2.2.3 already stated that road works, driver and vehicle population and weather conditions influence the occurrence of incidents. This is however especially the case for accidents. The geometrical properties of road sections also are an important factor for the occurrence of accidents. Accidents mainly occur at road sections with an on or off ramp, at weaving sections and at sections on which one of the lanes ends (Kraaijeveld, 2008).

According to SWOV (2009) the crash or accident rate doubles during rain. For the Dutch state highways rainy conditions are reported to result in an increase in the number of accidents of between 25% and 182%. Black ice on the road surface results in an even larger increase: between 77% and 245%. The frequency of occurrence of ice forming can be found in Figure 2-26. The effect of snow is arbitrary, SWOV refers to a study in which it was concluded that snow seems to slightly lower the crash rate, because drivers overcompensate. While other studies are available that conclude that snowy weather increases the crash rate. For the Dutch situation the lower crash rate seems more plausible, because snowfall occurrence is very limited.

The presence of road works can influence the probability of an incident as well. Road works are associated with discontinuities in the road geometry, lane width reductions and distraction due to the road work activities.

It is also known that accident rates are high for high, free flow traffic volumes, but also for very low traffic volumes. The first is quite logical since the probability of traffic interacting increases with traffic volume. The latter might however be more surprising. An explanation for this is that mutual speed differences are relatively large and low traffic volumes typically occur during night time. This automatically leads to a connection between driver population and luminance. In darkness the accident rate is expected to be higher, while the driver population during night times might be less experienced. It is therefore unclear which factor or what combination of them is responsible for the increased accident rate.

When congestion occurs the accident rate can be influenced in both directions. Lower speeds may result in a decrease of the accident rate, but shockwaves might cause an increase of the accident rate. Which of these is dominant, or if they compensate each other, is not known from literature.

Because of the fact that many factors influence the occurrence of incidents, they are very hard to predict. To best way to predict the occurrence of an incident on a certain road stretch is probably to take all above mentioned factors into account in combination with the incident history of this specific road stretch. A more general value for predicting incidents is by taking a probability of incidents over a certain number of vehicle kilometers. Miete (2011) used a probability of 1.5e-6 for the number of breakdowns per vehicle kilometer and 0.5e-6 for the number of accidents per vehicle kilometer.

7. Traffic control actions

Rush-hour lane and dynamic speeds limits are the clearest examples of traffic control actions. The predictabilities of such actions are high, provided that the algorithms or schedules on which they operate are known. If a single road stretch is considered, the occurrence of traffic control actions is obviously completely dependent on whether a rush-hour lane or a dynamic speed limit is available on this road stretch. The predictability of the opening of a rush-hour lane is also dependent on weather conditions and occurrence of an incident.

Other forms of traffic control actions include incident management and mobility management. The effects of these will be discussed in the corresponding subparagraphs in the next paragraph.

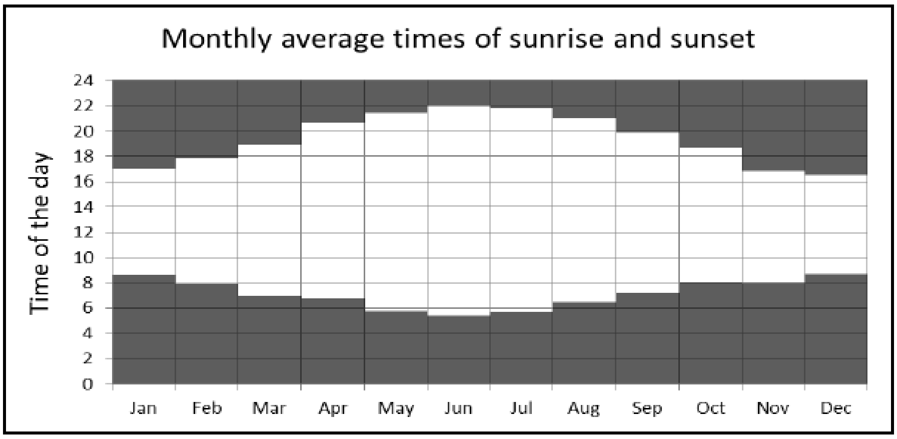
8. public holidays and vacation periods

Of course public holidays and vacation periods are 100% predictable, since they are planned in advance. For example the public holidays in the Netherlands are: New Year’s Day, Good Friday, Easter Sunday and Easter Monday, Queen’s Day, National Remembrance Day, Liberation Day, Ascension Day, Whit (Pentecost) Sunday and Whit (Pentecost) Monday, Christmas Day and Boxing Day. In the Netherlands vacation periods are: Spring break, May Holiday, Summer Holiday, Autumn Holiday and Christmas break.

9. Luminance

Luminance varies constantly over time, but the average times of sunrise and sunset can be used to distinguish light from dark. Figure 2-28 shows the monthly average times of sunrise and sunset for the Dutch situation.

Figure 2-28: Monthly average times of sunrise and sunset (Miete, 2011)



2.2.5 *Effects of influence factors*

This subparagraph discusses the effects of all identified influence factors on traffic demand and supply. Also the effects of the occurrence of factors on other factors will be discussed here.

1. Patterns in human travel behavior
From the patterns in human travel behavior, basic traffic demand is derived. There is a clear relation between the time of day, the day of the week and the time of the year and traffic demand. The effects of human travel behavior on traffic demand follow from peoples activities. Therefore during nighttime traffic demand is very low. In weekdays two clear peaks can be observed traffic demand. This is related to commuters traveling from home to work and back. In the weekends clear peaks are often lacking. But not only weekend and weekdays differ significantly. The days over the week are mutually divergent as well. For example the evening peak on Friday starts much earlier than on other days and also lasts longer. For each day of the week a different pattern can be estimated by analyzing historical data. These patterns are also very location specific.

Also patterns in human travel behavior of the periods of the year can be identified. Vacation periods play an large role in this, especially in the peaks the demand is lower during these periods. While at the start and end of vacation periods extra demand might occur due to people leaving or coming home from a holiday. However to determine these effects for a certain road stretch, data analysis has to be performed.

To deal with the vacation and other seasonal effects on traffic demand, quantitative data provided by Hilbers, Eck et al. (2004) can be used. Figure 2-29 shows these effects on the working day peak period traffic demand. Figure 2-30 shows these effects on the working day off-peak period traffic demand. These figures clearly show that the peak periods in the summer months are relatively small.

Figure 2-29: *Vacation effects and other seasonal effects on the working day peak period traffic demand (average working day peak period traffic demand = 1) (Hilbers, Eck et al., 2004)*

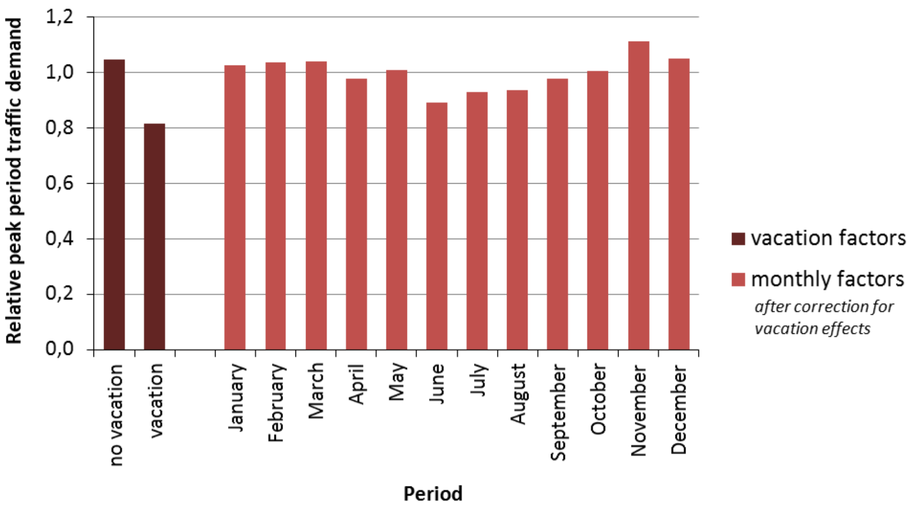
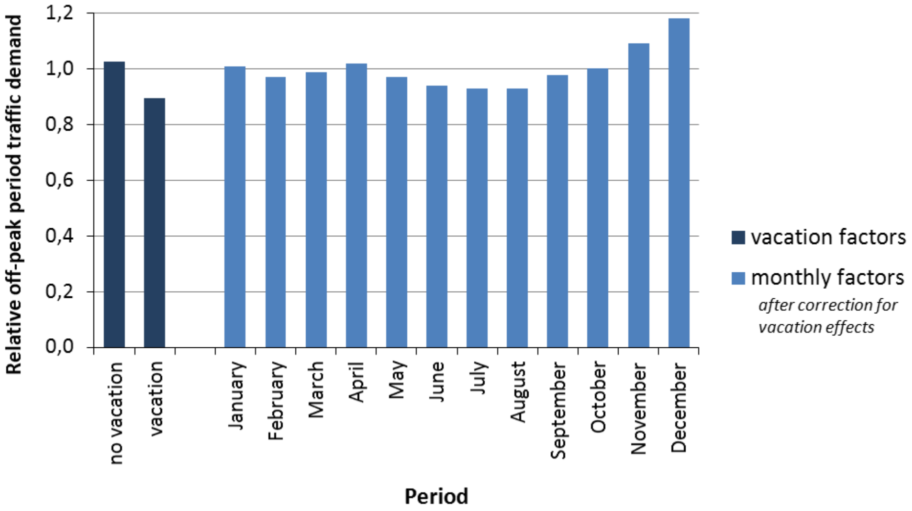


Figure 2-30: *Vacation effects and other seasonal effects on the working day off-peak period traffic demand (average working day peak period traffic demand = 1) (Hilbers, Eck et al., 2004)*



2. Variations in vehicle and driver population

For the variation in vehicle population a distinction between passenger cars and trucks is made. Characteristics for trucks are relatively low speeds and low acceleration rates. This has a negative effect on traffic supply. Since the speed limit for trucks is 80 km/h, the average speed decreases as the percentage trucks increases. This is not only due to the lower speeds of the trucks themselves, but also because trucks will slow passenger cars down. This effect increases for large traffic densities. Trucks also have a negative effect on the free flow capacity. A truck consumes more of the available capacity than a passenger car. The capacity expressed in vehicles per hour consequently decreases as the truck volume increases. This variation in capacity can be dealt with by applying a conversion factor: passenger car equivalents. For trucks a value of 1.5 is often used in the Netherlands. The effect of trucks on the queue discharge capacity is found to be even bigger (Al-Kaisy, Hall et al., 2002). An explanation for this is the lower acceleration rates of trucks. Mean conversion factors of 2.4 to 3.2 were found. The difference in the effect free flow capacity and queue discharge rate may explain the capacity drop phenomenon discussed in paragraph 2.1.

Different drivers behave differently in terms of desired free speed, lane changing, predecessor following etc. These characteristics directly affect traffic supply, as was already explained in paragraph 2.1. Subparagraph 2.2.4 already stated that there are different user-classes and that a clear distinction can be made between peak and off-peak drivers. The more experienced drivers in the peak periods ensure that the available capacity is used to a maximum extent. A group of less experienced drivers might cause congestion at smaller densities. In Table 2-1 correction factors on the critical density are shown that have been used by Miete (2011).

***Table 2-1:** Correction factors for free flow capacities used by Miete (2011)*

Peak drivers population	1,00
Off-peak drivers population	0,96
Saturday drivers population	0,94
Sunday drivers population	0,92

3. Weather conditions

As stated before, weather conditions can both influence the traffic supply as the traffic demand. Adverse weather conditions (rain, snow, black ice, fog) may reduce driving speeds and road capacity. The traffic demand can be affected by adverse weather conditions in two opposing ways. There might be a modal shift from modes that are characterized by a larger exposure to the weather, but road users might also decide not to take a certain trip. The latter is likely to occur caused by extreme weather conditions such as heavy snowfall. The size of the effect on traffic demand also depends on the trip purposes. Commuter traffic tends to be less flexible and thus sensitive to adverse weather conditions than traffic with leisure destinations. The effect of adverse weather conditions on route choices is likely to be rather limited. Road users do have a higher propensity to change their departure time.

Besides adverse weather conditions, beautiful weather conditions can affect traffic demand as well. Outdoor events or other recreational area’s will attract more visitors, which results in an increase of traffic demand. The quantitative effects of these weather conditions are however location bound and cannot be generally quantified.

The effects of adverse weather conditions on traffic supply can be of great magnitude. Snow and black ice can result in a slippery road surface. Rain might cause a similar but smaller effect. Fog and any kind of precipitation can reduce the visibility. Low sun could reduce the visibility as well. Drivers deal with these effects by reducing their speeds and keeping more distance to their predecessor. This results in lower capacities. Capacity may also be lowered due to a reduction of available lanes. This will especially be the case with extreme weather conditions. The magnitude of the effect on traffic supply depends on the type of weather conditions and their intensity, but also the road surface and the spatial scale of the weather conditions have a significant effect. Another factor that should be taken into account is that on roads with a rush-hour lane, weather conditions might also affect the capacity by prohibiting the opining of this lane. Before opening such a lane, cameras are used to verify if the lane is cleared from obstacles. For example reduced visibility could make this verification impossible.

Quantitative effects of rain

A lot of research has been done to quantify the effects of rain on traffic supply. Table 2-2 shows an overview of the discovered quantitative effects of rain on road capacity.

Table 2-2: *Quantitative effects of rain on capacity, derived from Miete (2011)*

Source and location	Rain intensity (mm/h)	Capacity reduction
Smith et al (2003), Virginia	0.25 - 6.35	4%-10%
	> 6.35	25%-30%
Agarwal et al (2005), Minneapolis & St. Paul	0.25 - 6.35	5% - 10%
	> 6.35	10% - 17%
Hranac et al (2006), Seattle, Baltimore, Minneapolis-St. Paul	0 - 17	10% - 11%
Chung et al (2005), Tokyo	1	4% - 7%
	10-20	8% - 14%

It has also been found that rainfall reduces the vehicle speed. An overview of the discovered quantitative effects of rain on free speeds and speeds-at-capacity are shown in Table 2-3.

Table 2-3: *Quantitative effects of rain on vehicle speeds, derived from Miete (2011)*

Source and location	Rain intensity	Free speed reduction	Speed-at-capacity reduction
Brilon and Ponzlet (1996), Germany	“rainy weather”	9.5 km/h (2 lanes) 12 km/h (3 lanes)	-
Hogema (1996), Dutch A16	“rainy weather”	11 km/h	-
Smith et al (2003), Virginia / Agarwal et al (2005), Minneapolis & St. Paul	“Both light and heavy rain”	5% - 6.5%	-
Hranac et al (2006), Seattle, Baltimore, Minneapolis-St. Paul	< 0.1 mm/h	2%-3.6%	8%-10%
	± 16 mm/h	6%-9%	8%-14%
Chung et al (2005), Tokyo	0 - 1 mm/h	4.5%	-
	5 - 10 mm/h	8.2%	-

The quantitative effect of rain on traffic demand has a strong correlation with trip purposes and can therefore not be generally described here. It can however be said that the effect of rain on commuter traffic is negligible.

Quantitative effects of snow

Obviously, snow can have major undesirable effects on traffic supply. This concerns both capacity as uncongested speed. The quantity of the effect is however dependent on the snowfall rate, on the form in falls in and to what extent the road is cleared by authorities. Table 2-4 shows capacity and uncongested speed reduction factors for different snowfall rates.

Table 2-4: *Quantitative effects of snow on traffic supply (Agarwal, Maze et al., 2005)*

Snowfall rate (mm/h)	Capacity reduction	Uncongested speed reduction
0 - 1.3	3% - 5%	3% - 5%
1.5 - 12.7	6% - 13%	7% - 10%
> 12.7	19% - 27%	11% - 15%

Another study however revealed different results. These are presented in Table 2-5. Remarkably, they found that the capacity reduction is not dependent on the snow intensity and that the reductions in speed typically increase with snow intensity.

Table 2-5: *Quantitative effects of snow on traffic supply (Hranac, Sterzin et al., 2006)*

Snowfall rate (mm/h)	Capacity reduction	Uncongested speed reduction
0.1	12% - 20%	5% - 16%
3		5% - 19%

Quantitative effects of other weather conditions

For reduced visibility conditions due to fog events, the capacity and speed reductions are presented in

Table 2-6: *Quantitative effects of fog on traffic supply (Agarwal, Maze et al., 2005)*

Visibility (km)	Capacity reduction	Uncongested speed reduction
< 0.4	10% - 12%	12%
0.4 – 1.6		7%

For the effects of temperature and wind in the opposite direction of travel no significant effects were found. For the effects of low sun conditions on capacity and operating speeds, little literature is available.

4. Road works

Road works has both a significant influence on traffic supply as on traffic demand. Both will be described here.

The presence of road works usually result in a reduction of the traffic demand for the road sections in question. If the road works have been announced, part of the road users might divert from their usual behavior. These drivers might take another route, change their departure time, change transport mode, change their destination or even cancel their trip. Road authorities might also use demand management to stimulate road users to avoid the affected road sections. Examples of this are rewarding systems and temporary reductions on public transport fares. The most drastic measure is the closure of on- and off-ramps in the work zone. When road works lasts for several days, the same change in behavior can follow from personal experience. Another source of information can be traffic information received before departure or during the trip, possibly reporting traffic congestion.

The magnitude of the effect on traffic demand depends on the specific situation (i.e. the remaining capacity, relative to the traffic demand under normal circumstances; the duration of the road works; the availability of alternative travel options; the traffic and demand management measures taken by the road authority; etc.). However, a rule of thumb for road works on major roads is that the traffic volume is reduced by half. One half of this reduction is due to road users diverting to parallel roads. Usually it remains unclear where the other half went. For small road works this effect will be much smaller, if not negligible.

The effect of road works on traffic supply strongly depends on the type of road work. Road works affect the traffic supply in two ways, i.e. a temporarily lowered speed limit over the length of the work zone and a reduction in capacity due to a reduction in the number of available lanes and less efficient use of the (remaining) lanes. Table 2-7, Table 2-8 and Table 2-9 show the effects for the most common road work lay-outs. These capacities are based on model studies in combination with empirical research.

Table 2-7: *Work zone capacity – road with two lanes (DVS, 2011)*

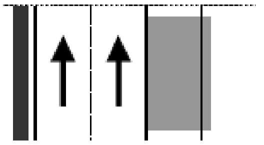
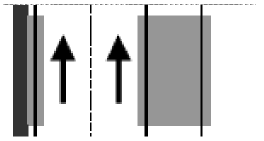
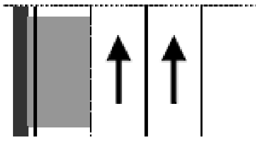
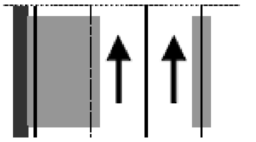
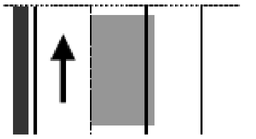
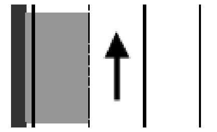
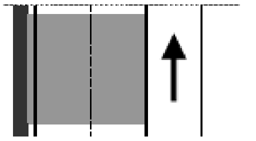
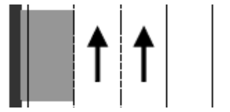
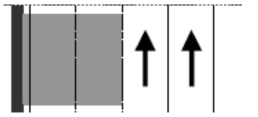
Work zone lay-out	Description	Capacity
	closure of hard shoulder - without lane narrowing, v = 90 km/h	3.600
	closure of hard shoulder - With lane narrowing: left 2,75 m, right 3,00 m v = 70 km/h	3.200
	closure of left lane with usage of hard shoulder - without lane narrowing, v = 90 km/h	3.400
	closure of left lane with usage of hard shoulder - staggered driving. left 1,95 m, right 2,85 m v = 70 km/h - left 2,50 m, right 3,00 m, v = 70 km/h	2.600 3.000
	- closure of right lane, v = 90 km/h - ditto, short-term static and dynamic deposition v = 70 or 90 km/h	1.500 1.100
	- closure of left lane, v= 90 km/h - ditto, short-term static and dynamic deposition v = 70 or 90 km/h	1.500 1.200
	- closure of two lanes with usage of hard shoulder v = 90 km/h - ditto, short-term static and dynamic deposition v = 70 or 90 km/h	1.300 1.000

Table 2-8: *Work zone capacity – road with three lanes (DVS, 2011)*

Work zone lay-out	Description	Capacity
	closure of left lane - without lane narrowing v = 90 km/h	3.600
	closure of two lanes with usage of hard shoulder - without lane narrowing, v = 90 km/h	3.200

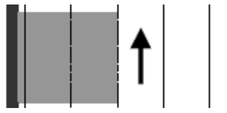
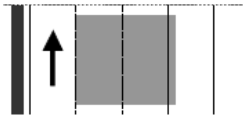
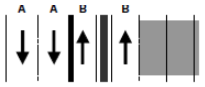
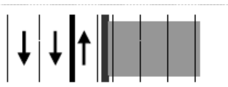
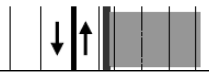
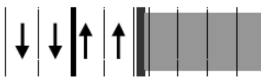
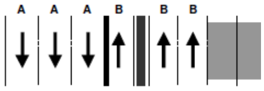
	- closure of two left lanes, v = 90 km/h - ditto, short-term static and dynamic deposition v = 70 or 90 km/h	1.500 1.200
	- closure of two right lanes, v = 90 km/h - ditto, short-term static and dynamic deposition v = 70 or 90 km/h	1.500 1.100

Table 2-9: *Work zone capacity – systems (DVS, 2011)*

Work zone lay-out	Description	Capacity
	3 – 1 lane shift system - direction A without lane division, left 3,00 m, right 3,25 m, v = 90 km/h - direction B with lane division, left 3,00 m, right 3,25 m, v = 90 km/h	3.400 3.000
	3 – 0 lane shift system - direction A with two lanes, left 3,00 m, right 3,25 m, v = 90 km/h - direction B with one lane 3,25 m, v= 90 km/h	3.400 1.500
	2 – 0 lane shift system - both directions 3,25 m, v = 90 km/h	1.500
	4 – 0 lane shift system - staggered driving left 1,95 m, right 2,85 m v = 90 km/h - left 2,35 m, right 2,85 m, v = 70 km/h - left 2,50 m, right 3,00 m, v = 70 km/h - left 3,00 m, right 3,25 m, v = 90 km/h	2.600 2.800 3.000 3.400
	4 – 2 lane shift system - direction A without lane division 2,80 m, 2,80 m, 3,25 m, v = 90 km/h - direction B with lane division 3,00 m, 2,80 m and 3,00 m, v = 90 km/h	4.500 4.300

The most important variables that have an influence on road work capacity are listed in Table 2-10.

Table 2-10: *Most important freeway work zone variables (Homan, 2012)*

Day of week	Road grade
Distance to ramps	Temporary speed limit
Time of day	Percentage of heavy vehicles
Duration	Type of separation barrier
Length of work zone	Visibility of work
Lane narrowing	Weather conditions
Work zone location	

Some of these are already considered a source of variation separately. Based on some of the remaining variables, it is possible to determine capacity with a capacity reduction function. The following equation was proposed by Calvert (2009):

Equation 2-15

$$C_{RW} = (Cap - V_{Lat}) \cdot f_{LC} \cdot f_{OC} \cdot f_{LW} \cdot f_{RC} \cdot f_{HGV} \cdot f_{WA}$$

The values that each parameter can take are shown in Table 2-11.

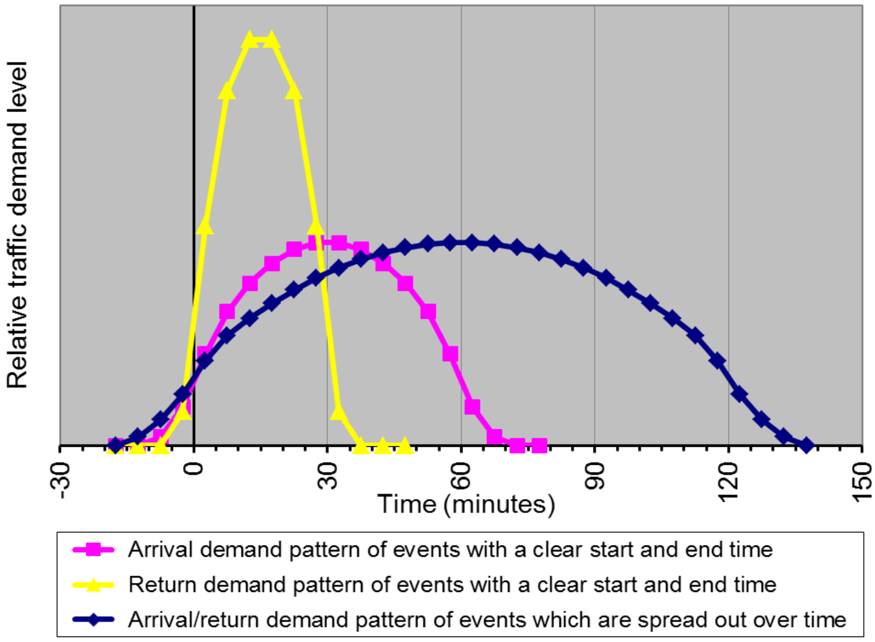
__Table 2-11:__ Reduced capacity function parameters (Calvert, 2009)

Factor		Chosen Relation (default value)
Lane Closure	f_{LC}	0.95 per closed lane
Use of opposite carriageway	f_{OC}	0.9 for 2&3-lanes switchover 0.93 for 2/3-lane switchover 0.95 for 1/2-lane & 1/3 switchover
Lane width reduction	f_{LW}	0.9 for 2.75m 0.95 for 3m 0.98 for 3.25m
Lateral clearance	V_{Lat}	100veh for <0.3m 50veh for 0.3m
Traffic composition	f_{TC}	1.0 peak hours 0.95 non-peak/rural 0.9 weekend/vacation
HGV (Heave Goods Vehicles)	f_{HGV}	$f_{HGV} = \frac{1}{(1-P_{HV})+P_{HV}\cdot PCE}$
Extent of work activity	f_{WA}	0.94 – 1.0, default = 0.98

5. Events

Events cause temporal peaks in demand. For each specific event these peaks can be of different form and size. A distinction can be made between events with and without a specific start and end time. In the last case the assumed traffic demand over the routes will be more spread over the time of day. The arrival and especially the return pattern generated by events with a well-defined start and end time will be more peaked of nature. Figure 2-31 shows the relative traffic demand level used by Miete (2011).

__Figure 2-31:__ Relative traffic demand level used by Miete (2011)



Another important aspect in relation to events is the influence of weather conditions. This interdependency has already been noted in paragraph 2.2.3. In case of adverse weather conditions, the demand generated by events will be lower. This is especially the case with outdoor events. Events were tickets are needed might be less sensitive to adverse weather conditions.

6. Incidents

Incidents cause capacity reductions and/or reduce the traffic speed, during a certain amount of time. Obviously incidents can physically affect the available capacity by blocking one or more lanes. Even though an incident might not block a lane, the capacity on it is still reduced. This is the result of driving behavior being different than during normal conditions. Probably this change in behavior can be attributed to the fact that incidents divert drivers' attention away from the driving task. Table 2-12 shows the fraction of freeway capacity available under incident conditions. It should be noted that these numbers are found in the United States and a more encompassing definition of 'incidents' is used here.

***Table 2-12:** Fraction of freeway capacity available under incident conditions (Farradyne, 2000)*

Number of freeway lanes in each direction	Shoulder disablement	Shoulder accident	Lanes blocked		
			One	Two	Three
2	0.95	0.81	0.35	0.00	N/A
3	0.99	0.83	0.49	0.17	0.00
4	0.99	0.85	0.58	0.25	0.13
5	0.99	0.87	0.65	0.40	0.20
6	0.99	0.89	0.71	0.50	0.25
7	0.99	0.91	0.75	0.57	0.36
8	0.99	0.93	0.78	0.63	0.41

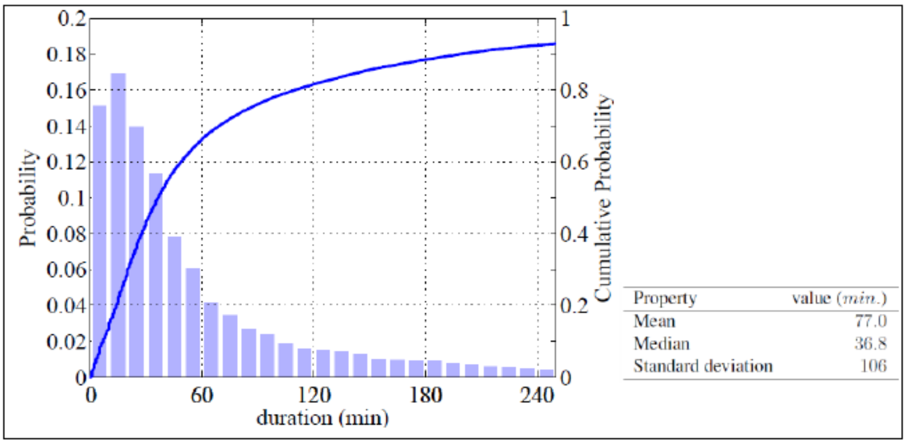
Table 2-13 shows the results of another research. These results are obtained from Dutch empirical data. The reductions found are the combined result of a reduction in the number of available lanes and a less efficient use of the remaining lanes. In both tables the results are queue discharge rates.

***Table 2-13:** Remaining capacities under incident conditions (Knoop, 2009)*

Incident type	Broken down vehicle on hard shoulder	1 out of 3 lanes blocked	2 out of 3 lanes blocked	Incident on roadway in opposite direction
Mean value of the capacity factor (between brackets: standard deviation)	0.72 (0.09)	0.36 (0.14)	0.18 (0.12)	0.69 (0.08
Efficiency use of remaining lanes	0.72	0.54	0.54	0.69

Besides the magnitude of the effect of the incident, the duration is of importance too. Figure 2-32 shows the empirical probability distribution of the duration of incidents on the Dutch motorway network.

Figure 2-32: *Distribution of incident duration (Knoop, 2009)*



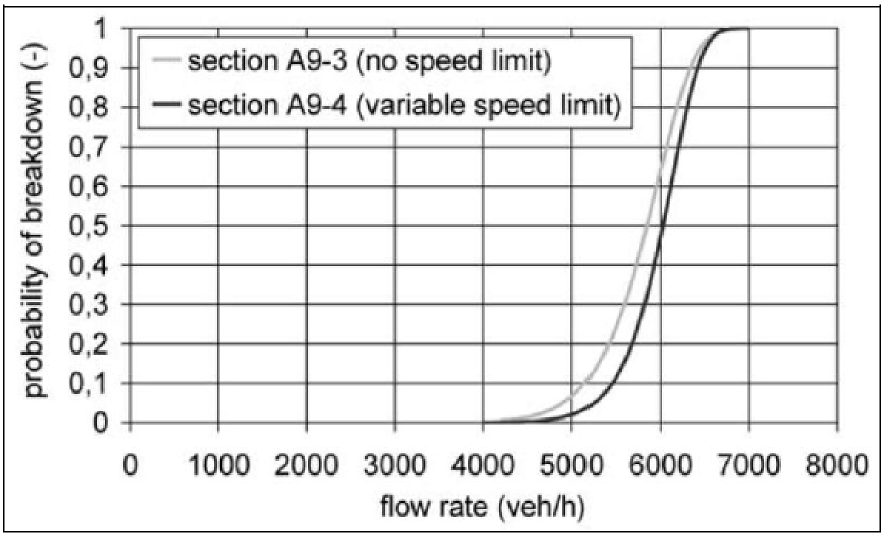
Property	value (*min.*)
Mean	77.0
Median	36.8
Standard deviation	106

The distribution is very skewed, fifty percent of all incidents are cleared in 37 minutes or less, but some incidents have a very long duration. About 8% of the incidents take longer than four hours. The duration of incidents is attempted to be minimized by incident management. However, no literature was found on the success rate of the taken measures.

7. Traffic control actions

It was already stated that rush-hour lanes and dynamic speed limits are predictable to a large extent. The effect of the first is a very clear one too. A rush-hour lane clearly has a direct effect on the traffic supply. If an extra lane is opened, extra capacity is available. Dynamic speed limits dynamically affect the speeds at roads. Figure 2-33 shows that variable speed limits might reduce the variability in capacity.

Figure 2-33: *Capacity distributions for 3-lane freeway sections with and without a variable speed limit (Brilon, Geistefeldt et al., 2005)*



8. Public holidays and vacation periods

Public holidays and vacation periods directly influence traffic demand, since the activity patterns of people differ from the 'normal' situation. On public holidays the usual peaks in traffic demand are less pronounced or even absent. In the case that a public holiday falls on a Tuesday or a Thursday, many people take the preceding Monday or following Friday off as well. However, on certain parts of the network the traffic demand might be higher due to recreational activities.

In vacation periods traffic demand is also lower, which is also most apparent in the peak periods due to the absence of commuting traffic. At the start and end of these vacation periods, peaks in demand can be identified due to leaving and returning vacation traffic. These peaks in demand are however location bound. The general effects of vacation on traffic demand have also been explained in 1. Patterns in human travel behavior, in the first part of this subparagraph.

9. Luminance

The effects of luminance on traffic supply are not trivial. For dark conditions a 1.5% reduction is used on the free flow capacity and the queue discharge rate by Miete (2011). Any possible effects on the free speeds are neglected.

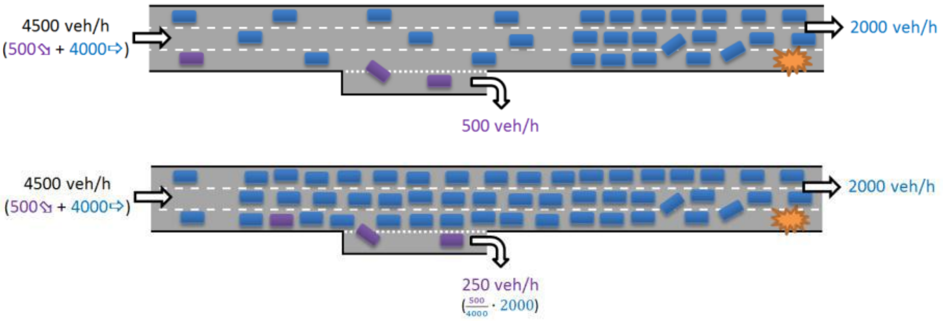
2.2.6 Network effects

Aside from all factors discussed so far, there are also strong spatiotemporal dependencies between traffic conditions on the various sections of a road. These will be discussed here.

Blocking back

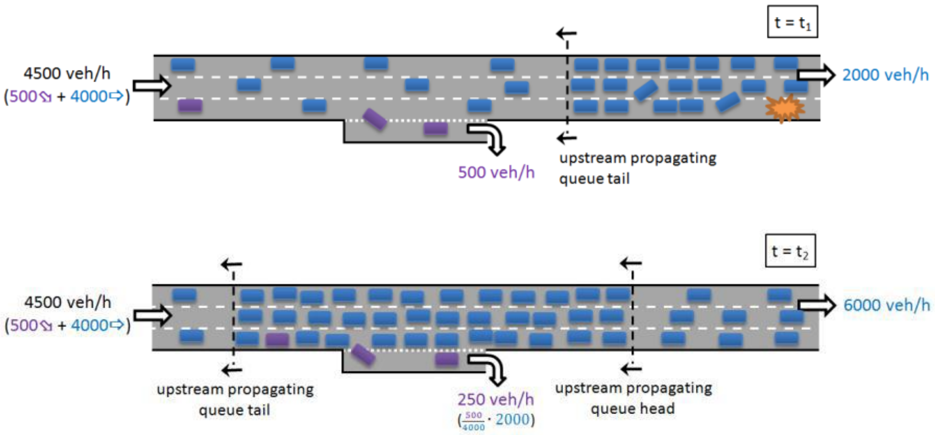
A traffic jam created by a certain bottleneck might block other traffic streams that might not even want to pass the bottleneck location. This is illustrated in Figure 2-34.

Figure 2-34: *Blocking back of a queue to an upstream off-ramp (Miete, 2011)*


4500 veh/h
(500 + 4000)
2000 veh/h
500 veh/h
4500 veh/h
(500 + 4000)
2000 veh/h
250 veh/h
($\frac{500}{4000}$ · 2000)

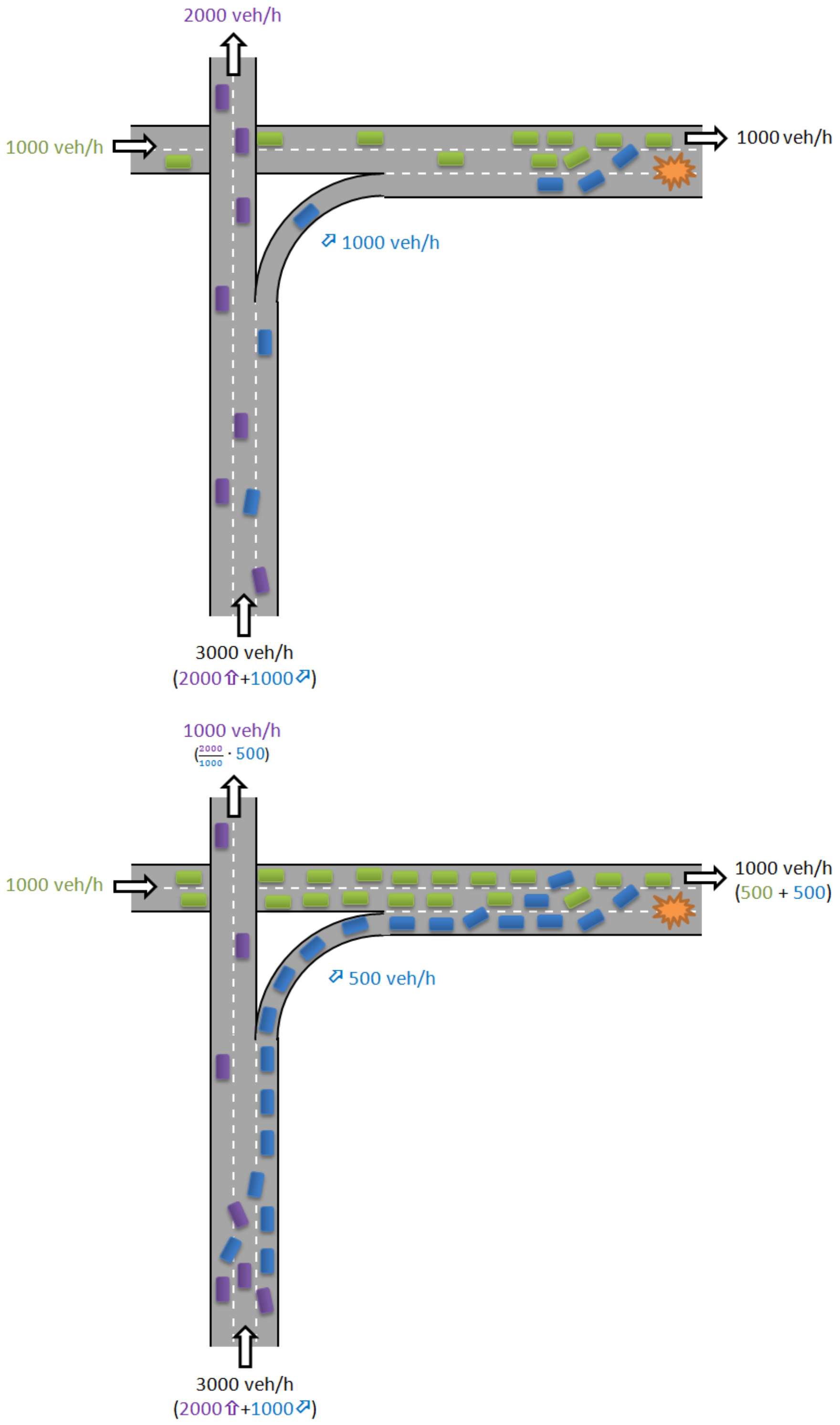
The length of the queue does not need to have a length greater than or equal to the distance between the bottleneck location and the off-ramp. The queue might travel upstream, this is illustrated in Figure 2-35.

Figure 2-35: *Blocking back of an upstream traveling queue to an upstream off-ramp (Miete, 2011)*


t = t$_1$
4500 veh/h
(500 + 4000)
2000 veh/h
500 veh/h
upstream propagating queue tail
t = t$_2$
4500 veh/h
(500 + 4000)
6000 veh/h
upstream propagating queue tail
250 veh/h
($\frac{500}{4000}$ · 2000)
upstream propagating queue head

This phenomenon of blocking back can also occur from one road to another. This is illustrated in Figure 2-36. The amount of traffic blocked by traffic spilling back is often much larger than the amount of traffic willing to take an off-ramp. Therefore the situation presented in Figure 2-36 is actually much worse than the situation in Figure 2-35.

Figure 2-36: *Blocking back of a queue to another road (Miete, 2011)*


2000 veh/h
1000 veh/h
1000 veh/h
1000 veh/h
3000 veh/h
(2000⇧+1000⬀)
1000 veh/h
(2000/1000 · 500)
1000 veh/h
1000 veh/h
(500 + 500)
500 veh/h
3000 veh/h
(2000⇧+1000⬀)

Temporal redistribution effect (filtering and releasing)

The temporal redistribution effect can have a negative or a positive effect on the traffic conditions. Figure 2-37 shows the positive, filtering effect. The situation at the upper part of the figure shows bottleneck location with recurring congestion. The lower part of the figure shows what happens if the capacity upstream of the usual bottleneck is reduced. Due to the throughput limitation at the upstream capacity reduction, the recurrent congestion at the usual bottleneck location does not manifest itself.

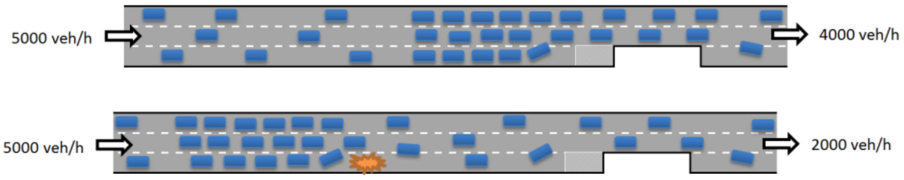


Figure 2-37: *Positive influence of traffic congestion on downstream traffic conditions (filter effect) (Miete, 2011)*

Figure 2-38 explains the release effect. In the figure again a road stretch with a bottleneck is shown. However, the bottlenecks capacity is sufficient in most cases and does not cause recurrent congestion. The middle part shows again a reduction in capacity at a location just upstream of the bottleneck. A queue starts to grow at this location. Downstream of the capacity reduction the traffic is still freely flowing. At a certain moment the capacity reduction disappears (e.g. an incident is cleared). At this point the queue is 'released'. The 'released' traffic stream is too large for the usual bottleneck and a queue starts to grow at this location as well. This negative effect is known as the release effect.

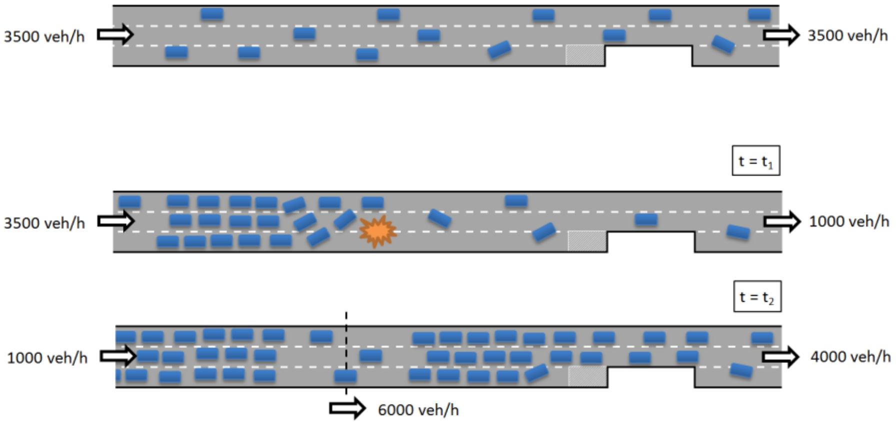


Figure 2-38: *Negative influence of traffic congestion on downstream traffic conditions (release effect) (Miete, 2011)*

Route choice effect

The effect of route choice on traffic conditions is significant, but not arbitrary. If the traffic conditions are considered 'normal', most drivers will stick to their standard routes. However, when the traffic conditions on a certain location in the network are significantly worse, drivers might deviate from their standard routes. The amount of diverting traffic is dependent on a number of factors:

- the existence and quality of alternative routes;
- knowledge about these alternative routes;
- knowledge about the traffic conditions on the 'standard' routes;
- the extent to which the drivers are willing to deviate from their standard routes;

- the characteristics of the underlying causes of the ‘unusual’ traffic conditions (e.g. duration of an incident).

Note diverting drivers cause a reduction in the traffic demand on their standard routes, which will positively influence the traffic conditions on these routes. While on the alternative routes chosen by these drivers, the traffic demand will increase.

2.2.7 Conclusions

In this paragraph multiple factors that have an influence on traffic supply or demand have been identified. Also a categorization of these factors into three (regular/irregular, continuous/only during well-defined spaces of time, network wide/in between/local) different classes is presented. This gives more insight in the characteristics of the identified factors.

The interdependencies between the factors have also been discussed. From this it became clear that the different factors cannot be taken into account separately. Some of them have very strong interdependencies in time, on the occurrence or on the effects of other factors.

The predictability of the factors vary extensively per factor. Some of them are almost completely predictable, such as luminance, public holidays and vacations. While some of them are only to a certain extent predictable (Road works, weather conditions etc.). Others are very hard to predict and only a very rough estimation of the probability of occurrence can be made (incidents).

Also the effects of the identified factors on the traffic supply and demand have been discussed. These also vary extensively per factor. It may have been noticed, that two identified factors have not been explained. This concerns ‘intrinsic variations in human behavior (traffic supply)’ and ‘other variations in human travel behavior (traffic demand)’. These two describe the variations in demand and supply that cannot be explained by all other factors.

For the traffic demand, the variations are to a large extent the result of variations in peoples’ activity patterns. These variations cannot be completely explained by a limited set of factors, independent of its size. As a result, the variations in traffic demand cannot be fully explained either.

The traffic supply or the capacity is dependent on the combined behavior of all individual drivers involved. A large part can be explained by the factors discussed above, another part however cannot be explained by these factors. This is due to the fact that human behavior is characterized by a certain ‘intrinsic randomness’. In spite of finding himself in similar circumstances, one and the same person may still behave differently. In addition, the factors that are explained might not be equally well observable and not all influences are fully understood. So even when all observable and understood influences are taken into account, still a certain ‘residual randomness’ will remain.

To complete this paragraph, network effects have been discussed. It was already stated that factors can influence the traffic conditions on a network wide, a local scale or somewhere in between. When analyzing a certain part of a network, these effects might play a significant role as well.

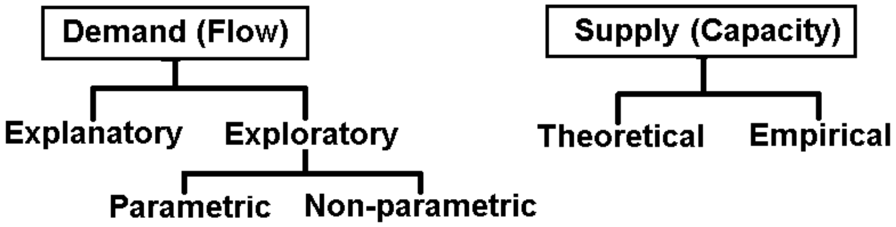
2.3 Model approach

Modeling traffic can be done in many different fashions. Paragraph 2.1 already made a distinction between microscopic and macroscopic traffic models. Microscopic models consider individual vehicles and their interaction with the surrounding infrastructure and other vehicles. The purpose of this research is to predict congestion or other traffic performance indicators. For this purpose, it is not necessary to model each individual vehicle separately. Microscopic models also have a large computational load which will negatively influence the calculation speed. Microscopic models will therefore not be considered for the model approach.

Macroscopic models consider the collective behavior of multiple vehicles. This is done by formulating the relationships among the traffic flow characteristics like density, flow and mean speed. In Paragraph 2.1 basic queuing and first order traffic flow models already have been discussed. As explained before, traffic flow is governed by the interaction between traffic demand and traffic supply. To explicitly take the variability of traffic into account, it is essential that the model considers both of these ingredients.

This paragraph gives an overview of methods that can be used to determine the traffic demand and traffic supply from available data. For the analysis of the different methods, a distinction will be made between methods which deal with the demand side and methods which deal with the supply side. The different types of methods can be classified as shown in Figure 2-39.

Figure 2-39: *Traffic modeling types (Calvert, 2009)*



The considered methods for determining the traffic demand and the traffic supply are listed in Table 2-14.

Table 2-14: *Considered flow and capacity estimation methods*

Flow methods	Capacity methods
ARIMA	Factor Method
Data Fusion	Headway Distribution
Smoothing	Fundamental Diagram
	Queue Discharge Distribution
	Product Limit Method

2.3.1 Traffic demand estimation

To be able to predict traffic conditions on a certain road stretch, both traffic supply and traffic demand should be predicted. A basic demand profile prediction has to be created before the influences of factors mentioned in paragraph 2.2 can be used to create a demand profile distribution.

Flow modeling can be performed by both explanatory and exploratory methods. Explanatory methods are based on the principles of traffic flow theory. Exploratory methods do not directly take the governing traffic flow theories into account, but yield good results due to the fact that these methods can determine the daily and weekly patterns that are present in real life traffic flows.

Explanatory methods
The two main types of explanative methods are ‘traffic assignment’ and ‘traffic state based methods’.

Traffic assignment uses an origin-destination matrix to assign traffic along routes depending on a cost function. This type of explanative method will not be considered for a number of reasons. Firstly, the type and amount of data needed to determine route-choice and assignment under variable conditions would be very extensive. Secondly, the used road layout is a single road stretch and does not allow for multiple routes. Finally, the method is based on simulations and does not directly take real life data into account.

Traffic state based methods uses knowledge of the traffic state, such as intensities and speeds, to determine future traffic conditions. The main advantage of these methods is that they are based on traffic theory, but are allowed to take non-theoretical influences into account. This type of method will be considered for the main modeling part, but not for creating a demand profile.

Exploratory methods
Explorative methods do not directly take governing traffic flow theories into account. These methods can determine the daily and weekly patterns that are present in real life traffic flows along a set of road section. In this way they are able to predict ex-ante flows. Hence, an explorative method will be selected for determining the traffic demand profile.

Exploratory methods can be parametric or non-parametric. Parametric methods use a specific functional form for the dependent and independent variables, while non-parametric methods do not assume a specific function and approximate the governing functions by extensive iteration. The pros and cons of the different types of exploratory methods are listed in Table 2-15. For determining a traffic flow pattern, only parametric methods have been considered.

Table 2-15: *Pros and cons of exploratory methods*

Parametric methods	Non-parametric methods
Bound by a certain function, therefore accuracy and reliability depend on the assumed function	*Not bound by a certain function, therefore greater accuracy and reliability is possible*
Small amount of data needed	Large amount of data needed to train the model
Determines results explicitly	Determines results implicitly

ARIMA
ARIMA is a statistical method that can be used to predict travel times. The method makes use of an autoregressive part and a moving average part. The autoregressive part analyses the data and derives relations from it, while the moving average part

integrates multiple data inputs and forms an average value from the data and computed relations. The main disadvantage of this method is that it has difficulties processing outliers.

Data Fusion
This method combines various input data to produce a completer and more accurate output of the required quantity. In traffic the use of speed and flow data can be used. Raw traffic data can be corrected for various errors. A disadvantage of this method is that it often introduces a bias at and near locations where the corrupted or missing data was present. Such a filter will therefore only be considered if provided data corrupted or incomplete.

Smoothing
From empirical data, flow patterns can be derived. However, these patterns will show fluctuations in space and time. Simple smoothing can be applied to remove these short-term fluctuations. An example of this is given in Figure 2-40.

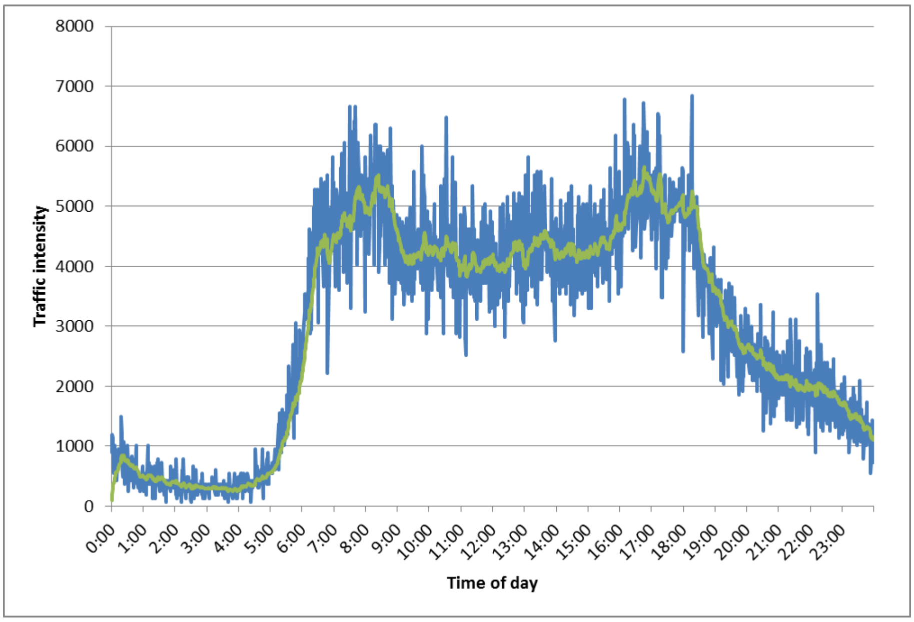


Figure 2-40:
Smoothing

2.3.2 Traffic supply estimation

Traffic supply can be described as the result of human travel behavior. This travel behavior can be translated into a fundamental diagram. A fundamental diagram can be described with several traffic supply variables. One of the main traffic supply variables in this fundamental diagram is capacity. The methods discussed in this subparagraph are all relate to capacity rather than all traffic supply variables.

Capacity is the maximum hourly rate at which vehicles can reasonably be expected to transverse a point or uniform section of a lane or roadway during a given time period under prevailing roadway, traffic and control conditions (HCM, 2000).

In theory capacity is one single value, in practice the capacity is variable. To include this variability, first the theoretical capacity has to be approximated as well as possible. In the paragraph about traffic flow theory the capacity drop has been described as well. For both the free flow capacity as the queue discharge capacity methods are available.

Capacity can be estimated by theoretical methods as by empirical methods. Theoretical methods determine theoretical capacities based on the road layout. Empirical methods determine the operational capacity of a road by analyzing empirical data. The considered methods for capacity estimation are listed in Table 2-16.

Table 2-16: *Considered capacity estimation methods*

Theoretical methods	Empirical methods
Basic Capacity Estimation method	Queue Discharge method
Headway Distribution method	Product-Limit method
Fundamental Diagram method	

Theoretical methods

Three theoretical methods will be discussed here. The first one makes a basic capacity estimation, the second one uses the headway distribution and the third makes use of the fundamental diagram.

Basic capacity estimation methods take the theoretical design or ideal capacity of a road and apply a number of factors to derive an acceptable capacity estimation. A capacity drop is not included in such models. Such a method is described in the HCM (2000):

Equation 2-16

$$c = c_j \cdot N \cdot f_w \cdot f_{HV} \cdot f_p$$

Where:
c_j = lane capacity under ideal conditions
N = number of lanes
f_w = lane width and lateral clearance factor
f_{HV} = HGV factor
f_p = drive population factor

Headway distribution methods use average headways between vehicles to determine capacity. For roads with specific speeds these average headways are in most cases generic (Verhaeghe, 2007).

Equation 2-17

$$q_{cap} = \frac{k_c}{h}$$

Where:
q_{cap} = capacity flow
k_c = critical density
h = headway

The chosen values are however susceptible to subjectivity and choosing them is not a trivial task. The capacity drop is also not considered here.

The *fundamental diagram method* uses a fundamental diagram to estimate capacity without using measured data points. With this method a certain form of the fundamental diagram is chosen and estimates must be made of the critical density. Physical characteristics of the road and expected driver behavior can be used to make these estimates.

Empirical methods

The two main methods for determining capacity by using empirical data are discussed here. These methods are the queue discharge distribution method and the product-limit method.

The *queue discharge method* uses observations of the discharge flow out of bottlenecks. With these observations a capacity distribution or a value for capacity can be obtained. Please note that this method estimates the queue discharge capacity (capacity after the capacity drop) and not the free flow capacity. The main (generally accepted) assumption of this method is that the capacity can be observed at a short distance downstream of a bottleneck.

The *product-limit method (PLM)* uses observations of both flows below capacity and at capacity to determine a more complete capacity distribution. Both a parametric and non-parametric type of the product-limit method is available. The non-parametric product-limit method determines the capacity distribution by using cumulative estimations of traffic volumes causing traffic breakdown:

Equation 2-18

$$F_c(q) = 1 - \prod_{i:q_i \leq q} \frac{k_i - d_i}{k_i}$$

Where:
$F_c(q)$ = distribution function of capacity c
q = traffic volume
q_i = traffic volume in interval i
k_i = number of intervals with a traffic volume of $q \geq q_i$
d_j = number of breakdowns at a volume of q_i

The parametric method uses a (in most cases the natural logarithm of a) likelihood function to fit measured data to a distribution to determine the capacity:

Equation 2-19

$$L = \prod_{i=1}^{n} f_c(q_i)^{\delta_i} [1 - F_c(q_i)]^{1-\delta_i}$$

Where:
$f_c(q_i)$ = statistical density function of capacity c
$F_c(q_i)$ = cumulative distribution function of capacity c
n = number of intervals
δ_i = 1, if uncensored; 0, elsewhere

The Weibull distribution function proved to be the best fit for observations on freeways (Brilon, Geistefeldt et al., 2005):

Equation 2-20

$$F(x) = 1 - e^{-\left(\frac{x}{\beta}\right)^{\alpha}} \, for \; x \geq 0$$

Where:
α = shape parameter
β = scale parameter

2.3.3 *Conclusions*

In this paragraph it has become clear that there are a large number of different approaches and methods available for the estimation of flow patterns and capacity distributions. The focus in this literature study was on the use of traffic demand and supply as separate modeling steps.

The difference between exploratory and explanatory methods has been explained. Only exploratory methods based on historical data have been considered, because they give real options for determining a basic demand pattern.

Methods for determining the capacity are split into theoretical and empirical methods. Theoretical methods use theories and formula to determine road capacity. However, in practice there might be imperfections in these theories and road conditions. Therefore an empirical method might be more advantageous. However, a prerequisite of an empirical method is that historical data is available.

2.4 Probabilistic method

To take the variability of traffic into account, some kind of probabilistic modeling has to be applied. On the one hand this can be done through probability in the model core, while on the other hand repetitive simulation can offer the desired results. Both will be described and discussed.

2.4.1 Probabilistic modeling through probability in the model core

Modeling probability in the core of traffic models considers multiple stochastic factors in model equations. Multiple simulations are not needed and therefore this method is sometimes also known as the one-shot method. A number of different approaches can be distinguished in which variability is incorporated in the core of a traffic model. Distinction can be made between methods with an analytical or numerical propagation extension and methods with stochasticity in the fundamental relations. An analytical approach to probability in the model core, or simply one shot, probabilistic traffic modeling has proven an extremely difficult undertaking. Also no model has yet been developed that is capable of matching accuracies of the computationally heavy repetitive simulation through a one-shot approach on a comprehensive network (Calvert, Taale et al., 2012).

2.4.2 Probabilistic modeling through repetitive simulation

This method has been widely applied to describe probabilistic and stochastic systems. The method, commonly known as Monte Carlo simulation, presumes predefined probabilities for each of the input variables, indicating the probability of occurrence and the corresponding value. Random values are sampled from each input variable, which are applied simultaneously. This process is then repeated and results in a distribution of outputs.
This method is simple and effective, however it has drawbacks as well. Main concerns are the computational load and the negligence of the presence of correlation between input variables. The computational load depends on the desired accuracy level and the number of input variables. While correlation between input variables may be considered prior to simulation at the sampling stage.

Solutions for these difficulties can be found in the use of intelligent sampling methods. The use of intelligent sampling methods will reduce the variance from sampling and therefore the required number of simulations. Therefore some of these intelligent sampling techniques are discussed here. The following techniques are considered:

- Systematic sampling
- Importance sampling
- Latin hypercube sampling

Systematic sampling

With systematic sampling the target population is arranged in some ordering scheme, then the elements are selected at regular intervals through that ordered list. Systematic sampling involves a random start and then proceeds with the selection of every *k*th element from then onwards. The sampling interval, or the 'skip', is defined as

Equation 2-21

$$K = \frac{N}{n}$$

Where: n = sample size
N = population size

Another form of systematic sampling is systematic stratified selection. In this case regular samples are selected in a pre-set manner. For example taking every 5th percentile of a cumulative distribution function. Table 2-17 shows the pros and cons of systematic sampling

Table 2-17: *Pros and cons of systematic sampling*

Pros	Cons
More efficient than simple random sampling	Risk of hiding patterns in data due to chosen sampling interval
Easy to implement	Can only be applied if the population is logically homogeneous

Importance sampling

This technique gives extra consideration to the outlying sections of a distribution, which have a lower probability of being sampled, but have a relatively large influence on the output variable. The extremities of the distribution get a greater probability than they actually have and thus the chance that they are sampled is higher. This increases the chance that the output distribution is 'complete'. The pros and cons of importance sampling are shown in Table 2-18.

Table 2-18: *Pros and cons of Importance sampling*

Pros	Cons
If the predefined 'dummy' distribution is chosen well, the method shows great improvement.	The determination of the needed predefined 'dummy' distribution, which increases the probabilities of certain values, is not trivial and requires a lot of trial-and-error.
	Difficult and time consuming to implement

Latin hypercube sampling
Latin hypercube sampling is a stratified sampling technique that ensures that the entire sample space for multiple input variables is sufficiently covered. The total probability space of the random variables is divided in a number of equally sized intervals in terms of probability. The number of intervals should be equal to the number of performed simulation runs. After randomly selecting one of the intervals, a random realization can be taken from this specific interval. The difference between Latin hypercube sampling and other stratified sampling techniques is that each interval can only be sampled once. In this way, the randomly generated values are very likely more evenly spread over the total probability space. Table 2-19 shows the pros and cons of Latin hypercube sampling.

Table 2-19: *Pros and cons of Latin hypercube sampling*

Pros	Cons
Capable of reducing the number of simulation runs.	Due to the division in intervals, a part of the randomness is removed.
Ensures that the entire sample space for multiple input variables is sufficiently covered, taking even unlikely extremities into account	
Easy to implement	

2.4.3 *Conclusions*

Three sampling techniques have been described. Based on the tables with pros and cons, a comparison is made between the main characteristics of the considered techniques. An overview of this comparison is given in Table 2-20.

Table 2-20: *Evaluation of intelligent sampling techniques*

	Systematic sampling	Importance sampling	Latin hypercube sampling
Ease of implementation	++	-	+
Expected efficiency	0	++	+
Risk of inefficiency or hiding patterns in data	- (risk of hiding patterns in data)	-- (risk of inefficiency)	0
*Legend: **+** = good, **0** = average, **-** = poor*			

2.5 Conclusions

In this chapter the literature research is conducted. Traffic flow theory, factors and effects influencing traffic demand and supply, model approaches and probabilistic methods are discussed and explained.

Traffic flow theory explains basic traffic flow theory and that traffic states are depicted from the interaction between traffic supply and demand. With the information provided in this paragraph, a traffic model can be constructed later in this research.

The next paragraph identifies multiple factors that have an influence on traffic demand or supply. Categorizations, interdependencies, probability of occurrence and the effects of these factors will help to create the theoretical framework and incorporate the variability of traffic.

In the third paragraph some model approaches are explained. One of these model approaches will be chosen in the next chapter. With the possibilities laid out, a deliberate choice can be made.

To take the variability of traffic into account, a probabilistic method is needed. The fourth paragraph gives an overview of probabilistic methods, including pros and cons. With this, also a deliberate choice for the probabilistic method can be made in the next chapter.

3 Research Methodology & Approach

In this chapter the available modeling approaches and the approach used in this research will be discussed. After this, the selected model will be explained. The main data sources, which are used to do case study's, along with the chosen locations to be used in the calibration and validation of the developed model. The last part of this chapter contains the evaluation criteria with which the model will be evaluated for performance and accuracy.

3.1 Model approach

The overall modeling approach used to make predictions of the future traffic state will be discussed here. Table 3-1 shows the types of methods considered for this approach. This subparagraph will explain the decisions related to the type of methods.

Table 3-1: *Considered modeling options*

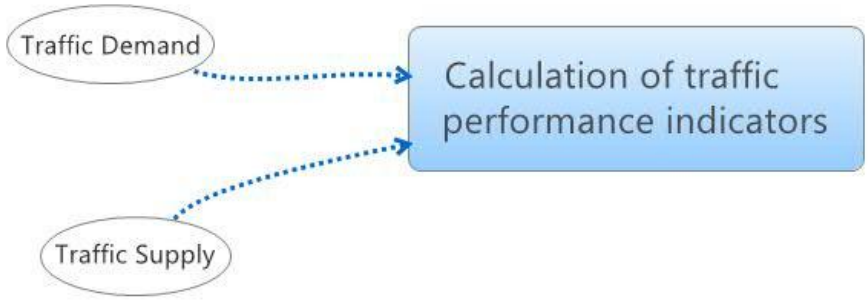
	Considered options
Approach	Complete solution, **Indirect approach**
Model type	Microscopic, **Macroscopic**
Data processing	Unprocessed, Filtered, Smoothed
Probabilistic method	Model core, Repetitive simulation, **Intelligent sampling**

3.1.1 Approach

Two types of approaches to predict are identified. It is possible to calculate travel time, or other performance indicators, directly from the input data. Such methods are for example neural networks. These complete solutions limit imperfections in the theory and observed road characteristic, but do not take traffic theory into account explicitly. The other possibility is to separate the various influencing parts of the traffic process and calculate these individually. Later the different parts can be put together to get the desired outcome.

It was already mentioned in the literature study that it is essential in this research that, to take the variability of traffic into account, a distinction between traffic demand and supply is made. An indirect approach is therefore chosen. Figure 3-1 gives a basic representation of this approach.

Figure 3-1: *General model approach*



3.1.2 *Model type*

In the literature study the difference between microscopic and macroscopic models has already been explained. Microscopic traffic models focus on the characteristics of individual vehicles, while macroscopic models consider traffic from a collective point of view. Considering fictive individual drivers will generally lead to higher complexity in the model. It is therefore not advisable nor necessary to do this when predicting for example travel times. It was already discussed in paragraph 2.3 that the microscopic approach is not considered in this research for a number of reasons. Therefore the developed model will focus on macroscopic traffic flows. This offers the greatest potential for incorporating the variability of traffic and does not lead to unnecessary complication of the model.

3.1.3 *Data processing*

Both historical traffic data and road characteristics are used for predictions. The demand profile will be deduced from historical traffic data. A smoothed profile (as in Figure 2-40) will be generated. The traffic supply profile will be created using calibrated operational capacities. Once a traffic demand and a traffic supply profile are created, these must be processed to produce forecasts. The selected modeling approach is described in the next paragraph.

3.1.4 *Probabilistic method*

The manner in which the variability of traffic is incorporated in the model is obviously important as it influences the computational load and therefore the calculation time.

The model is developed for prediction purposes. It is therefore not desirable that the model needs multiple hours or even days to come up with a prediction. Of course the probabilistic method is not the only factor that influences computational load, but certainly an important one.

Distinction has been made between probabilistic modeling through probability in the model core and probabilistic modeling through repetitive simulation. The latter included also some intelligent sampling methods. The pros and cons of both approaches are briefly evaluated in Table 3-2.

***Table 3-2:** Evaluation of probabilistic methods*

	Probability in model core	**Repetitive simulation**
Ease of implementation / complexity	--	++
Accuracy	+	+
Computational load	++	--
*Legend: **+** = good, **0** = average, **-** = poor*		

From paragraph 2.4 it has become clear that implementing probability in the model core is complex. The accuracy of repetitive simulation obviously depends on the number of simulations, while the accuracy of probability in the model core depends on how well it is implemented. Therefore no distinction has been made in Table 3-2.

For this research the benefits of probabilistic modeling through probability in the model core do not seem to outweigh the benefits of repetitive simulation. In this consideration the ease of implementation is the most compelling factor.

Therefore the variability of traffic will be incorporated by probabilistic modeling through repetitive simulation. Paragraph 2.4 also discussed some intelligent sampling techniques. These can be used to reduce the computational load and interdependencies between input variables could be taken account as well. Based on Table 2-20, latin hypercube sampling is chosen to be used to take the variability of traffic into account.

3.2 Selected model

In this paragraph the selected model will be discussed and explained.

3.2.1 Model selection

In the literature research the difference between explanative and explorative models was already explained. It was also stated that the main model will be an explanatory model.

In macroscopic traffic flow modeling, two main types of explanative models are available. The first order and the second order traffic flow models (Hoogendoorn, 2007). The basics of the first order models were already explained in paragraph 2.1. Second order models differ from first order models by attempting to more accurately describe and model the dynamics of traffic. The main areas in which this improvement is attempted in comparison to first order models are:

- dynamic mean speeds instead of a static mean speed for each road section;
- higher headways as vehicles approach a jam, which are not included in first order models;
- traffic instability is considered, i.e. small disturbances at certain traffic densities, which have the capability to result in a larger breakdown of traffic flow.

Due to these improvements, second order models have a higher expected accuracy. However, second order models also have their drawbacks. The complexity of these models makes it hard to solve them, but also to completely understand their mathematical properties is quite unachievable. The main advantage of the second order model as well as the drawback is its detail and complexity. It has been questioned of such a level of complexity is required for the considered problem.

The choice is made to make use of the first order traffic flow model using a Godunov scheme to solve the model. The main reasons for this are:

- using a Godunov scheme to solve the model has proved to give a good representation of traffic flow during congestion;
- the main traffic flow characteristics are taken into account.

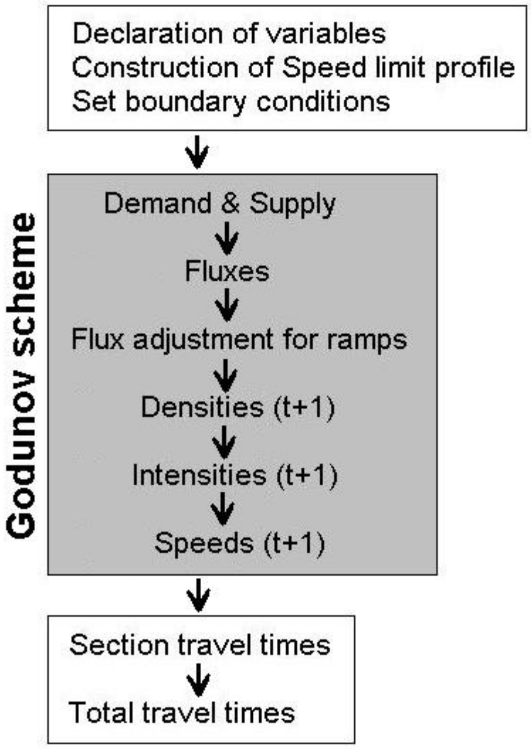
For making predictions on a road stretch of probably a few tens of kilometers, the potential improvements of second order models is not expected to be sufficient.

Also the computational load of second order models might be higher, which could result in high calculation times (also due to repetitive modeling). And although first order models do not consider detailed phenomena as second order models, the overall performance of the first order model is deemed sufficient.

3.2.2 Model explanation

To build the model, the scientific programming tool MatLab is used. The traffic dynamics are modeled with the Godunov scheme. The manner in which this is done is shown in Figure 3-2. This explanation only concerns the traffic flow modeling part. The implementation of traffic variability will be discussed later.

__Figure 3-2:__ Godunov scheme (Calvert, 2009)


Declaration of variables
Construction of Speed limit profile
Set boundary conditions
Godunov scheme
Demand & Supply
Fluxes
Flux adjustment for ramps
Densities (t+1)
Intensities (t+1)
Speeds (t+1)
Section travel times
Total travel times

The demand and supply variables, which will follow from the original demand and supply variables in combination with the present influence factors, will be collected. The time steps for the traffic demand will be adjusted from one-minute values to six-second values to meet the celerity conditions. The section distances are 200 meters corresponding to the average loop distance on main motorways. With a speed of 120 km/u, it would take exactly six seconds to pass through one section.

The main boundary conditions are the initial flow, the initial densities and the outflow. The initial flow is set to the flow demand (corrected for the different sources of variability) at the start of the road stretch. The initial densities for each road section are set at an infinitely small number, while the default outflow is set to an infinitely large number, which allows vehicles to flow out of the model freely. The outflow can be corrected due to variability in traffic as well.

Each run of the model will simulate a whole day, which includes 14400 six-second time steps. In each time step the following steps of the Godunov scheme will be repeated:

- the *traffic demand and supply* of each section are collected;
- the *flux* between each section is determined;
- the flux is adjusted for inflowing and outflowing vehicles from *on- and off-ramps*;
- the *densities* for the next iteration step are determined using the calculated fluxes and the flow definition equation;
- The corresponding *intensitie*s for the next step are derived using the fundamental relation and the calculated densities
- The average space mean *speeds* per section are calculated from the determined intensities and densities using the flow definition equation.

The three equations used to perform calculations in the Godunov scheme are: the conservation equation, the flow definition equations and the equilibrium fundamental relation. The in- and outflow of vehicles at ramps is dealt with by adjusting the flux at ramp locations.

After applying the Godunov scheme, the output variables can be derived. From the section speeds calculated in the Godunov scheme, the trajectories of the vehicles are determined, resulting in the travel times per section. The overall travel time of the total road stretch can be derived from this. The queue length can also be calculated at each time instance. This can be done summating the sections in which there is congestion (density > critical density) and multiply by the section length.

3.3 Data sources

The data source for the case study is the Dutch monitoring system, managed by Rijkswaterstaat. The case study location is also discussed in this paragraph.

3.3.1 Historical traffic data

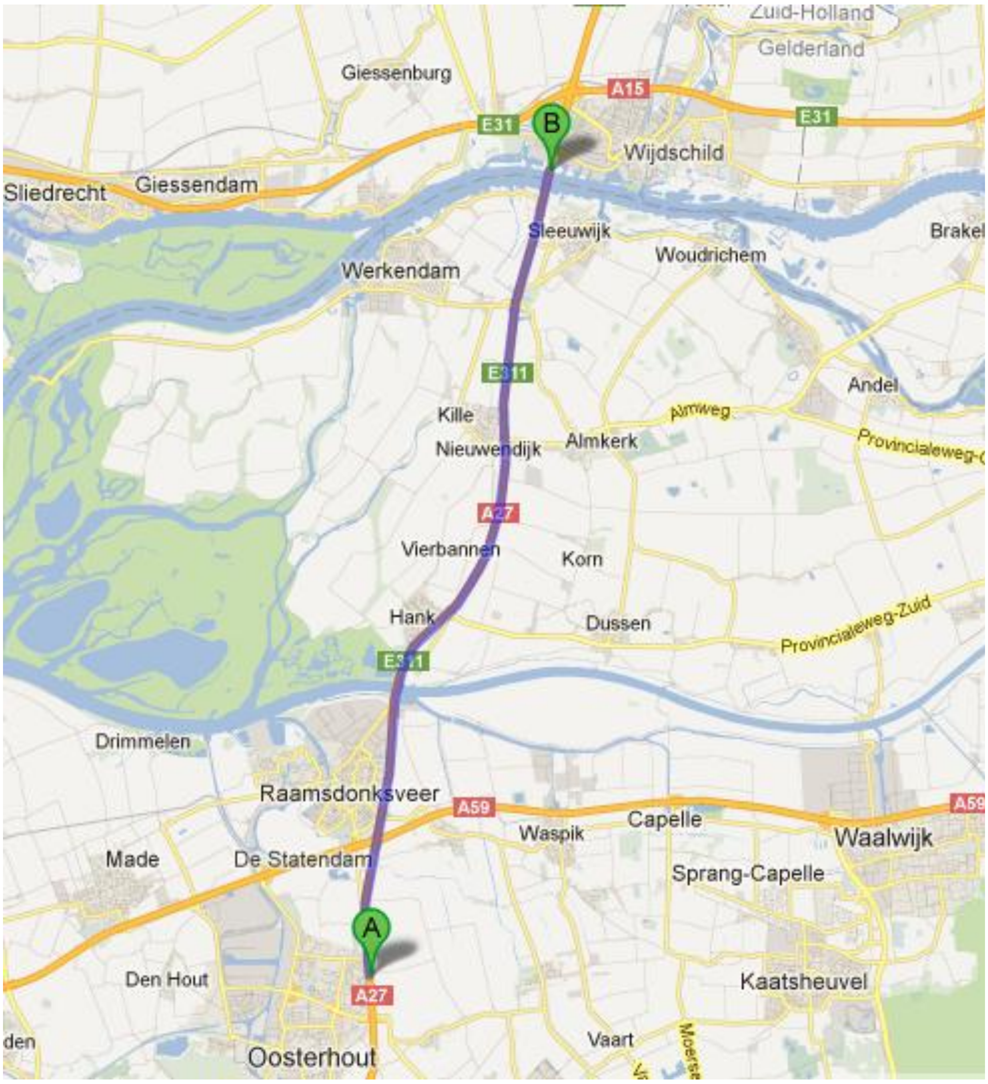
The Dutch motorway monitoring system known as MoniCa (Monitoring Casco) can be used to collect historical traffic data. This system records the presence of vehicles at various cross sections on motorways. The collected data is processed to give average speeds and flow intensities on a minute-by-minute basis. The detection is performed using induction loops. These are generally placed at an approximate distance of 200 to 500 meters apart. The accuracy of the data produced has been shown to be higher than 95%. This data is therefore sufficiently accurate for determining the traffic characteristics.

3.3.2 Case study selection

The case study location will be a motorway corridor in the Dutch motorway network. Since the project of Witteveen+Bos includes the south of the Dutch network, it was advised to choose a location in the south of the Netherlands. Data for this would then already be available and maybe results can be compared.

For these reasons the A27 from Hooipolder to Gorinchem is selected for the case study. The exact location is also presented in Figure 3-3. Also the direction, which is "R" in terms used by Rijkswaterstaat, is indicated (from A to B).

Figure 3-3: *Selected location for calibration and case study*


Zuid-Holland
Gelderland
Giessenburg
A15
E31
B
Wijdschild
Sliedrecht
Giessendam
Sleeuwijk
Woudrichem
Brakel
Werkendam
E311
Andel
Kille
Nieuwendijk
Almkerk
Almweg
Provincialeweg
A27
Vierbannen
Korn
Hank
Dussen
Provincialeweg-Zuid
E311
Drimmelen
Raamsdonksveer
A59
Waspik
Capelle
Waalwijk
A59
Made
De Statendam
Sprang-Capelle
A
Den Hout
A27
Kaatsheuvel
den
Vaart
Oosterhout

3.4 Evaluation method

The calibration and validation of the developed model can be done by comparing the model output with data.

The process for the evaluation of the model is as follows:

- Gather measured travel times from the motorway corridor.
- Give the necessary input for the model and run the model. (revealed uncertainty's can be left out, e.g. uncertainty in weather conditions)
- Extract travel time predictions from the model for varying days/times.
- Compare the travel time predictions with the measured travel times (both are actual travel times).

The travel times, both measured and predicted, are compared using two performance indicators:

- Absolute difference (MAE)

Equation 3-1

$$\frac{1}{N}\sum_{N}\left(|tt_{N.m} - tt_{N.p}|\right)$$

- Relative difference (MARE, MRE)

Equation 3-2

$$\frac{1}{N}\sum_{N}\left(\frac{|tt_{N.m} - tt_{N.p}|}{tt_{N.p}}\right)$$

The results of the comparisons offer and insight into the accuracy of the model and may indicate structural errors in the model.

However, not only comparisons on single days will be conducted. Since the developed model considers the variability of traffic in its output, distributions can be compared as well. The Kolmogorov-Smirnov test seems most suitable for this.

The Kolmogorov-Smirnov test compares the experimentally found empirical distribution function with the assumed distribution function or two empirical distribution functions themselves. In this case the latter will be used. Equation 3-3 shows the Kolmogorov-Smirnov statistic.

Equation 3-3

$$D_{n,m} = \underset{x}{sup}\ |F_{X,n}(x) - F_{Y,m}(x)|$$

This test checks whether two datasets come from the same distribution.

3.5 Conclusions

In this chapter the research methodology is defined. The main modeling approach is selected. The general algorithm of the selected model is graphically presented. Also the data source and the case study location are selected.

An indirect approach is chosen for the model approach. Traffic demand and traffic supply will be combined to generate output.

In order to deal with the variability of traffic, the intelligent sampling technique Latin Hypercube Sampling is selected. This technique needs significantly less samples to converge, than the conventional random sampling techniques.

The model method chosen is a first order traffic flow model making use of a numerical Godunov Scheme to solve the model. This is a macroscopic modeling approach, which makes use of traffic demand profiles and traffic supply variables to determine congestion and travel times.

The data required to develop the model is collected from the MoniCa system. This data source collects traffic data on the Dutch motorways. The A27 from Hooipolder to Gorinchem is selected for a case study.

The evaluation of the model will be carried out using the mean absolute error and the mean absolute relative error for travel times and the Kolmogorov-Smirnov test for travel time distributions.

4 Theoretical Framework

The theoretical framework consists of three parts. First an overview of the considered influence factors is given. Next their predictabilities will be discussed and quantified. Then the effects on traffic supply and traffic demand will be discussed and quantified.

4.1 Overview of influence factors

This paragraph gives an overview of the effects of the considered influence factors on traffic demand and supply. First all identified sources of variability will be listed and graphically presented. Then their relations will be briefly described.

Identified sources of variability on traffic supply:

1. Weather conditions
2. Luminance
3. Incidents
4. Road works
5. Traffic control actions
6. Variations in vehicle population
7. Variations in driver population
   'Intrinsic' variations in human behavior

Identified sources of variability on traffic demand:

8. Patterns of variation in human travel behavior (time of day, day of week, month)
9. Public holidays / vacations
10. Events
11. Weather conditions
12. Road works
    Other variations in human travel behavior

Interdependencies of the different identified sources of variability:

13. Weather conditions → Events
14. Weather conditions → Incidents
15. Weather conditions → Road works
16. Weather conditions → Traffic control actions
17. Traffic demand → Traffic control actions
18. Traffic demand → Incidents
19. Incidents → Traffic control actions
20. Variations in vehicle population → Incidents
21. Variations in driver population → Incidents
22. Public holidays / vacations → variations in vehicle population
23. Public holidays / vacations → variations in driver population
24. Public holidays / vacations → events

Figure 4-1 shows an overview of the identified influence factors and their interdependencies.

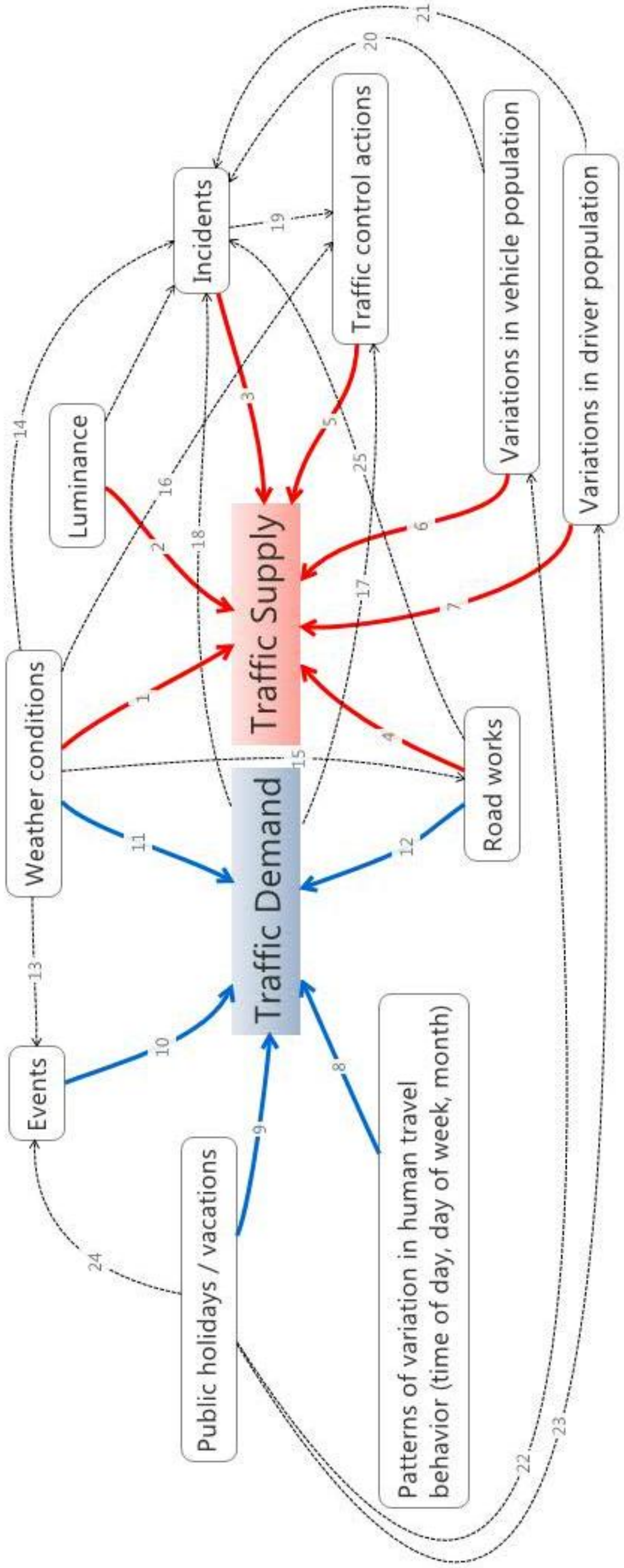

Traffic Supply
Traffic Demand
Incidents
Traffic control actions
Variations in vehicle population
Variations in driver population
Luminance
Weather conditions
Road works
Events
Public holidays / vacations
Patterns of variation in human travel behavior (time of day, day of week, month)
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Figure 4-1: *Overview of the identified influence factors and their interdependencies*

In Table 4-1 an overview of the effects of the factors on traffic demand and traffic supply is given.

Table 4-1: *Effects of factors on traffic demand and traffic supply*

influence on Factor	**Traffic demand**	**Traffic supply**
Weather conditions	People react on weather conditions by changing mode, departure time or destination, or decide not to take a certain trip	Adverse weather conditions have a negative effect on both capacity (larger headways) and speed
Luminance		In dark conditions capacity is generally slightly lower
Incidents	Incidents have minor impact on traffic demand	Incidents have negative effect on capacity, the magnitude of the effect depends on the duration and type of the incident
Road Works	Demand during road works is generally lower. Road works may have been announced or known from personal experience/traffic information	Road works have a negative effect on capacity
Traffic control actions		Capacity is temporarily increased or variability in capacity is reduced
Variations in vehicle population		Especially trucks ‘consume’ more capacity, due to their lower acceleration/deceleration rates and lower maximum speeds
Variations in driver population		Less experienced drivers may drive slower and keep larger headways resulting in lower capacity
Patterns of variation in human travel behavior	Activity patterns determine traffic demand (work, leisure etc.)	
Public holidays / vacations	More or less traffic is on the roads due to different activity patterns	The composition of driver and vehicle population is different, often resulting in lower capacity
Events	Extra traffic will be generated at certain moments of the day	

Table 4-2 gives an explanation for the interdependencies between the factors.

Table 4-2: *Explanation of the interdependencies between factors*

Interdependency between two factors	**Explanation**
Weather conditions → Events	Event may be cancelled Demand for event may be lower
Weather conditions → Incidents	Incidents are more likely to occur
Weather conditions → Road works	Road works may be cancelled
Weather conditions → Traffic control actions	Rush-hour lanes might not be opened
Traffic demand → Traffic control actions	Depending on the traffic flow, an action is carried out or not
Traffic demand → Incidents	Incidents are more likely to occur with very low and very high traffic intensities
Incidents → Traffic control actions	An incident may prohibit carrying out a traffic control action
Variations in vehicle population → Incidents	Incidents are more likely to occur as the percentage of trucks is high
Variations in driver population → Incidents	Incidents are more likely to occur as the percentage of inexperienced drivers is high
Public holidays / vacations → variations in vehicle population	During public holidays and vacation periods, the mix of traffic is expected to be different
Public holidays / vacations → variations in driver population	During public holidays and vacation periods, less commuter and more leisure traffic is expected to be on the road
Public holidays / vacations → events	Events are often planned during public holidays or vacation periods
Road works → Incidents	Due to different road geometry, incidents are more likely to occur at work zones

4.2 Predictabilities of influence factors

This paragraph will discuss and quantify the predictabilities of all considered factors. First a classification will be made to distinguish very predictable factors from factors that are less predictable. Then the predictabilities of the influence factors will be quantified.

4.2.1 *Classification*

In paragraph 2.2 factors influencing the traffic supply and traffic demand have been discussed. Statements about their predictabilities were made. This subparagraph gives a categorization of these predictabilities. Some are very well predictable while others are quite uncertain. In the middle we have factors of which their predictabilities highly depend on the availability of data. The following three classes are proposed:

- **Always predictable** / Data needed for prediction is assumed to be present
- **Sometimes predictable** / Data needed for prediction could be present
- **Not very predictable** / Data needed for prediction is not available

Table 4-3 shows to which category the considered influence factors are assigned.

Table 4-3: *Classification of predictabilities*

Always predictable / Data needed for prediction is assumed to be present	Patterns in human travel behavior Public holidays / vacation periods Luminance Traffic control actions Driver population
Sometimes predictable / Data needed for prediction could be present	Vehicle population (pattern for specific location known or not) Road works (knowledge of occurrence or not) Events (knowledge of occurrence or not) Weather conditions (short- or long-term)
Not very predictable / Data needed for prediction is not available	Incidents

Especially for the factors of which the needed data is not always present, it would be interesting to know how the availability of this data influences the quality of a prediction.

In the next subparagraph, the predictability of each factor will be quantified.

4.2.2 *Quantification of predictabilities*

Here the predictabilities of the identified factors will be quantified. For each factor a way will be given to specify how its occurrence can be determined. For the ‘very predictable’ factors this will be done differently than for the other two types of factors. For the ‘very predictable’ factors, the assumption can be made that their occurrence and their effects do not vary on a certain time instance (i.e. these factors are ‘case specific’). A difference between the ‘fairly predictable’ and the ‘not very predictable’ factors is that the latter has a wider spread of possibilities.

Patterns in human travel behavior

For each day of the week, a pattern in human travel behavior can be derived. This can be done by taking the average intensity on a certain road stretch, preferably at an upstream location were congestion does not occur often. Days with incidents, events, road works or other factors that will be taken into account explicitly, should not be included. This factor is considered the main input for the traffic demand in the traffic model.

Public holidays / vacation periods

Public holidays and vacation periods are obviously very easy to predict. The public holidays and vacation periods have already been mentioned in subparagraph 2.2.4. It should be noted that if a public holiday falls on a Thursday, the next Friday is considered a special day as well.

Luminance

For all time intervals before the monthly average time of sunrise and after the monthly average time of sunset, conditions are assumed to be dark. The monthly average times of sunrise and sunset were already shown in Figure 2-28.

Traffic control actions

For traffic control actions only rush-hour lanes are considered. Clearly it depends on the selected road stretch whether such a lane is present or not. Generally, rush-hour lanes open at a certain intensity measured on the considered road stretch and sometimes in combination with the intensity measured just upstream of the relevant road stretch. However, the opening of a rush-hour lane can be prohibited by incidents or certain weather conditions. The criteria for opening a rush-hour lane are listed in Table 4-4.

***Table 4-4:** Criteria for opening a rush-hour lane*

Criterion	Consequence	
Measured flow on the considered road stretch	I / C > 0.8	Lane opens
	I / C < 0.8 for 5 consecutive minutes	Lane closes
Incident	Prohibits the lane from opening, if already opened, lane remains opened	
Weather condition	Heavy rain, snow, ice forming and fog prohibit the lane from opening, if already opened, lane remains opened	

Driver population

The driver population can be divided in various groups. Here, four different groups are identified:

- Peak driver population (largely commuter traffic)
- Off-peak driver population (a mix of mainly: social traffic, leisure traffic, commercial traffic and commuter traffic)
- Saturday driver population (largely social and leisure traffic)
- Sunday driver population (almost exclusively social and leisure traffic)

Depending on the simulated time window, one of these groups will be selected.

Table 4-5: *Selection of a driver population as a function of the day of the week and time of day*

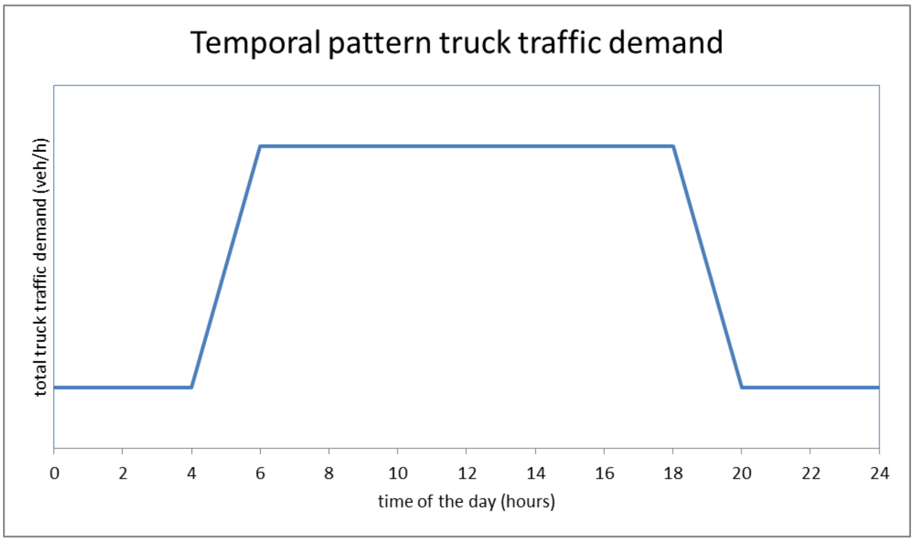
Day of the week	Time window	Type of driver population
Weekday	6:00 – 10:00; 15:00 – 19:00	Peak drivers
	Rest of the day	Off-peak drivers
Saturday	Whole day	Saturday drivers
Sunday	Whole day	Sunday drivers

During public holidays or in a vacation period, the off-peak driver population is assumed for weekdays, independent of the time of day.

Vehicle population

For the vehicle population a distinction is made between trucks and other traffic. The assumed temporal pattern for the truck demand is shown in Figure 4-2. The 24-hours truck fraction is generally 14.5%, but this percentage can be different for various road stretches and will be added as an adjustable variable in the model. The temporal pattern is however assumed to be constant.

Figure 4-2: *Temporal pattern of the truck traffic demand*



Road works

Because all (foreseen) road works are planned in advance, the occurrence of road works can be predicted fairly well. Unforeseen road works are not taken into account. However, it is also possible that a certain road work is cancelled or rescheduled. The assumption is made, that the larger the gap between the date of prediction and the date of the planned road work, the larger the probability of cancellation will be. For example, a road work planned tomorrow is less likely to be cancelled then a road work planned in five months. The cancellation of a road work also or maybe even mainly depends on adverse weather conditions. So when an adverse weather condition is predicted, the chance a road work will be cancelled increases. The probability of cancellation can then be calculated as follows:

Equation 4-1

$$P(cancellation) = \alpha_r \cdot N_i + \beta_r \cdot W_i$$

Where:

α_r = Scale parameter

N_i = Number of days between date of prediction and date of planned road work i

β_r = Scale parameter
W_i = Probability of the weather conditions being adverse (definition of weather conditions being adverse can differ between road works)

Events

Like road works, the start and end times of events are generally planned well in advance. These planned events can be used for simulation. However, there is a probability a certain event is cancelled. The same assumption for events is made as for road works (i.e. the larger the gap between the date of prediction and the date of the planned road work, the larger the probability of cancellation will be). However, here only the probability of cancellation of outdoor events mainly depends on the weather conditions. So a dummy variable is introduced.

Equation 4-2

$$P(cancellation) = \alpha_e \cdot N_i + \beta_e \cdot k_i \cdot W_i$$

Where:
α_e = Scale parameter
N_i = Number of days between date of prediction and date of planned event i
β_e = Scale parameter
k_i = Dummy variable: 1 if event is outdoor, 0 otherwise
W_i = Probability of the weather conditions being adverse (definition of weather conditions being adverse can differ between events)

Weather conditions

Short-term weather conditions can be predicted with more certainty than long-term weather conditions. In paragraph 2.2 a number of types of weather conditions have been discussed. These were rain, snow, fog, ice forming and summery days. The predictabilities of these weather conditions are dependent on each other. For example, on a summery day the other four mentioned weather conditions do not occur. Table 4-6 shows an example of the probabilities of occurrence of the different weather types. This probability holds for a certain day.
However it is not likely that it either rains all day (5% chance) 3-5 mm/h or it does not (95% chance). Another possibility is to take each minute a sample and assume the resulting weather condition lasts 30 minutes. When in these 30 minutes a contradicting weather condition is sampled (e.g. summery weather while it is raining), this will be neglected. However, further simplification of the sampling has been applied. The probability will hold for half a day, meaning that the weather is assumed to be ‘constant’ over the two halves of the day.

Table 4-6: *Example of probabilities of occurrence of different weather types*

Type of weather condition	Probability of occurrence	Intensity
Summery day	20%	-
Rain	5%	3 – 5 mm/h
Snow	0%	0 mm/h
Ice forming	0%	-
Fog	0%	-

In most cases, when a summery day is expected, the chance on snow will be 0%.

When snow is predicted, it is less likely that there will be rainfall. Even though it is unlikely, it might be possible that all types of weather conditions have a probability of occurrence higher than zero. The weather types will therefore be simulated sequentially. First it has to be determined whether it is a summery day or not. If not, other types of weather conditions can occur. It is also assumed that rain, snow and black ice will not occur at the same time. Fog can be simulated simultaneously with rain, snow and black ice.

Similar to the weather predictions on the short-term, the weather conditions on the long-term will be predicted. First it has to be determined whether it is a summery day or not. If not, other types of weather conditions can occur. Rain, snow and black ice will also not occur at the same time. Therefore these weather types will be simulated sequentially. From the data presented in Figure 2-22, Figure 2-23, Figure 2-24, Figure 2-25 and Figure 2-26 cumulative probability functions will be subtracted.

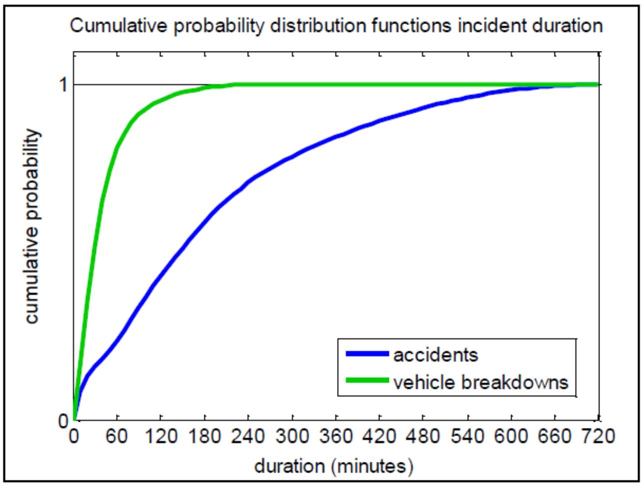
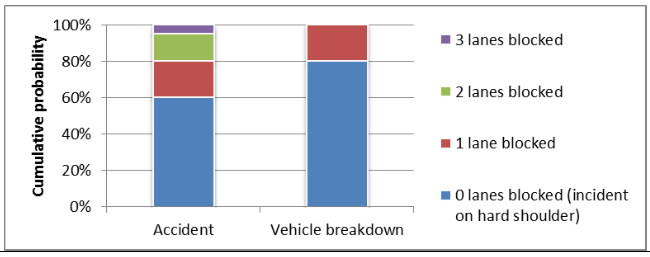
Incidents

Incidents have significant influence on traffic conditions, but are hard to predict. It is generally recognized that incidents occur every so many vehicle-kilometers. However, not only incidents that occur on the considered road stretch have effects on the traffic conditions on this road stretch. Incidents that occur somewhere downstream might result into blocking back, while incidents that occur somewhere upstream might cause a decrease in demand. Two types of incidents are considered: accidents and vehicle breakdowns. For both types, separate prediction steps need to be taken.

For accidents, the probability of occurrence needs to be corrected for the driver population, vehicle population, weather conditions and maybe for the time of day and road works. For vehicle breakdowns only a correction for the vehicle population will be applied. After it has been determined that an incident will occur at a certain moment, the location has to be chosen as well. Three kinds of possibilities are available for this: downstream of the considered road stretch, on the considered road stretch, or upstream of the considered road stretch. While vehicle breakdowns do not occur on specific locations on the road, accidents mainly occur at road sections with an on or off ramp, at weaving sections and at sections on which one of the lanes ends. These road sections are called vulnerable road sections. The procedure for simulating the occurrence of incidents is illustrated in Table 4-7.

Table 4-7: *Procedure for generating incidents*

	Accident	Vehicle breakdown
Determination of probability of occurrence	↳ accident probability (nr. of accidents/vehicle-kilometer) ↳ correct probability for driver population, vehicle population, weather conditions ↳ nr of vehicle-kilometers travelled on the considered road section for each time instance t ↳ probability of accident on time instance t	↳ vehicle breakdown probability (nr. of vehicle breakdowns/vehicle-kilometer) ↳ correct for vehicle population ↳ nr of vehicle-kilometers travelled on the considered road section for each time instance t ↳ probability of vehicle breakdown on time instance t

<table>
<tr><td>Determination of location</td><td>↳ Determine nr of kilometers of the considered road stretch and the significant upstream and downstream road stretches and create a cumulative function
↳ Identify the number of vulnerable road sections
↳ Identify the number of vulnerable road sections on the considered road stretch and the significant upstream and downstream road stretches
↳ Determine whether the accident occurs on a vulnerable road section or not
↳ Randomly select a location from the vulnerable road sections or from the residual road sections</td><td>↳ Determine nr of kilometers of the considered road stretch and the significant upstream and downstream road stretches and create a cumulative function
↳ Randomly select a point of this function</td></tr>
<tr><td>Determination of duration</td><td colspan="2">Based on data from Knoop (2009) a cumulative probability distribution function for both incident types has been assumed by Miete (2011):

Hence, a similar cumulative probability distribution will be used.</td></tr>
<tr><td>Determination of incident type (in terms of nr of blocked lanes)</td><td colspan="2">Based on the data provided in Figure 2-27 and further assumptions, the following cumulative probability distributions is assumed for the incident severity:
 </td></tr>
</table>

4.3 Effects of influence factors on traffic demand and traffic supply

This paragraph will discuss and quantify the effects of all considered factors. For each factor a way will be given to specify how its effect on traffic demand or supply can be determined. The intrinsic randomness in human travel and human driving behavior will also be discussed.

4.3.1 Classification

In paragraph 2.2 factors influencing the traffic supply and traffic demand have been discussed. In this paragraph the effects of these factors will be quantified. Similar to the categorization in Figure 2-15 and Figure 2-16, a categorization for the effects on traffic demand and traffic supply on a single motorway corridor is made here. The classes to which the factors will be assigned are:

- continuously present versus only at on certain moments in time (event / disturbance)
- on every cell of the motorway corridor versus on a selection of cells of the motorway corridor

Table 4-3 shows to which category the considered influence factors are assigned.

Table 4-8: *Classification of predictabilities*

Time span **Effect**	**Continuously present**	**Event / Disturbance**
Present on every cell of the motorway corridor	Patterns in human travel behavior Public holidays / vacation periods Driver population Vehicle population Luminance	Weather conditions
Present on a selection of cells of the motorway corridor		Road works Events Incidents

Some notes on this categorization are made. The assignment of public holidays / vacation periods is debatable, the effect of public holidays could also only be manifested on certain periods of time. For example only during the peak periods. Weather conditions are assumed to be present on every cell of the motorway corridor. This seems reasonable because a motorway the surface area of a motorway is very small relatively small compared to a motorway network. Road works, events and incidents are assumed not to last a whole day. For road works, this assumption is not always valid and could therefore also be continuously present (on a certain day).

4.3.2 Quantification of effects

In this subparagraph the effect on both traffic demand and traffic supply will be quantified. Every identified influence factor will be further elaborated and an explanation will be given on how the effect will be incorporated. The chosen reduction factors will be modeled as variables and can be adapted in the model.

The traffic supply can be affected on four different aspects: free speeds, free flow capacity, queue discharge capacity and jam density. The relations between these traffic flow variables have been discussed in paragraph 2.1. The effect on the free flow capacity needs to be further elaborated. Since the critical intensity (free flow capacity) is equal to the critical density times the critical speed, a reduction or addition to the capacity needs to be 'divided' over the critical density and the critical speed. Some factors might have a large effect on the critical density, while others will have a larger effect on the critical speed. Therefore a division parameter d_i for every factor i is introduced.

Equation 4-3

$$correction\ factor_{critical\ density} = correction\ factor_{capacity}{}^{d_i}$$
$$correction\ factor_{critical\ speed} = correction\ factor_{capacity}{}^{1-d_i}$$

Patterns in human travel behavior

The basic traffic demand profile will be derived from human travel behavior patterns. This will be done for each day of the week. Days in which one of the identified factors has significant influence, should be filtered. The patterns are location bound, so this data analysis has to be done separately for each case study. In this way the daily and weekly patterns are incorporated, however the seasonal effects have not yet been taken into account.

The seasonal effects will be taken into account using Figure 2-29 and Figure 2-30. After determining whether it concerns a vacation or a non-vacation day, the peak and off-peak traffic demand levels are adjusted with the month-dependent correction factors. It is assumed that for the weekend days the same correction factors can be used as for the off-peaks on workdays.

Public holidays / vacations

The effects of public holidays and vacations can be contradicting. Demand during peak periods may be lower, due to absence of commuter traffic. But more leisure traffic can be expected in vacation periods. Extra demand can also be expected from people leaving or coming back from a holiday. Part of the seasonal effects has already been dealt with above. In addition to this the following discrepancies, or a combination of these, can happen:

- Evening peak absent
- Morning peak absent
- Vacation peak present

Which combination of the discrepancies will happen on a certain public holiday or vacation period, depends on data.

The application of the discrepancies on traffic demand needs further elaboration. Morning and evening peaks will be capped to the maximum non-peak demand. Vacation peaks affect the total demand over the day, the correction factor is assumed to be 1.15, but can be calibrated. If a vacation peak is present and one of the commuter peaks is absent, the value will be applied after the commuter peak is removed from the demand profile.

Traffic control actions

When a rush-hour lane is opened, the free speed will be reduced to a maximum of 100 km/h. The free flow capacity of the extra lane will be the theoretical capacity of a rush-hour lane. All other traffic supply variables for the additional lane are assumed to be similar to the ones on the other lanes.

Driver population

Any possible effects on the free speeds will be neglected. The reduction factors for the capacities are shown in Table 4-9.

Table 4-9: *Correction factors for different driver populations*

Driver population	Correction factors
Peak drivers	1,00
Off-peak drivers	0,96
Saturday drivers	0,94
Sunday drivers	0,92

Peak drivers are assumed to be the most experienced drivers, probably resulting in more efficient driving behavior. Weekend drivers are expected to be the least experienced. In absence of any information on this, no distinction between free flow capacity and queue discharge rate has been made.

In the absence of any information on this, it is assumed that the effect on the free flow capacity is equally distributed over the critical speed and the critical density. Therefore, a division parameter $d_{drivers}$ = 0.5 is used.

Vehicle population

Any possible effects on the free speeds will be neglected. The effects of trucks on capacities and jam densities will be expressed in terms of passenger car equivalents. This factor indicates the number of passenger cars that one truck is equivalent to. For the free flow capacities, queue discharge rates and jam density's, different PCE-values can be used.

The correction that should be made on the supply variables can now be calculated as:

Equation 4-4

$$correction\ factor = \frac{truckfrac_{default} \cdot PCE + (1 - truckfrac_{default})}{truckfrac(t) \cdot PCE + (1 - truckfrac(t))}$$

Where:

$truckfrac_{default}$	=	default truck fraction
truckfrac(t)	=	truck fraction simulated for time interval t
PCE	=	passenger car equivalent for a supply variable

So if a capacity has been measured with a percentage of truck of 0% and this capacity needs to be corrected for a truck percentage of 15%. The reduction factor will be $\frac{0 \cdot 2 + (1-0)}{0.15 \cdot 2 + (1-0.15)} = \frac{1}{1.15}$, when a PCE of 2 is assumed.

The vehicles-effect on the free flow capacity is assumed to be entirely associated with the critical density. Therefore, a division parameter $d_{vehicles}$ = 0 will be used.

Road works

As explained in subparagraph 2.2.5, the magnitude of the effect of road works on traffic demand depends on the specific situation. Here it is assumed that the total demand during a road work can be corrected by one correction factor. The size of this correction factor depends on

- the remaining capacity, relative to the traffic demand under normal circumstances;
- the duration of the road works;
- the availability of alternative travel options;
- the traffic and demand management measures taken by the road authority.

In Table 4-10 is explained how the components of Equation 4-5 will be determined.

Table 4-10: *Effect of road works on traffic demand*

Road work characteristic	Magnitude	x1, x2, x3, x4
the remaining capacity, relative to the traffic demand under normal circumstances	Large Average Small	0 0,05 0,10
the duration of the road works	Short (hours) Medium (day) Long (days)	0 0,03 0,05
the availability of alternative travel options	High Low None	0,05 0,01 0
the traffic and demand management measures taken by the road authority	Extensive Simple None	0,10 0,05 0

Equation 4-5

$$correction\ factor = 1 - (x1 + x2 + x3 + x4)$$

The effects of road works on traffic supply strongly depend on the type of road work. The capacity reduction depends mainly on the number of available lanes and on whether the lanes are narrowed or not. Therefore the following correction factor is conceived. This equation divides the remaining theoretical capacity by the original theoretical capacity. These capacities are based on Table 2-7, Table 2-8 and Table 2-9. The free speed is reduced to either 70 km/h or 90 km/h, depending on the type of road work.

Equation 4-6

$$correction\ factor = \frac{C_{reduced,j}{}^{\alpha} * C_{reduced+narrow,j}{}^{1-\alpha}}{C_i}$$

Table 4-11: *Explanation of road works correction factor variables*

Variable	Number of lanes i or j	Value
$C_{reduced,j}$	1	1500
	2	3600
	3	5400
	4	7000
	5	8500
	6	9800
$C_{reduced+narrow,j}$	1	1200

	2	3200
	3	4725
	4	6150
	5	7500
	6	8625
C_i	1	1900
	2	4200
	3	6300
	4	8200
	5	10000
	6	11500
α	-	0 in case of lane narrowing/short-term static or dynamic deposition; 1 otherwise

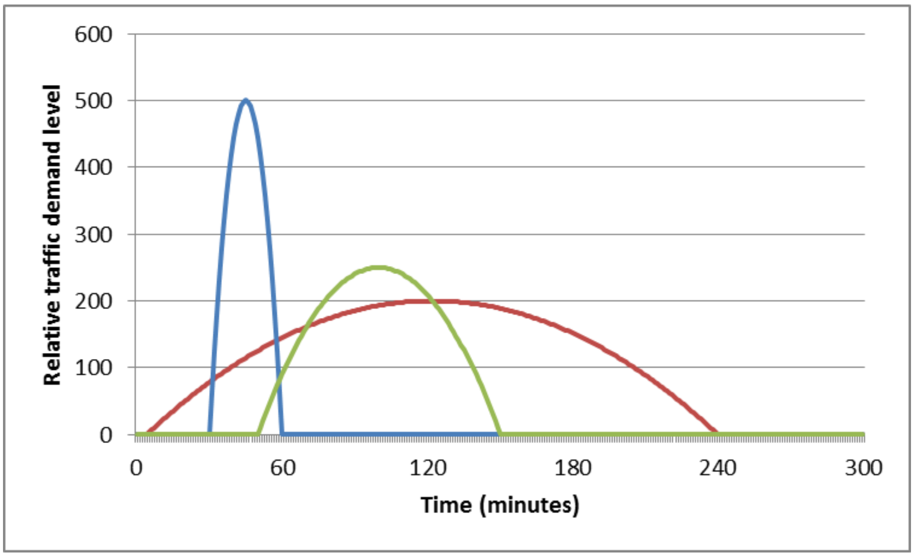
Because of the fact that the free speed is reduced, the critical speed needs to be reduced to at least this free speed as well. This already accounts for part of the effect on the free flow capacity. It is assumed that the remaining part of this effect can be fully assigned to the critical density.

Events
Events cause a temporal increase in traffic demand. This increase can be spread over the day, but also a peaked increase in demand is possible. The extent of this dissemination over time needs to be manually predefined for each event. The effect of event will be modeled using the following attributes:

- Start time of the increased flow
- End time of the increased flow
- Peak of the increased flow

Figure 4-3 shows the increase in demand over time for three different events (i.e. different start time, end time and peak of the increased flow).

Figure 4-3: *Increase of traffic demand due to events*



Weather conditions

The magnitude of the effects of weather conditions mainly depends on the precipitation intensity. However, the effects are not likely to increase linearly with the intensity of a certain weather type. Therefore a classification of weather types is shown in Table 4-12.

Table 4-12: *Classification of weather types by intensity*

Type of weather condition	Intensity	Classification
Rain	0 – 3 mm/u	'favorable/dry weather'
Snow	0 mm/u	
Black Ice	-	
Fog	-	
Rain	3 – 10 mm/u	Moderate rain
	> 10 mm/u	Heavy rain
Snow	< 10 mm/u	Moderate snow
	> 10 mm/u	Heavy snow
Black ice	Any	Black ice
Fog	Any	Fog

The effects of the different types of weather conditions on traffic demand are shown in Table 4-13. The definition of the time windows is the same as in Table 4-5.

Table 4-13: *Effects of the different weather types on traffic demand*

Type of weather condition	Demand effect (%)			
	Morning peak	Evening peak	Off-peak	Weekend
Moderate rain	+2	+2	-2	-5
Heavy rain	0	0	-4	-10
Moderate snow	-5	-2.5	-7	-18
Heavy snow	-20	-15	-30	-50
Black ice	-4	-1	-5	-15
Fog	0	0	0	0
Summery day	0	0	+1.5	+5

In case of moderate rain, it is assumed that people change their departure time. Therefore the morning peak will be shifted randomly to 0-10 minutes later.

To deal with the effects of weather conditions on traffic supply, also the categorization in Table 4-12 will be used. Based on the results from the researches presented in Table 2-2, Table 2-3, Table 2-4, Table 2-5 and Table 2-6 correction factors on free speed and capacities have been assumed. Table 4-14 shows the percentages the supply factors will be reduced by.

Table 4-14: *Effects of the different weather types on traffic supply*

Type of weather condition	Supply effect (%)	
	Free speeds	Capacities
Moderate rain	8	5
Heavy rain	12	15
Moderate snow	10	10
Heavy snow	15	25
Black ice	10	10
Fog	12	12
Summery day	0	0

In case of heavy snow, the number of available lanes is assumed to be reduced by half. In the absence of data regarding any possible differences in the effects on the free flow capacity and the queue discharge rate, no distinction is made between these.

In line with (Hranac, Sterzin et al., 2006), it is assumed that the largest part of the weather effect on the free flow capacity corresponds to an effect on the critical speed (rather than on the critical density). Therefore, a division parameter $d_{drivers}$ = 0.8 is used.

Incidents

The effects of an incident depend on location, duration and severity. In subparagraph 4.2.2 three possibilities for the location of an incident have been discussed: on the considered road section and downstream or upstream of the considered location. Table 4-15 shows the corrections made on the traffic supply variables in case the incident is on the considered road stretch. These will be applied throughout the duration of the incident.

Table 4-15: *Effects of incidents on the considered road stretch*

	Accidents	Vehicle breakdowns
Free speed	For incidents on the hard shoulder, the free speed is assumed to be reduced to 90 km/h. For incidents blocking one or more lanes, a reduction to 70 km/h is assumed.	
Free flow capacity Queue discharge capacity	For incidents on the hard shoulder, the capacities on the remaining lanes are assumed to be corrected with 0,65. For incidents blocking one or more lanes, a correction factor of 0,54 is assumed.	For incidents on the hard shoulder, the capacities on the remaining lanes are assumed to be corrected with 0,72. For incidents blocking one lane, a correction factor of 0,60 is assumed.

When the incident is simulated at a location upstream or downstream of the considered road stretch, respectively the inflow or the outflow of the considered road stretch will be limited. This will be done independently of the exact location of the incident. The correction factors on the inflow and the outflow of the considered road stretch are shown in Table 4-16. Here it is assumed that the number of lanes on the upstream location is equal to the number of lanes on the considered road stretch. When this assumption is clearly wrong, these factors may be adjusted.

Table 4-16: *Effects of incidents upstream or downstream of the considered road stretch on the capacities*

	Accidents	Vehicle breakdowns
Hard shoulder blocked	0,65	0,72
One or more lanes blocked	0,54 * number of lanes left / total number of lanes	0,60 * number of lanes left / total number of lanes

In the absence of any information on this, it is assumed that the effect on the free flow capacity is equally distributed over the critical speed and the critical density. Therefore, a division parameter $d_{drivers}$ = 0.5 is used.

Luminance
Any possible effects on the free speeds will be neglected. Capacities will be reduced with a correction factor. Corresponding to a 1.5% reduction, this reduction factor would be 0.985. In absence of any information on this, no distinction between free flow capacity and queue discharge rate has been made.

It is assumed that the effect on the free flow capacity is distributed over the critical speed and the critical density in the same way as the effects of adverse weather conditions. Therefore, a division parameter $z_{darkness} = z_{weather} = 0.8$ is used.

4.3.3 *Intrinsic randomness in driving and travel behavior*

A large part of the variations in traffic supply and demand can be explained by the identified factors discussed above. However, a residual randomness for both the traffic supply and demand remains. This intrinsic randomness has already been discussed briefly in subparagraph 2.2.7. This subparagraph will show how this intrinsic randomness will be dealt with.

Intrinsic randomness in human driving behavior
Intrinsic random variations can occur in occur in all supply variables. However, only the randomness in the capacities will be considered here. The intrinsic randomness in free speeds and jam densities are expected to be relatively limited and can be expected to partially counterbalance with local variations.

According to Brilon, Geistefeldt et al. (2005), the free flow capacities can be modeled by assuming them to be Weibull distributed. This was also demonstrated in subparagraph 2.3.2. The shape and scale parameters of this distribution should be determined for a certain road stretch using data analysis. When these parameters have been determined for the different parts of the considered road stretch, a sample can be taken for simulation. However, it is not accurate to sample each lane or cell independently as to assume full dependency. Therefore the following solution is proposed:

- take one sample randomly between 0 and 100, corresponding to the percentile that will be taken from the capacity distribution;
- for the next cell or lane, sample within a fixed interval relative to the first sampled percentile.

For example when a fixed interval of 20 is chosen and the first sample from the distribution is 60, the rest of the percentiles will be randomly picked from interval 50-70.

Intrinsic randomness in human travel behavior
The randomness in human travel behavior that cannot be explained by all other identified factors will be described here. This intrinsic randomness is caused by an independent part of variation in travel behavior of individual travelers. Examples in the work related traffic demand that cause fluctuations in traffic demand are: someone is sick, someone is working on another location, and someone will work at home. This part of the variation can be modeled with the Poisson distribution. The explanation below was adopted from Miete (2011). This explanation clarifies why this part of the variation can be modeled with the Poisson distribution.

This is the case, because the number of travelers on a given origin-destination relation can be considered as the summation of n Bernoulli (p_i) distributed variables. Where n represents the imaginary total number of potential travelers and p represents the probability that potential traveler i decides to make the trip. This probability would be different for each potential traveler. The summation of n Bern(p_i)-distributed variables can be approximated by one Binom(n,$<p_i>$ - distributed variable, where $<p_i>$ represents the average probability over all potential travelers. The main problem would be to choose appropriate values for n and $<p_i>$. But when approximating the Binom(n,$<p_i>$)-distributed variable with a Poiss(λ), it is no longer necessary to choose values for n and $<p_i>$. A value for λ, which is the expected value, would suffice. This expected value can be considered to be given by the demand value following from all other sources of variability. This makes the Poisson distribution conditional on all external influence factors.

Note that by approximating the Binom(n,$<p_i>$)-distributed variable by a Poiss(λ)-distributed variable, it is implicitly assumed that $n \rightarrow \infty$ and $<p_i> \rightarrow 0$. This results in an overestimation of the variance of the traffic demands. This does not seem problematic since variance from the other sources of variability is probably underestimated. This could be either due to absence of knowledge of a certain factor or on a certain factor influencing the traffic demand.

4.4 Conclusions

This chapter shows an overview of influence factors on traffic demand and traffic supply. For the traffic supply these are: weather conditions, luminance, incidents, road works, traffic control actions, variations in vehicle population, variations in driver population and ‘intrinsic’ variations in human driving behavior. For the traffic demand these are: patterns of variation in human travel behavior, public holidays and vacations, events, weather conditions, road works and other variations in human travel behavior. Also the interdependencies of the different identified sources of variability are given.

The predictabilities of the influence factors are discussed. First a classification is made. The factors are assigned to ‘always predictable’, ‘sometimes predictable’ and ‘not very predictable’. In this way it is possible to systematically implement the influence factors in the model. The quantification of the predictabilities is done using historical data of the concerned influence factor. In this way the probability occurrence of an influence factor can be determined.

The effects of the identified influence factors can be continuously present or only on certain moments in time. They can also be on every cell of the motorway corridor or only on a selection of cells of the motorway corridor. Accordingly, a categorization is made. This will help with the implementation of the effects in the model. The quantification of the effects is done using literature. The effects can be accounted for using correction factors on the traffic demand profile or the various traffic supply variables.

To the intrinsic variations in travel and driving behavior, special attention is given. For the traffic demand, the bandwidth is determined through a Poisson distribution. For the traffic supply, a different approach is conceived. This method reduces the bandwidth from which is sampled on a certain day. In this way cross-correlation over space and time is artificially accounted for.

The findings in this chapter will be used to develop the model. The model development is discussed in the next chapter.

5 Model Development

In this chapter first the model algorithm will be explained. Then the calibration and validation of the model will be discussed.

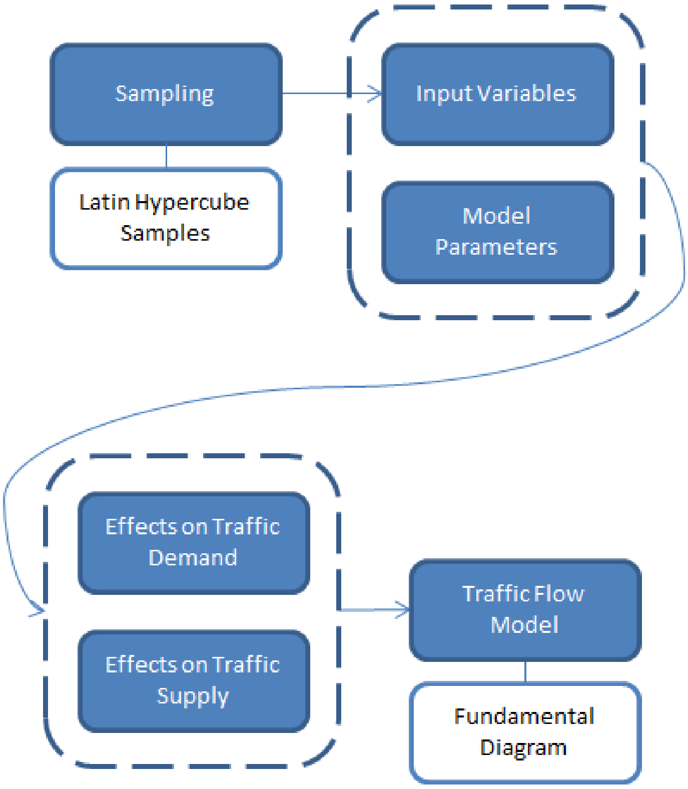
5.1 Model algorithm

The functioning of the model will be explained here. To take into account the discussed influence factors the basic first order traffic flow model needs to be extended. The created model therefore consists of following components:

- Sampling;
- Latin Hypercube Samples;
- Input Variables;
- Model Parameters
- Effects on Traffic Demand;
- Effects on Traffic Supply;
- Fundamental Diagram;
- Traffic Flow Model.

Figure 5-1 shows a schematic overview of these model components.

Figure 5-1: *Schematic overview of the model components*


Sampling
Input Variables
Latin Hypercube Samples
Model Parameters
Effects on Traffic Demand
Traffic Flow Model
Effects on Traffic Supply
Fundamental Diagram

Each of the model components will be described and explained in the next subparagraphs. Also the model output will be discussed. In the last subparagraph a more extensive schematic overview of the model will be presented.

5.1.1 *Input variables*

The input variables for the model are used to define the duration and type of all influence factors. There is also an option to turn off an influence factor. Table 5-1: shows al input variables and gives a short explanation.

***Table 5-1:** Input variables*

Influence factor	Input variable	Explanation
Road works	Start time Duration (or end time) Location Speed limit Number of lanes remaining Alpha Remaining capacity Duration Alternative routes Mobility management	Time at which the road works starts Time at which the road works ends Location of the road works (in terms of cells in the model) Speed limit at road works location cells (70 or 90 km/h) Number of lanes remaining at road works location (1 or 2) Indicator for lane narrowing/short-term static or dynamic deposition (0), 1 otherwise Large, average, small Short, medium, long High, low, none Extensive, simple, none
Event	Start time Duration (or end time) Peak	Time at which the increased flow due to the event starts Time at which the increased flow due to the event ends Peak of the increased flow due to the event
Incident	Start time Duration (or end time) Location Type Number of lanes blocked	Time at which the incident starts Time at which the incident ends Location of the incident (a cell in the model) Accident, vehicle breakdown, artificial accident, artificial vehicle breakdown Number of lanes blocked by the incident (0, 1,2 or 3)
Season effects	Day of week Month Vacation	Monday, Tuesday, etc. January, Februari, etc. Indicator for vacation period (yes/no)
Public holidays / vacation periods	Special day category	Eight categories as described in paragraph 4.3.2
Weather conditions	Start time Duration (or end time) Type	Time at which the weather condition starts Time at which the weather condition ends Moderate rain, heavy rain, moderate snow, heavy snow, black ice, fog, summery day, favorable
Vehicle population	Average truck fraction over the day	When no truck demand profile is available, an average percentage can be defined
Driver population	-	
Luminance	-	

For incidents and weather conditions it is also possible to define multiple entries. For example moderate rain from 10:43 to 12:23 and heavy rain from 18:00 to 21:23 and incident at 12:00 to 12:23 and at 14:09 to 15:02. The influence factors driver population and luminance can only be turned on or off.

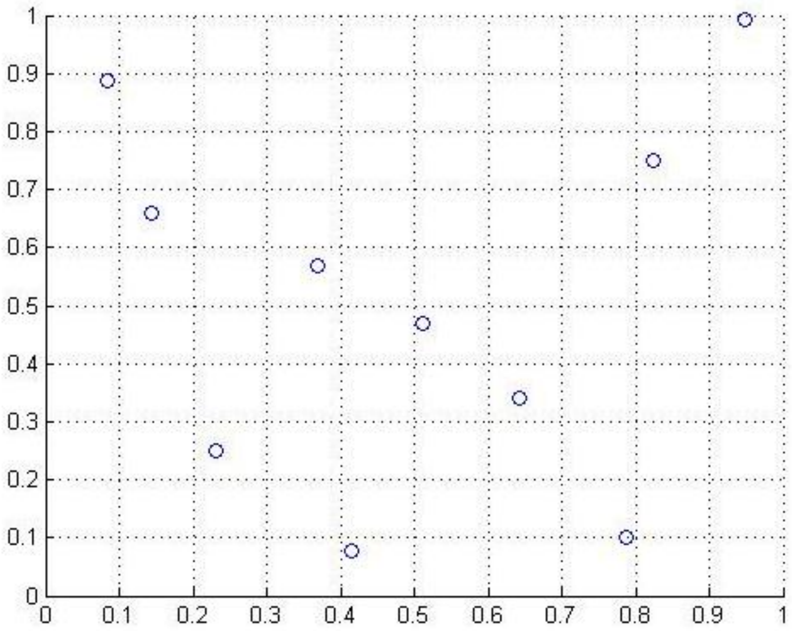
In the model it is possible to define these variables manually, with the consequence that the sampling component is skipped. In this way the model can be calibrated.

5.1.2 *Sampling*

The sampling component ensures that the input variables can be sampled. For each input variable a cumulative probability function can be defined. This is done by creating a matrix containing percentiles and their corresponding value. For example [50 100; 0 1] means 50% chance on 0 and 50% chance on 1. When for every percentile a corresponding value is added, a very detailed cumulative probability function can be created.

As shown in Figure 5-1 the sampling component uses latin hypercube samples. In paragraph 2.4 it has already been explained how latin hypercube sampling works. Figure 5-2 shows the probability space of two variables, it is clear that in each row and in each column only one sample is taken.

Figure 5-2: Probability space for 2 variables with 10 bins



The number of samples can be calculated by multiplying the number of minimum bins per variable with the number of variables. When a prediction is made under the assumption that a lot of variables are ‘known’, the number of runs will be sufficiently small. However, when for example the occurrence, the location, and the type of road works is unknown and incidents (five variables) are taken into account as well, already eight variables have to be sampled. If for each of these variables four bins would be assumed, then 10*8 = 80 runs are needed. Due to the intelligent sampling technique this takes less than an hour, but when all variables need to be sampled still a very long calculation time would be needed. It is therefore advised and practical to keep the number of variables to a minimum.

Note that since multiple weather conditions and incidents can occur theoretically, these factors need special attention here. For the weather conditions it is assumed that from 00:00 to 11:59 and from 12:00 to 23:59 only one weather type can be sampled. For incidents each category is sampled individually and twice, since in theory it is possible that multiple incidents occur in one day.

5.1.3 Model parameters

In this component the model parameters are defined. An overview of the defined parameters is given in Table 5-2.

Table 5-2: *Model parameters*

Category	Parameters
Model parameters / road geometry	Road stretch length Time step size Size of each cell / distance step size (in km) Number of cells Number of time steps
Initial Traffic Supply variables for each cell	Number of lanes Critical intensity Critical density Jam density Free speed Queue discharge capacity
Initial Traffic Demand variables	Traffic demand profile for each day of the week
Magnitude of effects on Traffic Supply	Vehicle population Driver population Road Works Weather Conditions Luminance Incidents
Magnitude of effects on Traffic Demand	Season/vacation effects (patterns over the year) Public holidays / vacation periods Road Works Weather conditions

The parameters in the last two categories (magnitude of effects on traffic demand and supply) are according to subparagraph 4.3.2. Note that also these parameters can be calibrated for case studies.

5.1.4 Effects on traffic demand and supply

Dependent on the chosen or sampled input variables, the initial traffic demand and supply variables are corrected for the effects of the influence factors. The traffic supply variables can be corrected separately for each cell and time step. Each minute in the traffic demand pattern can be modified individually as well. In this way both temporal and local variations can be incorporated. The reason to make different components for traffic demand and supply is that some supply factors are dependent on the flow, for example the incidents.

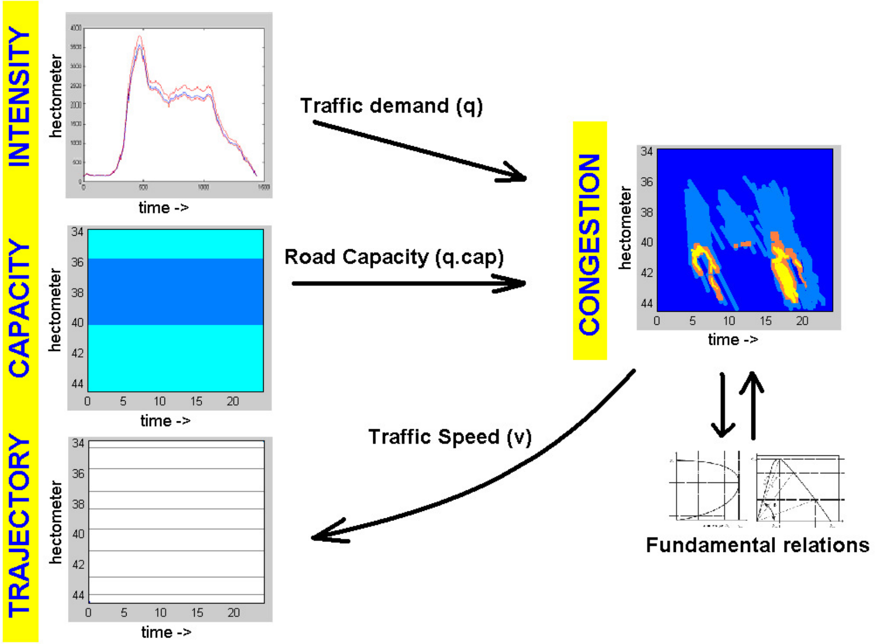
5.1.5 Traffic flow model and use of the fundamental diagram

As already explained in paragraph 3.2, the developed traffic flow model uses the LWR (Lighthill-Whitman-Richards) method with the Godunov scheme, which considers first order traffic flow theory on the basis of the conservation equation (paragraph 2.1 & 3.2). For each cell in the network (corresponding to sections of the motorway), the traffic characteristics (density and flow) are calculated iteratively for each time step. For the cell size, the average distance between induction loops is taken (approximately 200m). When the density reaches the critical density, congestion sets in. The fundamental diagram is used to calculate the traffic flows for the next time step. This method allows for forward traffic flow, while also allowing backward propagating congestion.

From the flow definition, traffic speeds are derived. This results in a mean speed over the section, which allows for the calculation of the travel time per section at a specific time. Using a trajectory method, the actual travel times over the entire motorway corridor can be calculated as well. Figure 5-3 illustrates this process.

When the traffic demand in a section drops below capacity, the queue disperses from the front of the section. This mean that shockwave theory is accounted for, and thus the place and time of congestion is more accurately determined. This also leads to more reliable travel times.

***Figure 5-3:** Flow-diagram of Travel time modeling including congestion calculation (Calvert, 2009)*



Use of the fundamental diagram

The fundamental diagram used in the model is similar to the Smulders fundamental diagram. However, all traffic supply variables can be varied independently. The input variables for the original Smulders fundamental diagram only consist of k, kc, kjam and u0 and the capacity drop is not accounted for. In the fundamental diagram illustrated in Figure 5-4 the input variables consist of k, kc, kjam, qcrit, qdisc and u0.

Figure 5-4: *Fundamental diagram used in the model*

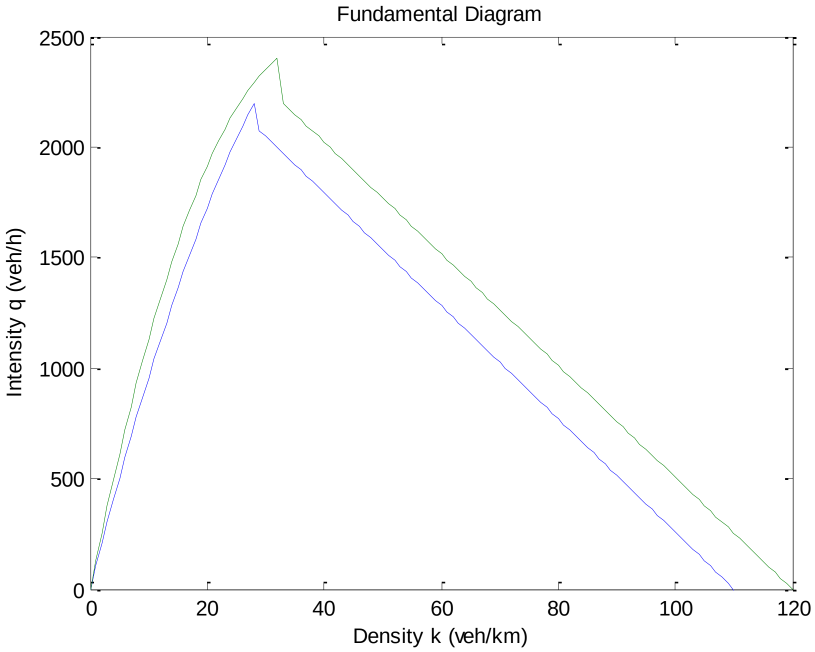


Figure 5-4 also shows how the variations in the traffic variables influence the fundamental diagram. The blue fundamental diagram has a smaller free flow speed (slope in line in the free flow branch), a smaller critical intensity (maximum intensity in graph), smaller density (density at maximum intensity), a smaller capacity drop (difference between maximum intensity at free flow branch and maximum intensity at the congested branch) and also a smaller jam density (density at traffic breakdown). Due to a smaller critical intensity and critical density also the critical speed is smaller.

5.1.6 Model output

After the traffic flow model is fed by the input variables and corrected model parameters and all traffic characteristics are iteratively calculated, the output variables can be derived. The generated output variables, in case the input variables are defined manually (sampling component is skipped), are presented in Table 5-3.

Table 5-3: *Model output variables (no sampling)*

Output variable	Form	Explanation	Unit
Flow	Vector	Initial traffic demand for each time step after correction for influence factors	Veh / h
qcrit	Matrix	Critical intensity for each cell and each time step after correction for influence factors	Veh / h
kcrit	Matrix	Critical density for each cell and each time step after correction for influence factors	Veh / km
ucrit	Matrix	Critical speed for each cell and each time step after correction for influence factors	Km / h
ufree	Matrix	Free speed for each cell and each time step after correction for influence factors	Km / h
kjam	Matrix	Jam density for each cell and each time step after correction for influence factors	Veh / km
qdisc	Matrix	Queue discharge rate for each cell and each	Veh / h

		time step after correction for influence factors	
q	Matrix	Intensity at each cell and each time step after correction for influence factors	Veh / h
k	Matrix	Density at each cell and each time step after correction for influence factors	Veh / km
u	Matrix	Speed at each cell and each time step after correction for influence factors	Km / h
tt	Vector	Actual travel time at each time step	Min
queue	Vector	Length of the queue for each time step	Km
vehiclesqueue	Vector	Vehicles in the queue for each time step	Veh
ttfree	Scalar	Free flow travel time	Min
delay	Vector	Difference between actual travel time and free flow travel time	Min
totaldelay	Vector	Difference between actual travel time and free flow travel time multiplied by the flow at each time step	Min
time spent	Vector	Actual travel time multiplied by the flow at each time step	Veh·h
TTS	Scalar	Total Time Spent (sum of timespent)	Veh·h
TD	Scalar	Total Delay (sum of totaldelay)	Veh·h
FZ	Scalar	Congestion severity, sum of the queue lengths at each minute (sum of queue)	Km·min
TT_mean	Scalar	Mean travel time (mean of tt)	Min
TT_median	Scalar	Median travel time (median of tt)	Min
TT_90	Scalar	90th percentile of the travel time	Min

Aggregated output variables
When sampling is used, the input and output variables are collected. Each scalar, vector or matrix is placed in an array, the number of entries in the array will correspond to the number of runs.

The collected output variables are logically the same as in Table 5-3, except each variable is calculated repetitively for each run. For each variable, a distribution can then be made.

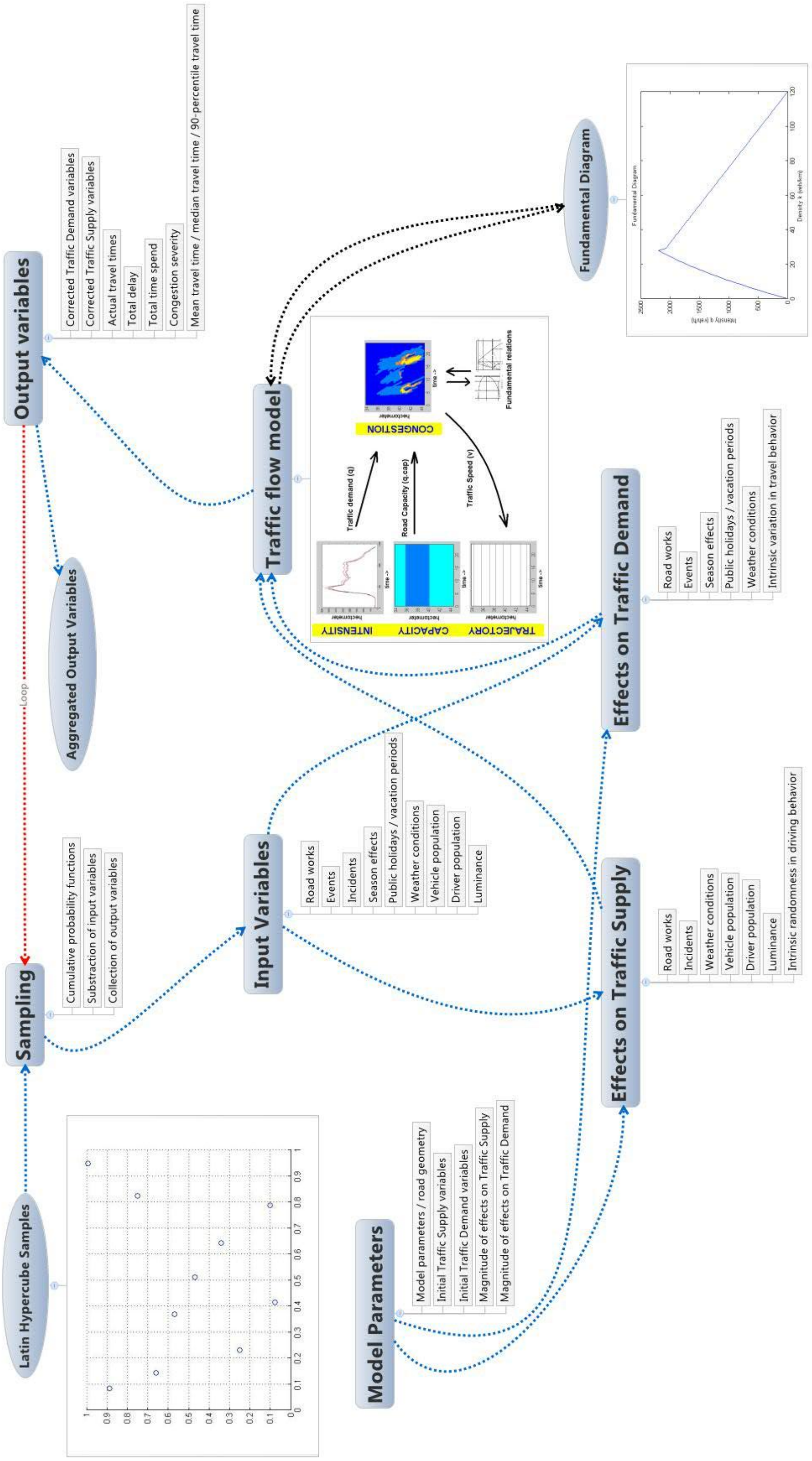
For example when the 20 model runs are executed, the output for TTS or TD will consist of 20 Scalars placed in an array, while the output for queue and tt will consist of 20 vectors placed in an array. The output for q, u or k will consist of 20 matrices placed in an array. So in theory, contour plots for each run could be made.

The considered indicators for the case study will be discussed in the next chapter.

5.1.7 *Complete schematic overview of the model components*

Figure 5-5 shows the a schematic overview of the components of the model algorithm including the content of these components. The main code, in which the sampling and the loop is programmed, is presented in Appendix A: Main model code.

Figure 5-5: *General model algorithm*


Latin Hypercube Samples
Sampling
Cumulative probability functions
Substraction of input variables
Collection of output variables
Loop
Input Variables
Road works
Events
Incidents
Season effects
Public holidays / vacation periods
Weather conditions
Vehicle population
Driver population
Luminance
Output variables
Corrected Traffic Demand variables
Corrected Traffic Supply variables
Actual travel times
Total delay
Total time spend
Congestion severity
Mean travel time / median travel time / 90-percentile travel time
Aggregated Output Variables
Traffic flow model
INTENSITY
CAPACITY
TRAJECTORY
CONGESTION
Traffic demand (q)
Road Capacity (q-cap)
Traffic Speed (v)
Fundamental relations
Fundamental Diagram
Effects on Traffic Demand
Road works
Events
Season effects
Public holidays / vacation periods
Weather conditions
Intrinsic variation in travel behavior
Effects on Traffic Supply
Road works
Incidents
Weather conditions
Vehicle population
Driver population
Luminance
Intrinsic randomness in driving behavior
Model Parameters
Model parameters / road geometry
Initial Traffic Supply variables
Initial Traffic Demand variables
Magnitude of effects on Traffic Supply
Magnitude of effects on Traffic Demand

5.2 Model calibration

This paragraph describes the model calibration. First the face validity of the model is discussed, next the data processing is explained and the calibration results are presented. Finally some statements are made about the construct en predictive validity of the model.

5.2.1 Face validity

A model is said to be face valid if its equations, parameters and characteristics are logically related to the characteristics of the system at hand and if it encompasses the minimally required detail to tackle the problem in question (Van Lint, 2011).

It can be argued that the developed model is face valid. This is ensured by the inclusion of all relevant influence factors and the use of a first order traffic flow model (to which the capacity drop phenomenon has been added).

However, this does not imply that the model is entirely face valid:

- Route choice effects are not considered in the model;
- Upstream and downstream network effects are only accounted for incidents.

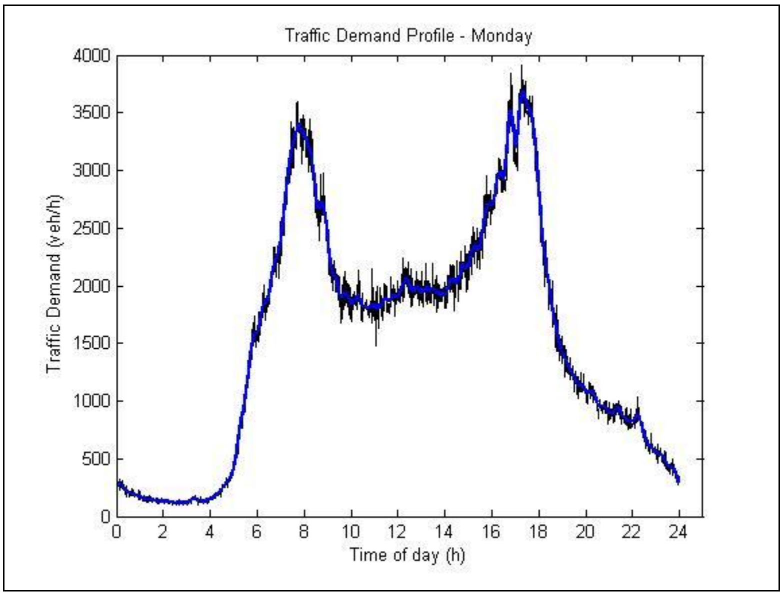
5.2.2 Data processing

The model will be calibrated using recorded data to ensure that the results are representative. First the traffic demand profiles will be generated from the data, next the traffic supply variables will be subtracted. Next the intrinsic variability is calibrated. These steps will be discussed here separately.

Traffic demand estimation

For each day of the week a traffic demand profile is created. From the data, days with adverse weather conditions, road works and incidents are excluded. Figure 5-6 shows the estimated traffic demand profile for the Monday. The profiles for the other weekdays can be found in Appendix B: Calibration results.

***Figure 5-6:** Traffic demand profile for the Monday*



Traffic supply estimation
From the data the free flow capacity can be estimated using the Product Limit Method. However, the queue discharge rates found using the queue discharge method were found to be more reliable (more data points). For the remaining traffic supply variables, theoretical values are used. At some data points no capacity estimation was possible (when no congestion occurred in the data). For these road segments also a value from theory was adopted. The traffic supply estimation results for the main bottleneck are shown in Figure 5-7. Further explanation can be found in Appendix B: Calibration results.

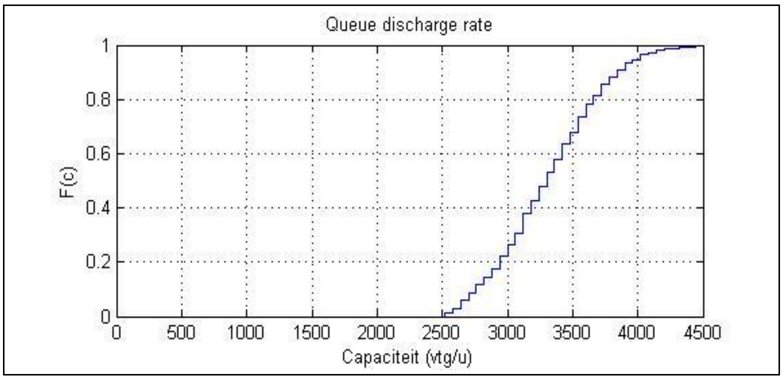


***Figure 5-7:** Traffic supply estimation results for the main bottleneck*

Intrinsic variability
The calibration of the intrinsic variability is done using the estimated demand and supply variables and the modeled intrinsic variation on traffic supply and demand. The aggregated model parameters are then compared to the real data. For this, the same days are excluded from the data as for the traffic demand estimation. This means that the other influence factors (effects of the seasons, not adverse weather conditions, vehicle population, driver population and luminance) are part of the travel time distribution. It is possible that the influence of these factors is wrongly taken into account in the calibration of the intrinsic variability. To correct for this error, the calibration is repeated with the season effects, luminance, driver population and vehicle population enabled in the model. The influence of these factors on the travel time distribution will also be discussed in the next chapter.

Influence factors
The effects of the identified influence factors have been discussed in paragraph 4.3. Calibration of the magnitude of effects will not be performed. The theoretical values are assumed to be representative and accurate enough for the research purpose.

5.2.3 Calibration results

For both the traffic flow model calibration as the calibration regarding to the uncertainty the traffic demand and traffic supply will be described here. For both calibrations, travel time will be used as the main performance indicator.

Calibration of the Traffic Flow Model
The calibration of the traffic flow model is done by taking the demand pattern of a certain day in combination with the determined traffic supply pattern. The

calibrated values are the queue discharge rate and the capacity drop. The queue discharge rates obtained from the data are increased by 0 to 50%, while values of 5%, 10% and 15% are tested for the capacity drop.

Based on the smallest MAE and the MRE values (discussed in paragraph 3.4) the queue discharge rates are increased by 40% and a capacity drop of 10% is assumed. The full calibration results for all considered days, including explanations, can be found in Appendix B: Calibration results. Figure 5-8 shows a comparison between the modeled speed contour plot and the speed contour plot from the data.

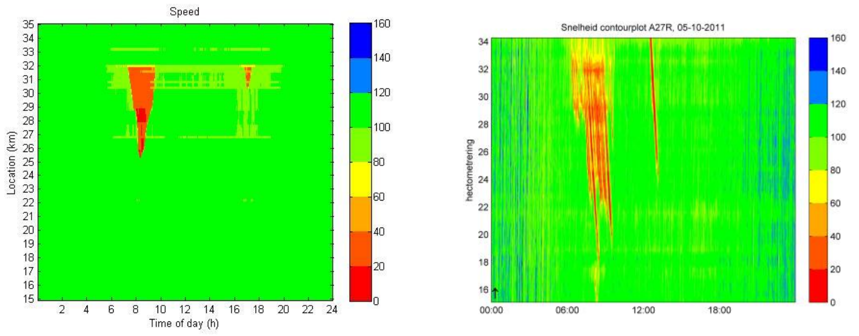


***Figure 5-8:** Speed contour plot generated by the model (left) and speed contour plot from data (right)*

Figure 5-9 shows a comparison between the calibrated travel time and the measured travel time.

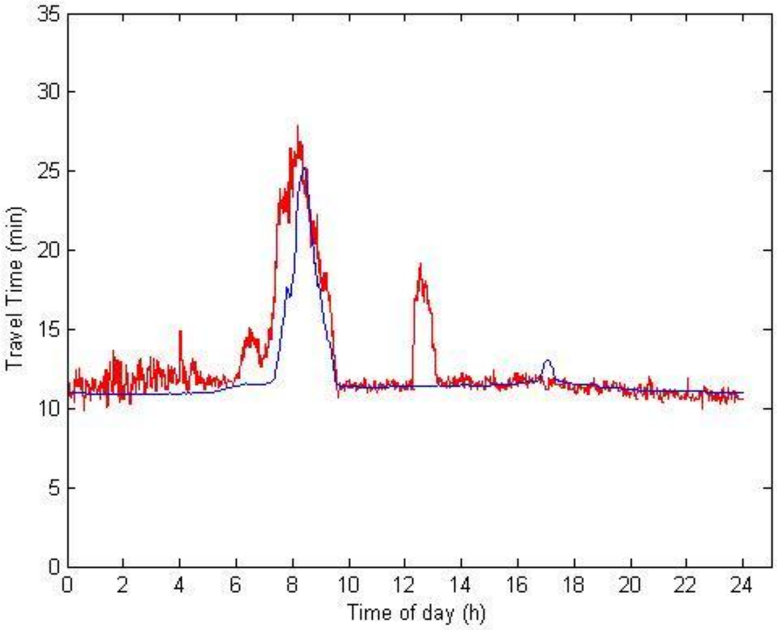


***Figure 5-9:** Comparison of travel times (Red = data, Blue = model)*

From these graphs it is clear that the model describes reality fairly well, apart from the shockwave caused upstream at approximately 12:30.

Calibration of uncertainty in traffic demand and traffic supply

By adding uncertainty in both the traffic demand as the traffic supply profiles, the output of the model consists of distributions. How this intrinsic variability is incorporated in the model has already been discussed in subparagraph 4.3.3. However, to make sure the model output is representative to the data, the maximum and minimum correction factor on the traffic supply is calibrated here.

The minimum correction factor on traffic supply was varied between 90%, 92.5%, 95% and 97.5%. The maximum correction factor was varied between sum of the minimum correction factor and 5%, 10% 15%, 20% and 25%. Using the Kolmogorov-Smirnov test an optimum bandwidth for the traffic supply variation of 92.5% - 112.5% was found. The full calibration results can be found in Appendix B: Calibration results.

Figure 5-10 shows 5th, the 50th and the 95th percentile of the travel time distribution from the data (left) and from the modeled travel time distribution (right).

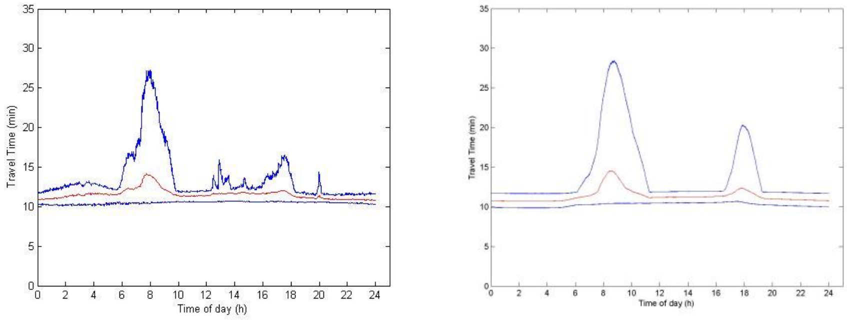


Figure 5-10: *Travel time distribution from data (left) and the modeled travel time distribution (right)*

In the subparagraph 5.2.2 it is mentioned that the manner in which the calibration is performed, results in an overestimation of the intrinsic variability. This is due to the fact that season effects, vehicle population, driver population and luminance are now included in the dataset and should therefore also be included in the model. Notice that also events and weather conditions might be included in the data.

Figure 5-11 shows 5th, the 50th and the 95th percentile of the travel time distribution from the data (left) and from the modeled travel time distribution with inclusion of the four mentioned influence factors.(right). The optimal bandwidth for the traffic supply variation is now 95% - 110%. This implies that the season effects, luminance, vehicle population and driver population reduce the bandwidth for supply variation. A bandwidth of 92.5% - 112.5% is thus roughly similar to a bandwidth of 95% - 110% including season effects, driver population, vehicle population and luminance.

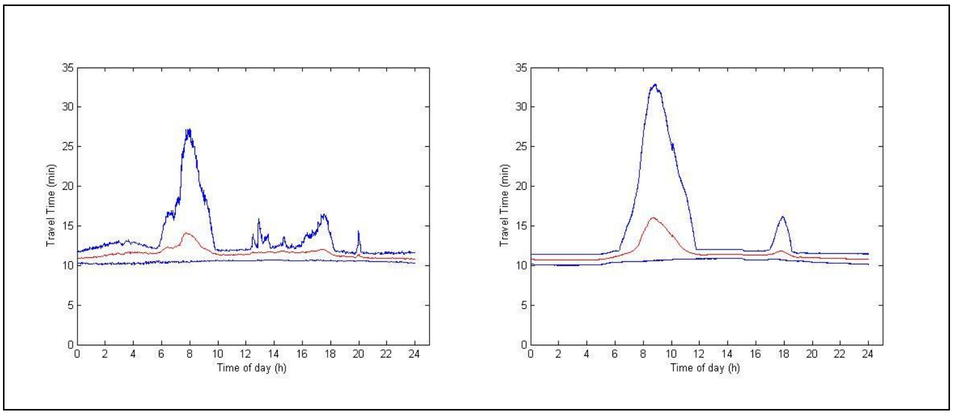


Figure 5-11: *Travel time distribution from data (left) and the modeled travel time distribution (right) 2*

5.2.4 *Construct and predictive validity*

A model is construct valid if it is face valid and if its parameter values and inputs are mutually consistent and consistent with observations in reality. Provided that the model is face valid, this construct validity can be obtained by calibrating the model to real-life observations (i.e. tuning the inputs and model parameters in such a way that the outputs of the model match the real-life observations to a satisfactory degree) (Van Lint, 2011). The previous paragraph indicates that the model is construct valid.

The third level of model validity is predictive validity. A model has predictive validity if the model is both face and construct valid and if the predictions made with the model are consistent with the observed evolution of the system. Obviously, the predictive validity of a model will not be better than its construct validity (which in turn is limited by any possible deficiencies in the face validity). As a result, the critical remarks regarding the face and construct validity of the model will apply equally well to its predictive validity. The relevance of the distinction between construct validity and predictive validity lies in the fact that if the model has been calibrated to a certain dataset (in order to achieve construct validity), it might still perform poorly in predicting the system behavior under slightly different circumstances (for instance due to over-fitting, as discussed above) (Van Lint, 2011).

To check whether the model has predictive validity, comparisons of its predictions with real (future) data should be made. This data is not available in the time span of this thesis, however, it seems reasonable to assume that the travel time distribution over a year would not significantly change over a one or maybe a few years.

5.3 Conclusions

In this chapter the model algorithm and the model calibration are explained. The model algorithm makes use of input variables. These input variables can be sampled. For example, the weather will be favorable, or the weather will be rainy. These samples are taken using the intelligent sampling technique: Latin Hypercube Sampling. This technique leads to significantly less calculation time, compared to conventional random sampling techniques.

Next to the input variables, the model makes use of model parameters. These define the magnitude of the effects on traffic demand or traffic supply. For example, a certain type of roadwork results in a certain decrease of capacity. The magnitude of this decrease is defined in de model parameters.

With the input variables and the model parameters available, the effects on traffic supply and demand can be calculated. The corrected traffic demand profile and traffic supply variables are the input for the traffic flow model, which will produce the model output.

After the model was created, the model is calibrated. Traffic demand profiles and traffic supply variables are estimated from data. With this information, the calibration is performed. First the queue discharge rate and the pre queue capacities are calibrated using travel times of five random days. The minimum mean absolute difference between the recorded and modeled travel times is 0.38, indicating good performance of the traffic flow model.

After the first calibration step, the intrinsic variability in the model is calibrated. The modeled travel time distribution is compared to the recorded travel time distribution on the A27 from Hooipolder to Gorinchem over the year 2011. This distribution was very well approximated by the model. The Kolmogorov-Smirnov test shows that over 80% of the modeled distribution is similar to the recorded distribution. This indicates that the proposed methodology is able to generate reliable predictions.

This chapter shows that the model is valid. The next chapter will use the model for a case study.

6 Model Results: Case study

In this chapter the model results are evaluated. This is done through a case study. First the case study set-up is defined, then the considered indicators are discussed and finally the case study results are presented.

6.1 Case study set-up

In the third research question of this thesis, the effects of incorporating the variability of traffic on congestion predictions are requested. This question will be answered for each of the identified influence factors separately. It would be interesting to know how the different influence factors affect the prediction, but also what happens to the prediction quality if little is known about a certain factor or if factors are not taken into account.

Table 6-1 shows some possibilities for the baseline situation. In line with the practical infeasibility mentioned in subparagraph 5.1.2, the first option seems to be the most logical choice (needs small number of runs). The last one is however also interesting. By adjusting the probability functions of the influence factors in such a way that they are representative for a certain month, statements could be made about the differences in predictability over the months of the year.

Table 6-1: *Baseline situation*

Principles / basic assumptions	Input variables
Information about all influence factors is present	All input variables are 'known'. The probability input consist of one value
No information is present about all influence factors	All input variables are sampled
Occurrence of all influence factors is neglected	Prediction is only based on the day of the week
The day of the week is unknown, the prediction holds for one month	Information about the occurrence of influence factors is available from what happened in this month in the past

In Table 6-2 the basic assumptions for all influence factors are presented. By comparing the different principles for each factor, while keeping (the probability functions of) all other factors constant, the effects of incorporating variability in the model can be investigated. An example will be given below.

When all information is present, the model outputs are expected to have small bandwidths. However, when no information about road works is present, the input variables corresponding to road works can be sampled. The model outputs are then expected to have larger bandwidths. But how much larger these bandwidths will be, can be very different for different influence factors. Also, when the occurrence of the road works is totally neglected, it can be determined how bad the prediction is in comparison to the situations in which all information is present and to the situations in which no information is present ('full' variability).

Table 6-2: *Subcases for each influence factor*

Influence factor	Principles / basic assumptions
Road works	- All information is present: location, start time, duration, type - No information is present - Occurrence is neglected
Weather conditions	- Short-term prediction - Long-term prediction - Occurrence is neglected
Events	- All information is present: start time, duration, amount of extra traffic - Only information about the event itself is present, time and duration of increased flow can vary widely, number of extra vehicles can vary from zero to the number of visitors - Occurrence is neglected
Incidents	- Occurrence is neglected - No information is present: location, start time, duration, type
Season effects	- All information is present: correction factors for each month from literature - Occurrence is neglected
Public holidays / vacation periods	- All information is present: category - No information is present - Occurrence is neglected
Vehicle population	- All information is present: truck demand for each day - No information is present: truck fraction pattern is assumed - Occurrence is neglected
Driver population	- All information is present: correction factors from literature - Occurrence is neglected
Luminance	- All information is present: correction factors from literature - Occurrence is neglected

6.1.1 Hypotheses

The hypotheses for the case study results are presented here.

1. When more information about a certain influence factor is known, the prediction will be more accurate.
2. Influence factors which have major effects on traffic demand or supply (such as road works, incidents or adverse weather conditions), ensure more uncertainty in the predictions.
3. Influence factors which have limited effects on traffic demand or supply (luminance, driver population), also have limited effect on the reliability of the prediction.
4. When congestion is likely to set in, the travel time bandwidth will become larger.

6.2 Considered indicators

Distributions of the following output variables can be produced by the model (for each minute of the day or summated over the time of day):

- Travel time
- Delay / Total Delay
- Time Spent
- Queue Length
- Congestion severity (Filezwaarte)
- Total Distance Travelled

The following subset of all indicators is considered for the evaluation of the case study.

Travel time
The travel time represents the actual travel time at each minute of the day. The distribution of these travel times will be presented using the mean, median and the 5th, 10th, 90th and 95th percentile of this distribution. Also the difference between the 95th and 5th percentile will be shown to show the uncertainty in the travel time at each time of day. The reliability of the travel time prediction will also be shown. This will be done using the median travel time as 'the best guess'. Next a confidence interval of 10% is assumed, the size of this confidence interval is then divided over the size of the total travel time bandwidth. The next paragraph will give an explanation with illustration.

Delay
The delay represents difference between the actual travel time and the free flow travel time for each minute of the day multiplied by the flow for each minute of the day. The distribution of the delays will also be presented using the mean, median and the 5th, 10th, 90th and 95th percentile of this distribution.

The total delay on the whole day can be calculated using the sum of the total delay at each minute of the day. The distribution of these total delays will be presented using a histogram.

Time spent
The time spent represents the actual travel time multiplied by the flow for each minute of the day. The distribution of the delays will also be presented using the mean, median and the 5th, 10th, 90th and 95th percentile of this distribution.

The total time spent represents the sum of the time spent at each minute of the day. The corresponding distribution will be presented using a histogram, similar to the delays.

Queue length
The queue length represents the length of the queue for each minute of the day, while the sum of all queue lengths at each minute of the day is referred to as congestion severity (filezwaarte). This indicator is not considered for evaluating the case study because it is strongly related to the delay and is therefore not expected to give more insights.

Vehicles in queue
The vehicles in queue represent the number of vehicles in queue for each minute of the day. The total number of vehicles in queue can be calculated using the sum of all the vehicles in queue for each minute of the day. This indicator is not considered for evaluating the case study because it is strongly related to the delay and is therefore not expected to give more insights.

Total Distance Travelled
The total distance travelled is defined as the distance travelled by each individual driver. However, since this model only accounts for one motorway corridor, the intensity multiplied by the road length would not give more information than just the intensity. Therefore this indicator is also not considered.

6.3 Results

In this paragraph the case study results are presented. First the results without any sources of variability are presented, next the results for each influence factor is presented.

6.3.1 *Results without any sources of variability*

For the results without any sources of variability, a Thursday is chosen for prediction (the day of week is the only source that cannot be left out in the model). Also the intrinsic variability is still applied here. So this is a prediction for a random Thursday in a 'average' period of the year, without knowledge of any of the other influence factors. Figure 6-1 gives an indication of the distribution of the travel time, the total delay and the time spent over the time of day.

Figure 6-1: *Results without any sources of variability*

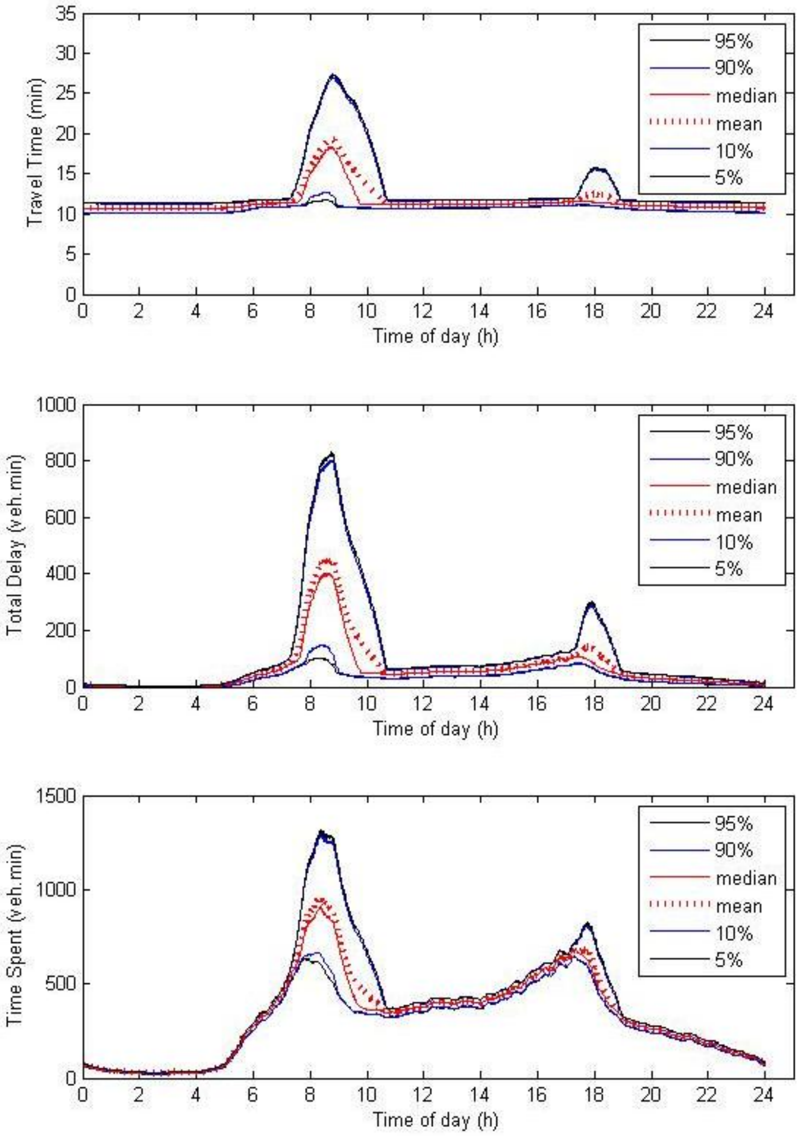
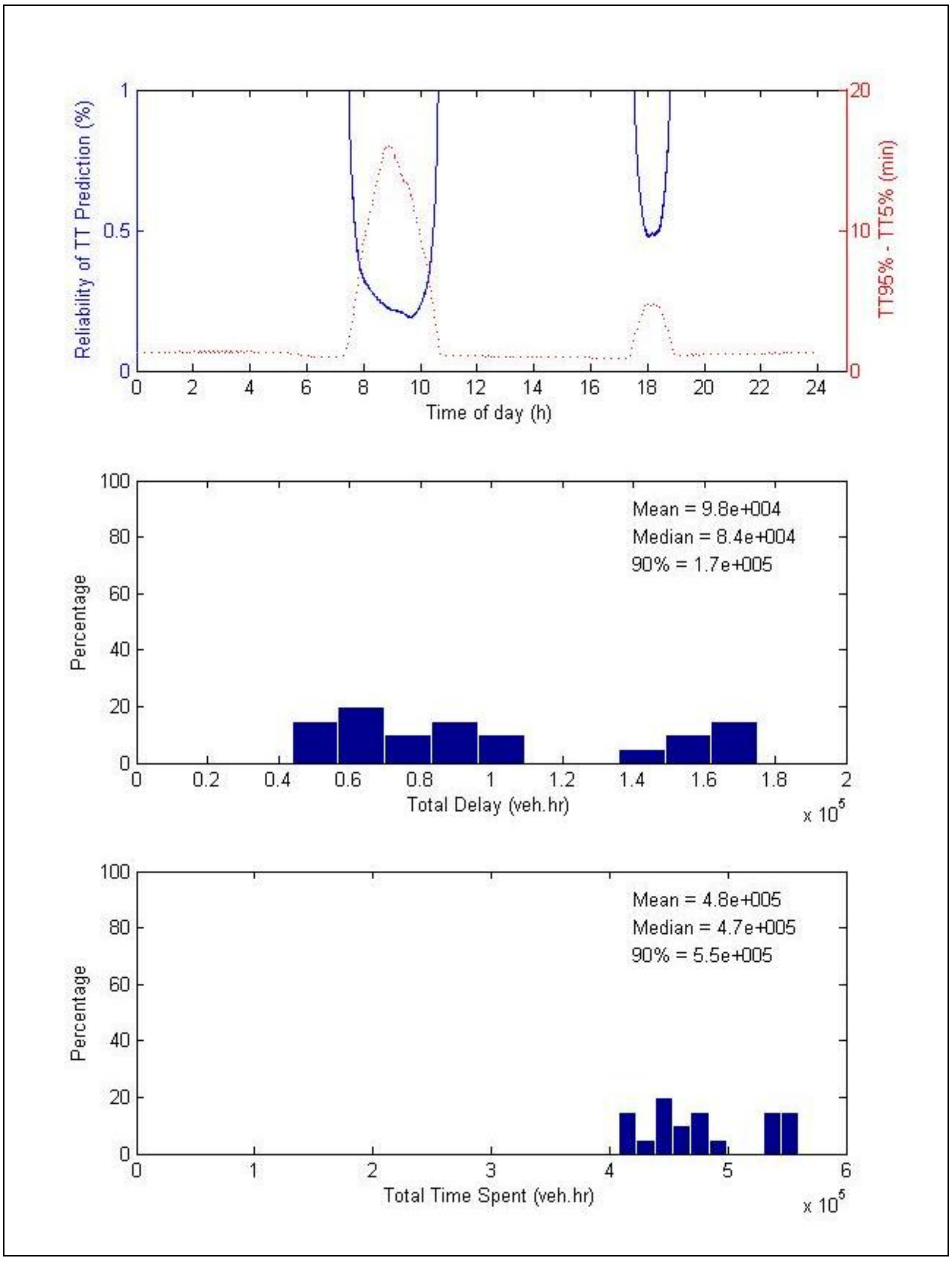


Figure 6-2 shows the reliability of the travel time prediction, the 95th percentile minus the 5th percentile of the travel time distribution, the distribution of the total delay and the total time spent (summated over the time of day). The reliability of the travel time prediction is calculated by dividing the difference between the 10% bandwidth around the median of the travel time over the difference between the 95th and 5th percentile.

Note that the first plot Figure 6-2 indicates that the travel times in the peak periods (congestion can occur) is much more uncertain.

__Figure 6-2:__ Results without any sources of variability 2



6.3.2 Results for each influence factor

To compare the results without any sources of variability with the results for each influence factor, one or two scenarios are proposed according to Table 6-2. In the first scenario the concerned influence factor is taken into account with as much information that could possibly be available. In the second scenario the concerned influence factor is also taken into account, but now with less or no information available.

The results are presented here in smaller figures, however the full sized results can be found in Appendix C: Model results.

Road works
Two scenarios are proposed for road works, in the first scenario a specific type of road work is carried out, while in the second scenario data containing the type, start time and duration is assumed to be missing.

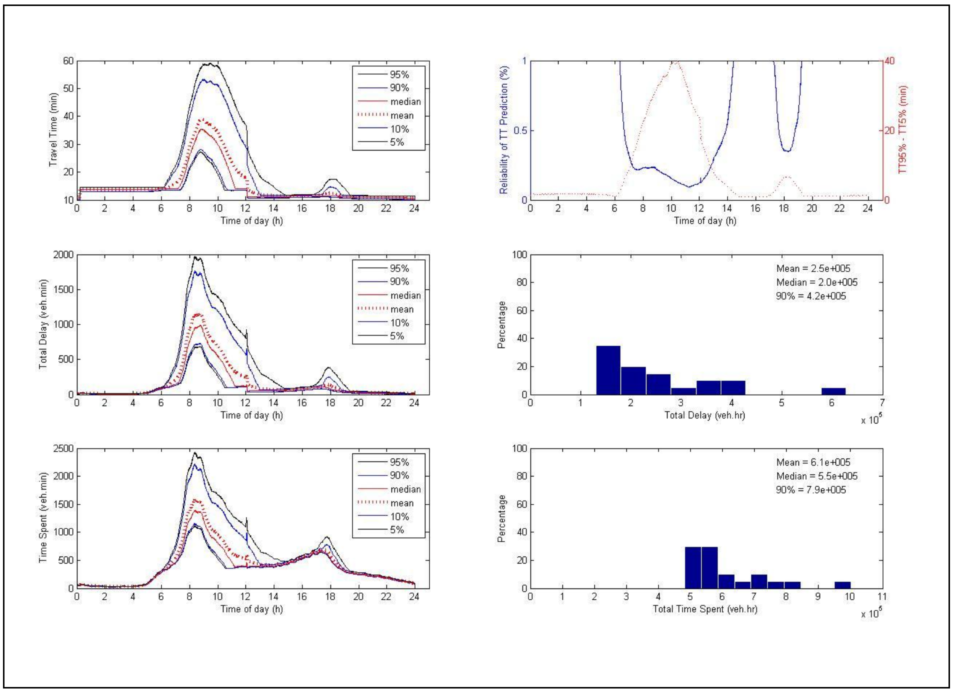
Scenario 1: All information is present

Road work characteristics:

Location = hm 23 - 33
Start time = 01:40
Duration = 12 hrs (end time = 13:40)
Type = Road works on hard shoulder / lane narrowing
Max. speed = 70 km/h

Demand factors:
Remaining capacity = average
Duration = medium
Alternative routes = low
Mobility management = simple

Figure 6-3: *Results for road works scenario 1*



Observations:

- Large uncertainty in morning travel times, total delays and times spent due to road works. The maximum modeled travel time is twice the maximum modeled travel time in the reference scenario.
- The morning travel times, total delays and time spent also generally higher.

Explanation:

- Due to lower speed limits, the increase in free travel time can be explained.
- Congestion is more likely to set in earlier as the capacity is lower.

Scenario 2: No actual information is present

In this scenario it is assumed some type of road work will be carried out, but we have no knowledge of the type, start time or duration. Probability functions based on historical data are used to simulate the road works. This scenario shows what effects road works can have on the predictions.

Probability functions for location and occurrence (based on findings of Miete (2011)):

Location = random
Start time = follows cumulative distribution illustrated in Figure 6-4
Duration = random
Type = approximately 80% chance on one lane closed and 20% on road works on hard shoulder
Max. speed = 70 km/h

Demand factors:
Remaining capacity = random
Duration = random
Alternative routes = random
Mobility management = random

Figure 6-4: *Cumulative distribution function start time road works (Miete, 2011)*

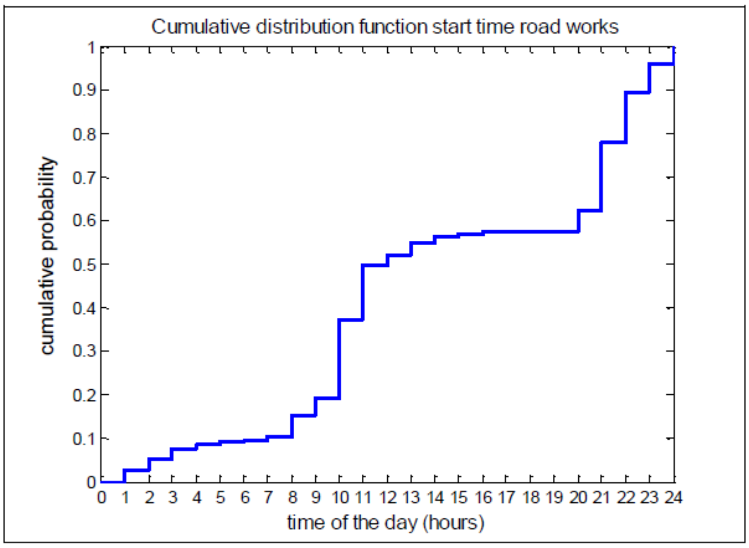
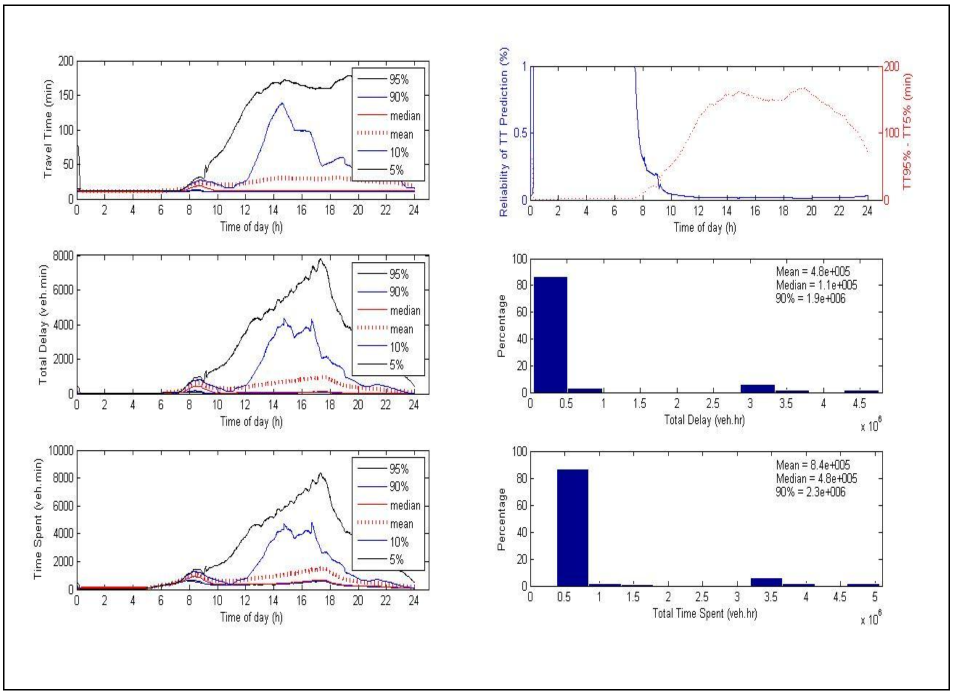


Figure 6-5: *Results for road works scenario 2*



Observations:

- Very high uncertainty in travel times, total delays and times spent.
- Skewed distribution, difference between mean, median with 95% is large.
- Small uncertainty in travel times, total delays, times spent between 00:00 and 07:00.
- From the histograms it is also clear that distribution is very skewed.

Explanation:

- The very high outliers in travel time can occur when certain types of road works occur in combination with unfavorable intrinsic characteristics (high demand and low supply). However, in practice these situations will be avoided.
- The minimal effects between 00:00 and 07:00 indicate sufficient residual capacity to prevent congestion. Note that road works for which the road needs to be closed entirely are neglected.

Weather conditions

The scenario’s for weather conditions are slightly different than others. Weather cannot be predicted with full certainty, therefore a distinction will be made between short-term and long-term predictions.

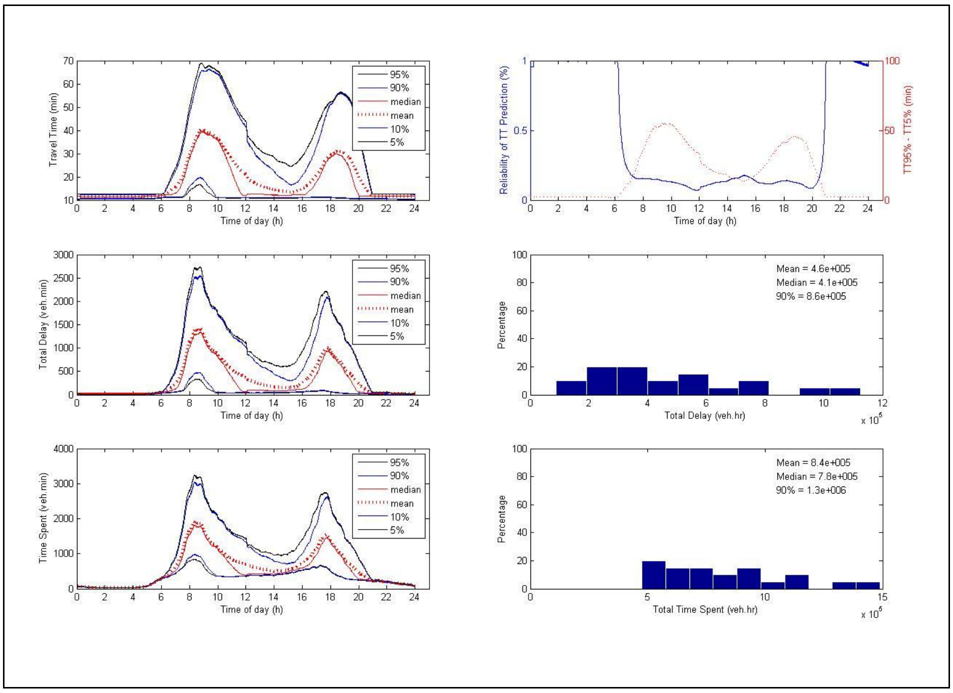
Scenario 1: Short-term prediction

In this scenario the forecast is as follows:

30% chance on moderate rain
70% chance on heavy rain

So it will certainly rain, but it can either be heavy or moderate rain.

Figure 6-6: *Results for weather conditions scenario 1*



Observations:

- Especially in the peak hours, uncertainty in bandwidths is high.
- Reliability of the travel time prediction in daytime is low.
- Total delay and Total time spent histograms not skewed, but more evenly spread.

Explanation:

- Even though the weather conditions are quite accurately available, high uncertainties are found. An explanation for this is that the as the I/C-ratio's increase, the probability on congestion increases. However, the intrinsic variability used in the model, ensures that the occurrence and magnitude of the congestion varies. The travel times corresponding to this have higher variability then free flow travel times.

Scenario 2a: Long-term prediction (January)

Figure 6-7 shows the generated probability input for January based on the data used in Figure 2-22, Figure 2-23, Figure 2-24, Figure 2-25, Figure 2-26.

Figure 6-7: *Probability input for weather conditions in January*

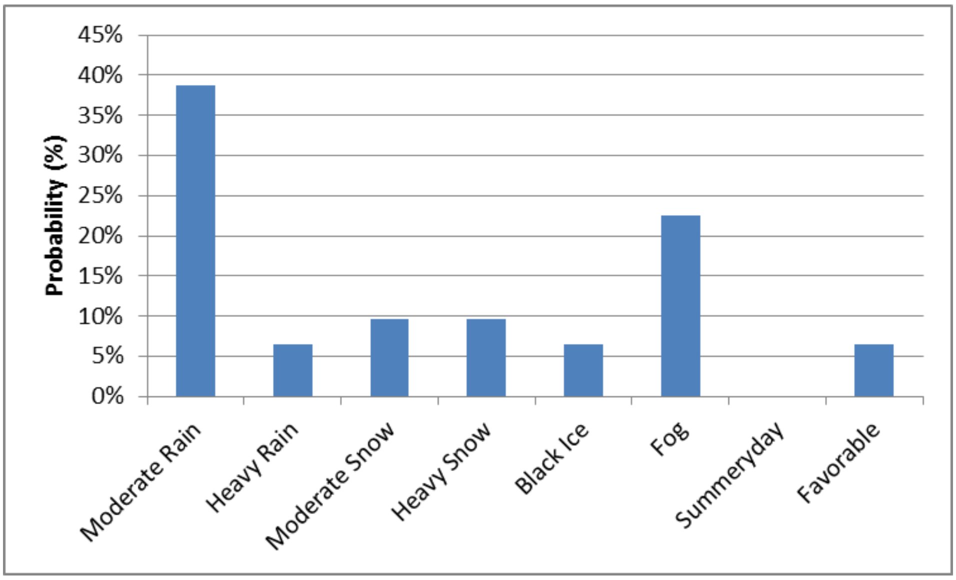
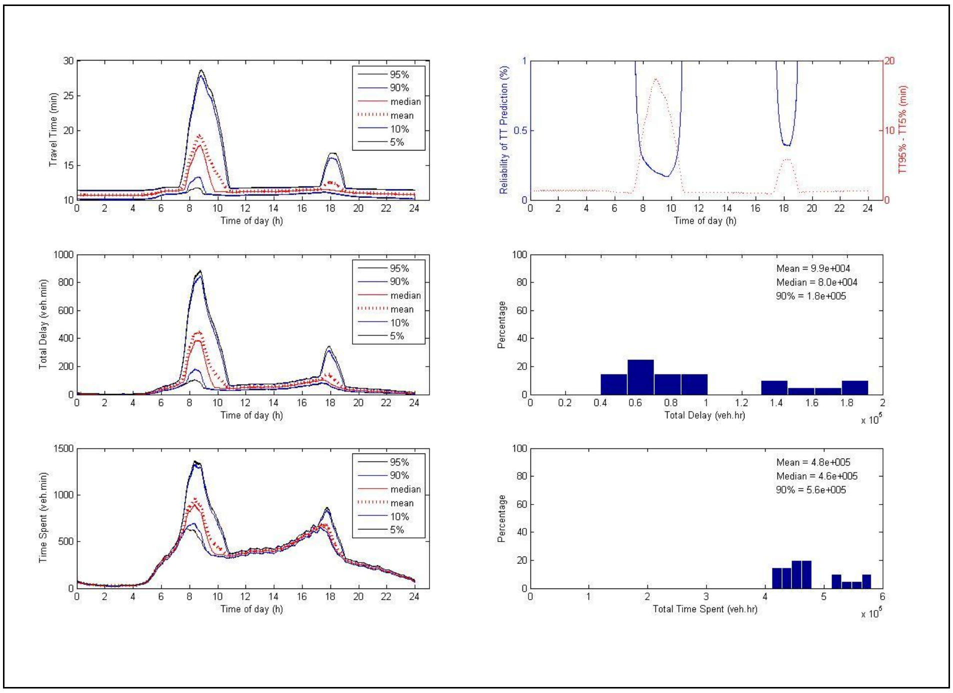


Figure 6-8: *Results for weather conditions scenario 2b*



Observations:

- Less uncertainty in in prediction than the in the short-term prediction, note that the chance on heavy rain is much lower here.

Explanation:

- Even though the type of weather is more uncertain than in the previous scenario, less uncertainty in the travel times is found. An explanation for this is that in this case also weather conditions are probable that have less negative effects on the traffic conditions.

Scenario 2b: Long-term prediction (July)

Figure 6-9 shows the generated probability input for January based on the data used in Figure 2-22, Figure 2-23, Figure 2-24, Figure 2-25, Figure 2-26.

Figure 6-9: *Probability input for weather conditions in July*

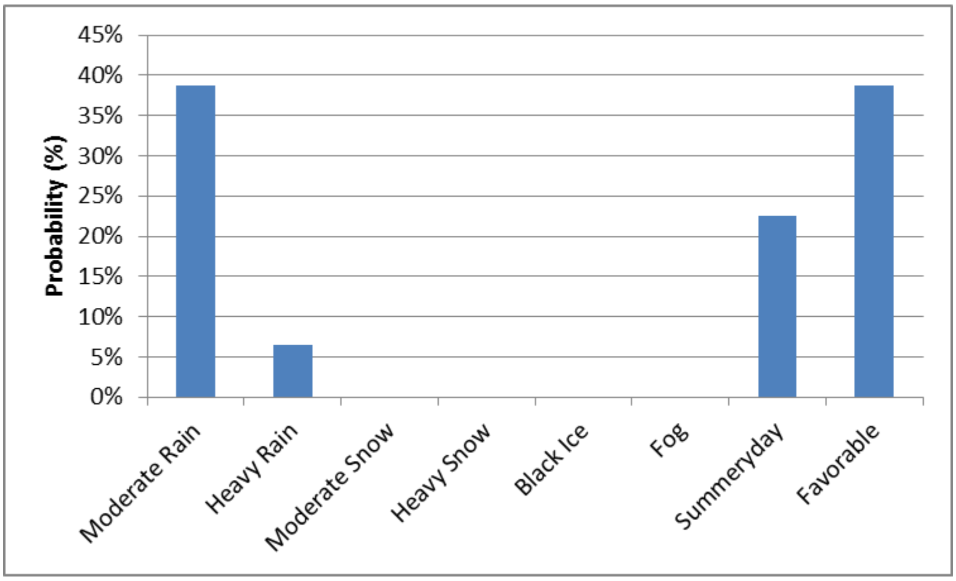
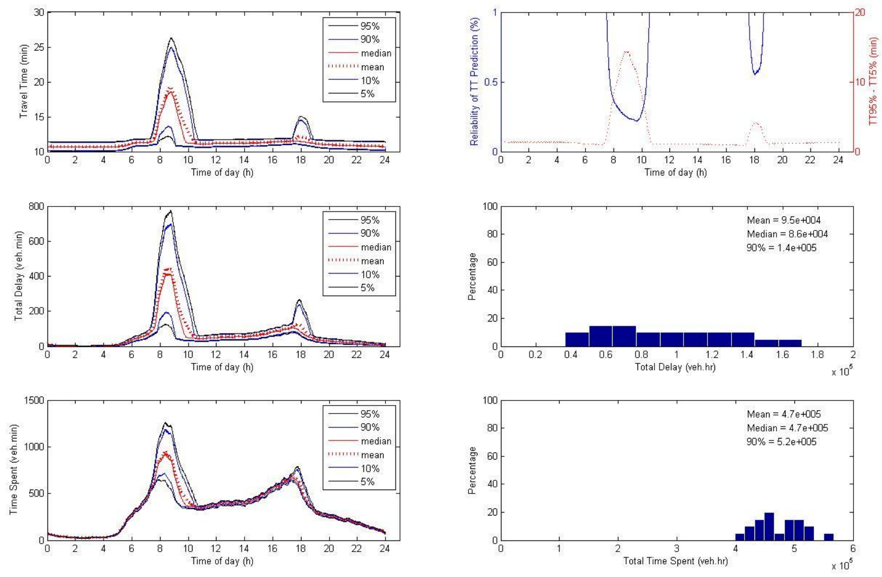


Figure 6-10: *Results for weather conditions scenario 2a*



Observations:

- The results are similar to the results for January. However, slightly less uncertainty in the prediction is found than in the long-term prediction for January. Note that here the chance on snow, black ice and fog is equal to zero.

Explanation:

- Since some adverse weather conditions (snow, black ice etc.) are excluded from the probability function in July, the chance on congestion decreases. This results in less uncertainty in the outcomes as explained before.

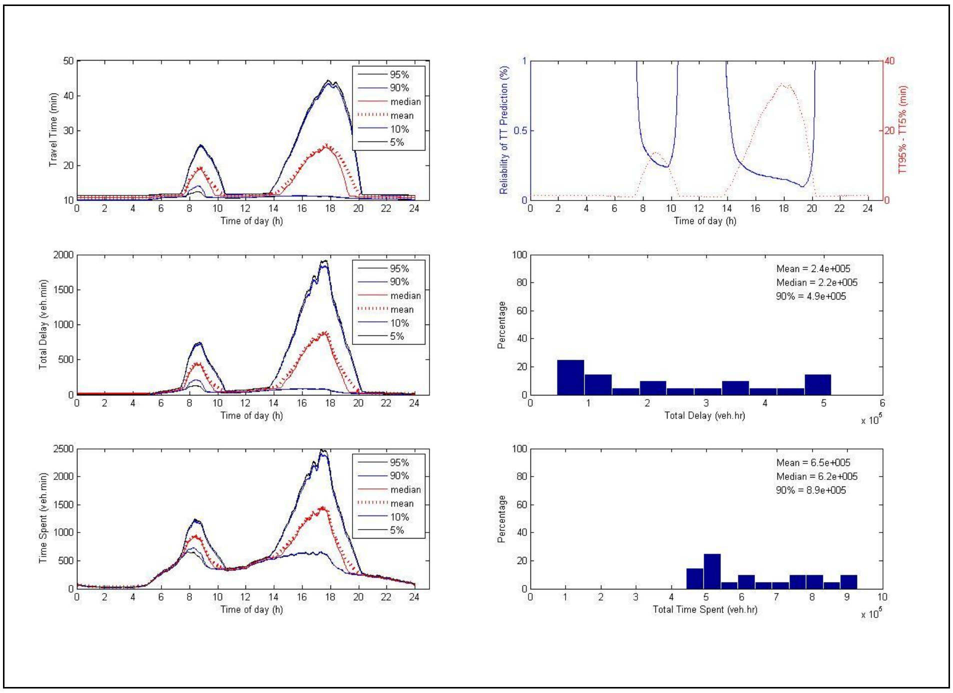
Events
For events two scenarios are proposed, in the first scenario an extensive amount of data is assumed to be available, the start and end time of the increased flow is known, but also the amount of extra vehicles caused by the event is available. In the second scenario exact knowledge about this amount is absent.

Scenario 1: All information is present

In this scenario the start and end time of the increased flow due to the event is exactly known, also the peak of the extra traffic demand is known. When this event would be held yearly, this could be based on empirical data.

Start time = 12:00
Duration = 5 hrs
Peak = 800 veh/h

Figure 6-11: *Results for events scenario 1*



Observations:

- Uncertainty in bandwidths increase especially in the evening peak.
- Though the increased flow due to the event starts at 12:00, the travel times, total delays and times spent start to increase from starting from 14:00.

Explanation:

- Due to the extra traffic demand, congestion sets in earlier and lasts longer.

Scenario 2:

The start and end time of the increased flow due to the event is exactly known, however, the peak of the extra traffic demand is not exactly known. In theory this peak could be sampled from zero to the expected number of visitors.

Start time = 12:00
Duration = 5 hrs
Peak = randomly sampled from 400, 800, 1200 and 1600 veh/h

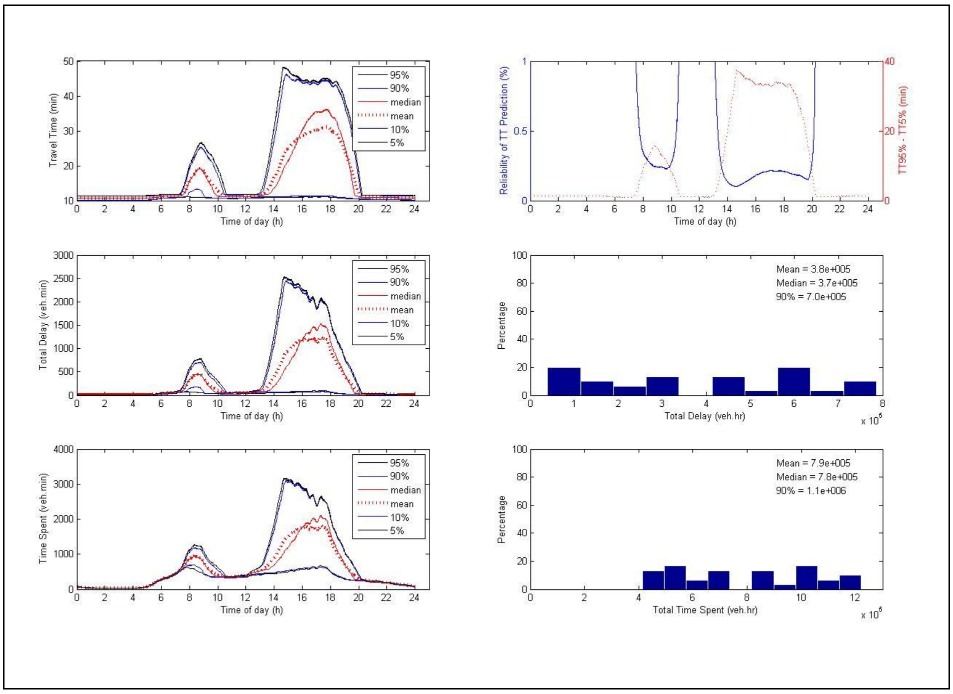


***Figure 6-12:** Results for events scenario 2*

Observations:

- Observation similar to the observations of scenario 1, however the uncertainty within the time limits of the event is higher.

Explanation:

- Due to the extra traffic demand, congestion also sets in earlier and lasts longer. However, in this case the amount of extra traffic is varied, congestion might set in at 13:00 and could be even heavier. The reliability of the travel time prediction is up to 10% worse than in the first scenario.

Incidents

Since the occurrence of incidents is never really certain, only one scenario has been proposed here. That is the scenario in which incidents are taken into account through its probability function.

For the probability input values, see Table 4-7.

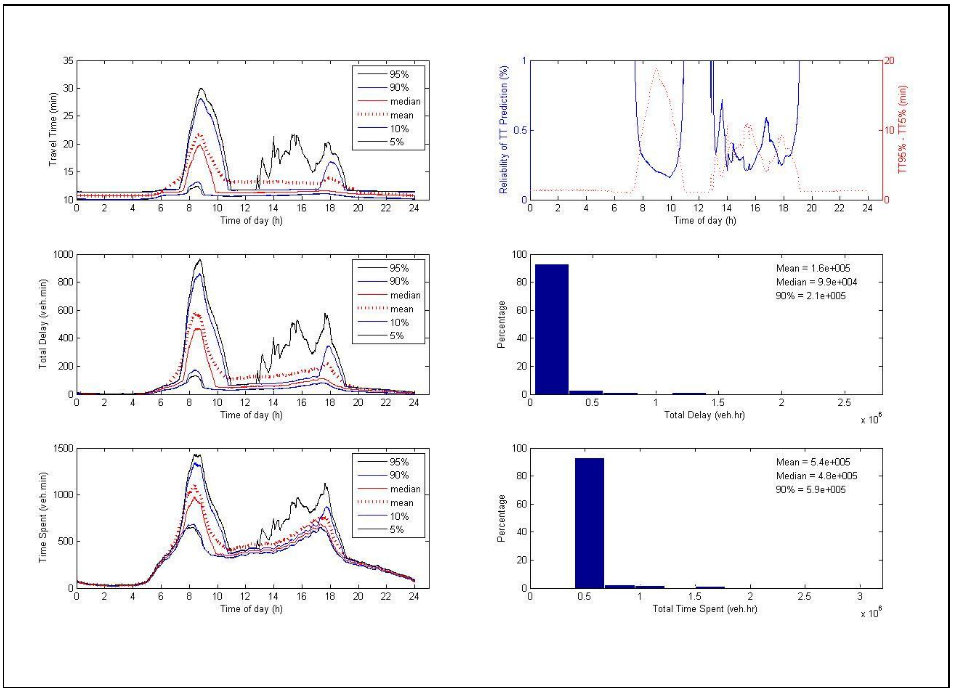


Figure 6-13: *Results for incidents*

Observations:

- Especially in the peak periods, uncertainty in the predictions is higher.
- From both histograms, it is clear that incidents ensure extra probability on the left tail.
- The effects of incidents are visible in in the regions of the 90 and 95 percentiles, but do not have large effects on the median outcomes.
- At night incidents do not seem to have large effects on travel times, delays and times spent.

Explanation:

- The minimal effects at night indicate sufficient residual capacity to prevent congestion. It has to be noted that incidents resulting in full closing of the road are not accounted for in the model.
- The incidents ensure more uncertainty in the predictions outcomes, especially at busy moments of the day. An explanation for this is that the uncertainty in travel time is prominently caused by congestion, when an incident does not lead to congestion, the experienced delay is deemed to be limited.

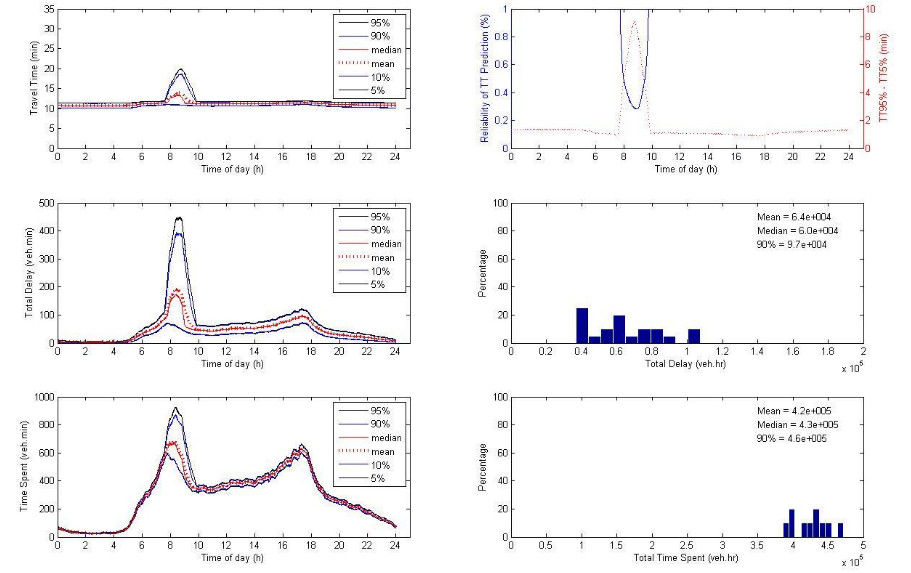
Season effects
The month of the year of which the prediction will be made is usually known. However, to show the variability in outcomes caused by the different seasons, the months of the year are randomly sampled in the second scenario.

Scenario 1: All information is present

In this scenario the season effects are taken into account. Compared to the reference situation (no variability), this is not just an 'average' period of the year, but a specific period of the year (i.e. June).

Month = June

Figure 6-14: *Results for season effects scenario 1*



Observations:

- The performance indicators are generally low.
- The uncertainty is smaller than in the reference scenario, also in the peak periods.

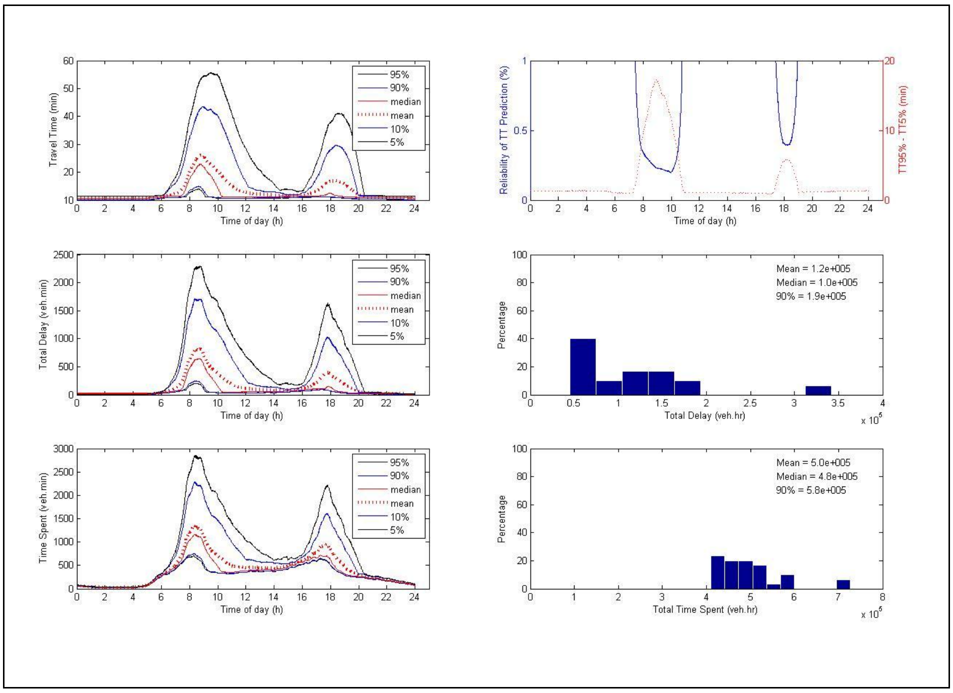
Explanation:

- Clearly, June is not a very busy month, in the evening peak congestion does not even set in. This results in less uncertainty in the prediction.

Scenario 2: Month is unknown

In this scenario the month of the year is randomly sampled.

Figure 6-15: *Results for season effects scenario 2*



Observations:

- Uncertainty in the predictions is especially visible in the peak periods.
- The total delay and tot time spent distribution are again skewed.

Explanation:

- In some of the months obviously more traffic demand is attracted than in other months. In these busy months, heavy congestion can occur, resulting in high uncertainties.

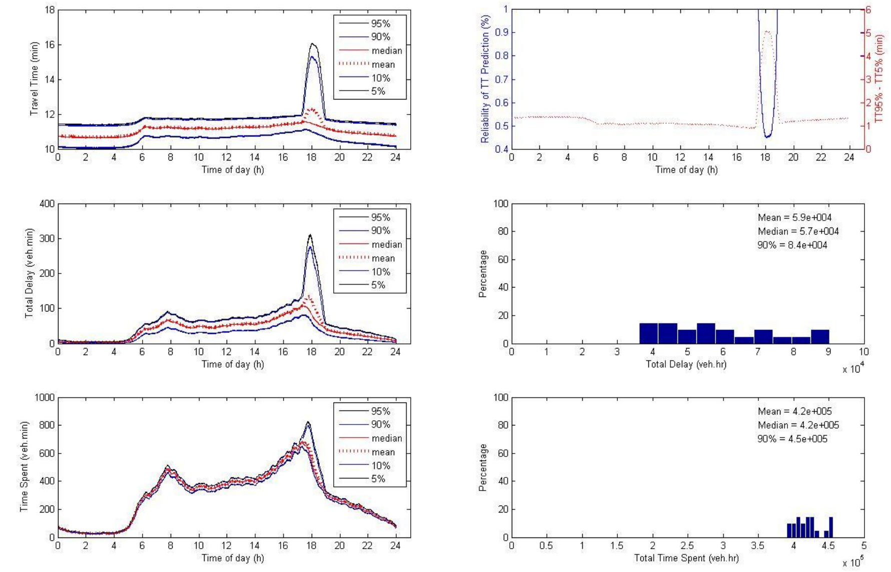
Public holidays / vacation periods

The occurrence of a public holiday or a vacation period is planned well in advance, however the effects on traffic demand (and supply) are less obvious. Therefore a scenario in which the effect is known and a scenario in which the category is unknown are discussed here.

Scenario 1: All information is present (category)

From the categories described in subparagraph 4.3.2 the second possibility has been chosen in the first scenario: the morning peak is absent.

***Figure 6-16:** Results for public holidays scenario 1*



Observations:

- The uncertainty of the prediction in the morning peak is reduced to a large extent.
- The mean and median predictions in the morning are also reduced greatly.

Explanation:

- Due to the absence (or flattening) of the morning peak, no congestion is modeled. This results in lower travel times and less delay in the morning.

Scenario 2:

In this scenario all categories are sampled randomly. For the categories, again see subparagraph 4.3.2.

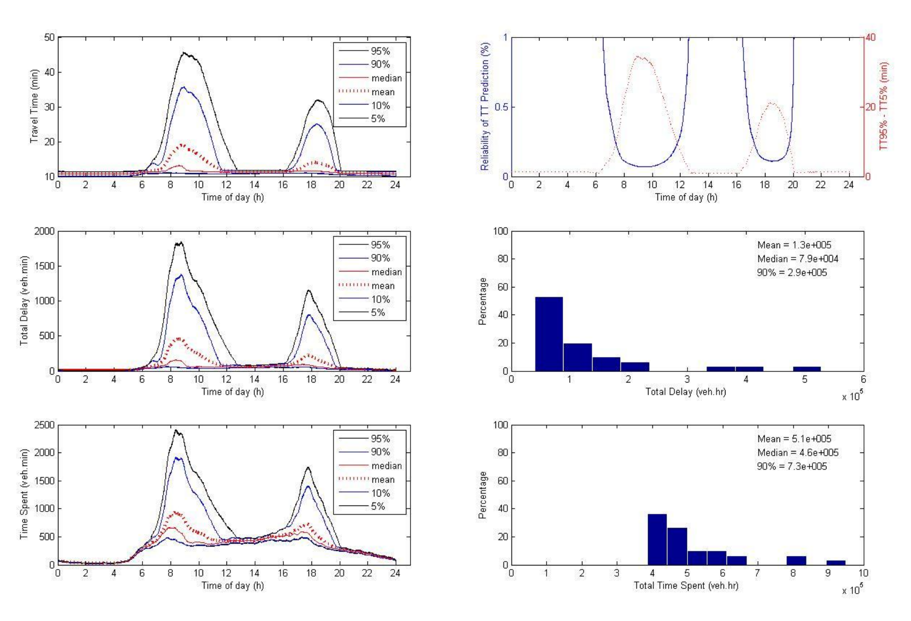


Figure 6-17: *Results for public holidays scenario 2*

Observations:

- The mean and median predictions are generally lower than in the reference situation, however the 90th and 95th percentiles are higher

Explanation:

- Due to the categories in which the morning or evening peak is absent, lower median and mean travel times are expected. An explanation for the high 90th and 95th percentiles is that in some cases the traffic demand is very high due to the category in which only an the vacation peak factor is applied.

Vehicle population

For the model parameters of vehicle population, see subparagraph 4.3.2. Figure 6-18 shows the results for a mean truck fraction of 15% (which was also assumed during calibration). Figure 6-19 shows the results when a mean truck fraction of 25% is assumed.

Figure 6-18: *Results for vehicle population; mean truck fraction 15%*

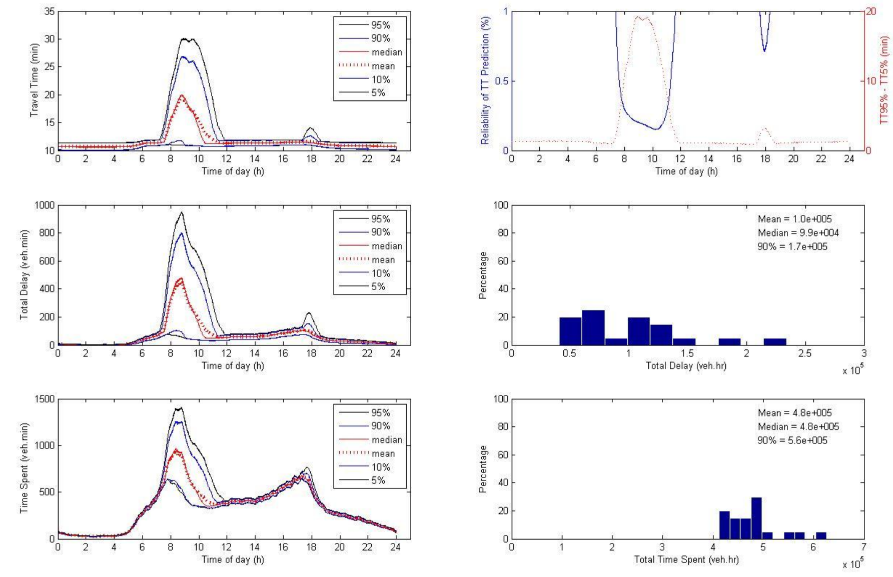
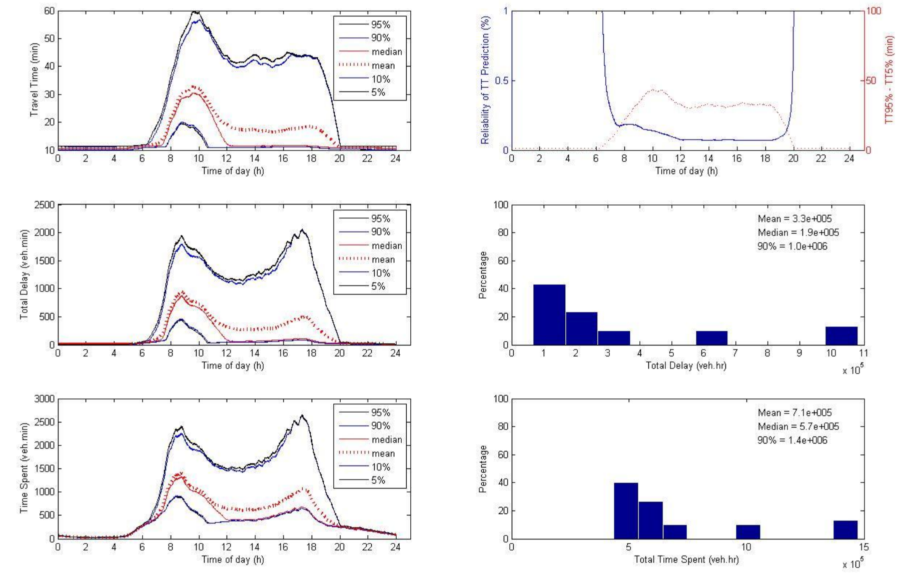


Figure 6-19: *Results for vehicle population; mean truck fraction 25%*



Observations:

- The results with a mean truck fraction of 25% reveal large uncertainties in the bandwidths (90th percentile and 95th percentile are generally high), while the increase in the median values is only small.

Explanation:

- An explanation for the high uncertainties is that the capacity is lowered at various time instants due to high truck fractions. It has to be noted that the model is calibrated on a truck percentage of 15% and that a truck fraction of 25% actually corresponds virtually to another case study.

Driver population
In this scenario, different driver classes have been assumed. For the model parameters of driver population, see Table 4-9.

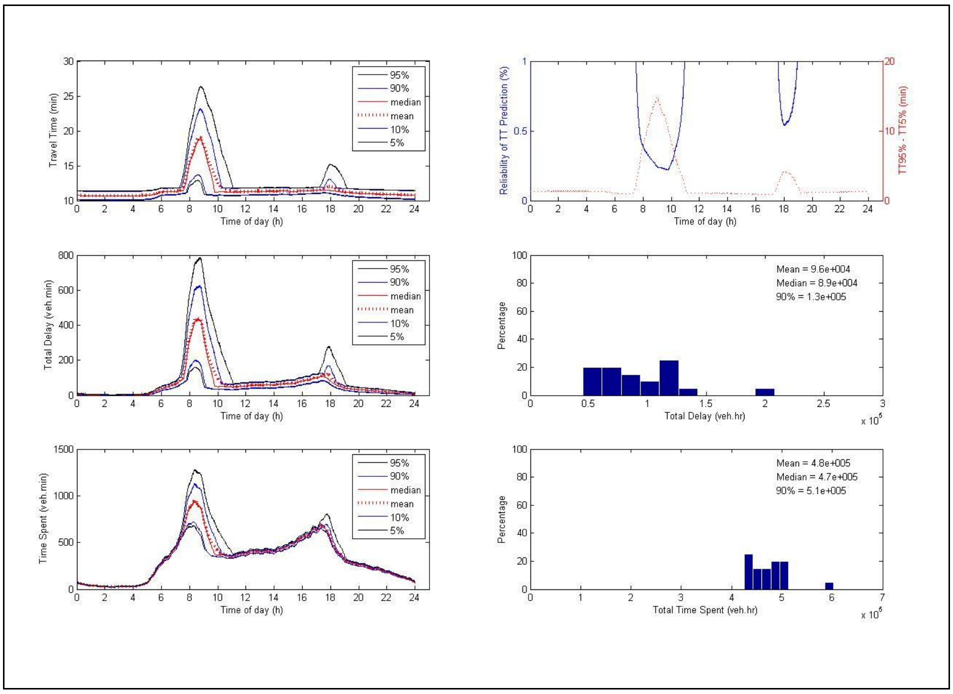


Figure 6-20: *Results for driver population*

Observations:

- Compared to the reference scenario, no significant differences are observed.

Explanation:

- The driver population feature in the model corrects the traffic supply variables for driver groups. On weekdays lower capacity values are used in the off peak periods. Apparently, this reduction does not induce more congestion at any time.
- Case studies involving this influence factor might be more interesting in combination with other influence factors.

Luminance

In this scenario luminance is taken into account. For the model parameters of luminance, see Figure 2-28. The month of the year is sampled randomly. In this case also only one scenario is proposed, since the 'occurrence' of luminance is assumed to be known quite well at all times.

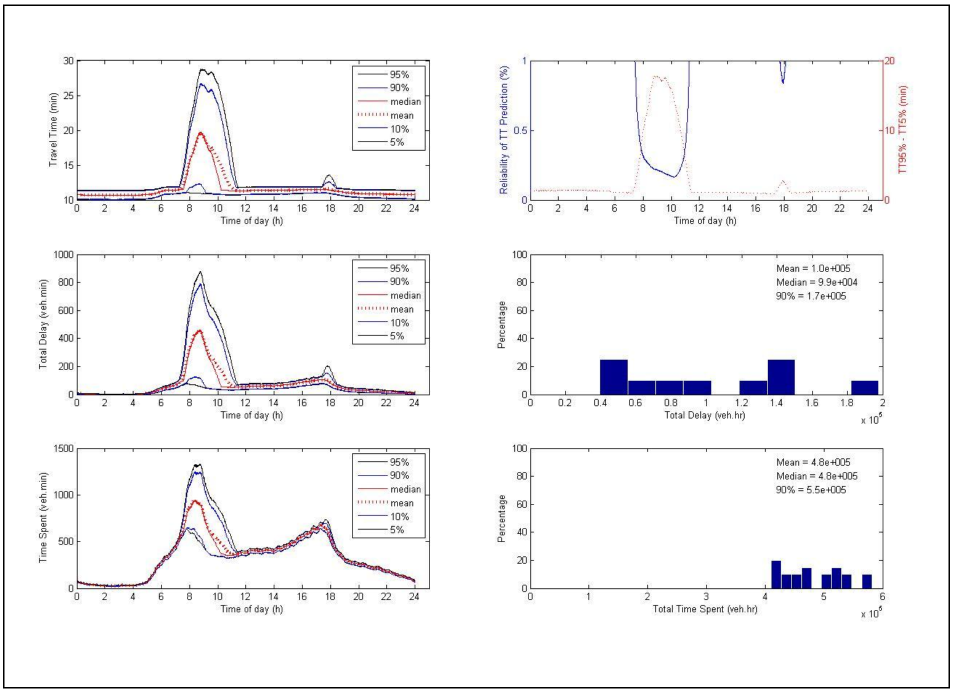


Figure 6-21: *Results for luminance*

Observations:

- Compared to the reference scenario, no significant differences are observed.

Explanation:

- The luminance feature in the model lowers the traffic supply variables at night. Apparently, this reduction does not induce more congestion at any time.
- Case studies involving this influence factor might be more interesting in combination with other influence factors.

6.4 Conclusions

In this chapter the case study is performed. First the case study is set up, next the considered indicators are described and finally many results are presented and briefly discussed.

In this paragraph the case study results are presented using a histogram. Figure 6-22 shows an overview of the travel times, collected from all scenario's in the case study results. In this figure, the 10th and 90th percentile and mean of the travel time are collected in de morning and evening peak. That is, at approximately 8.30 and 18.00. This is done for each scenario. The most striking results will be discussed and the hypotheses will be adopted or rejected.

Figure 6-22: *Overview of travel times*

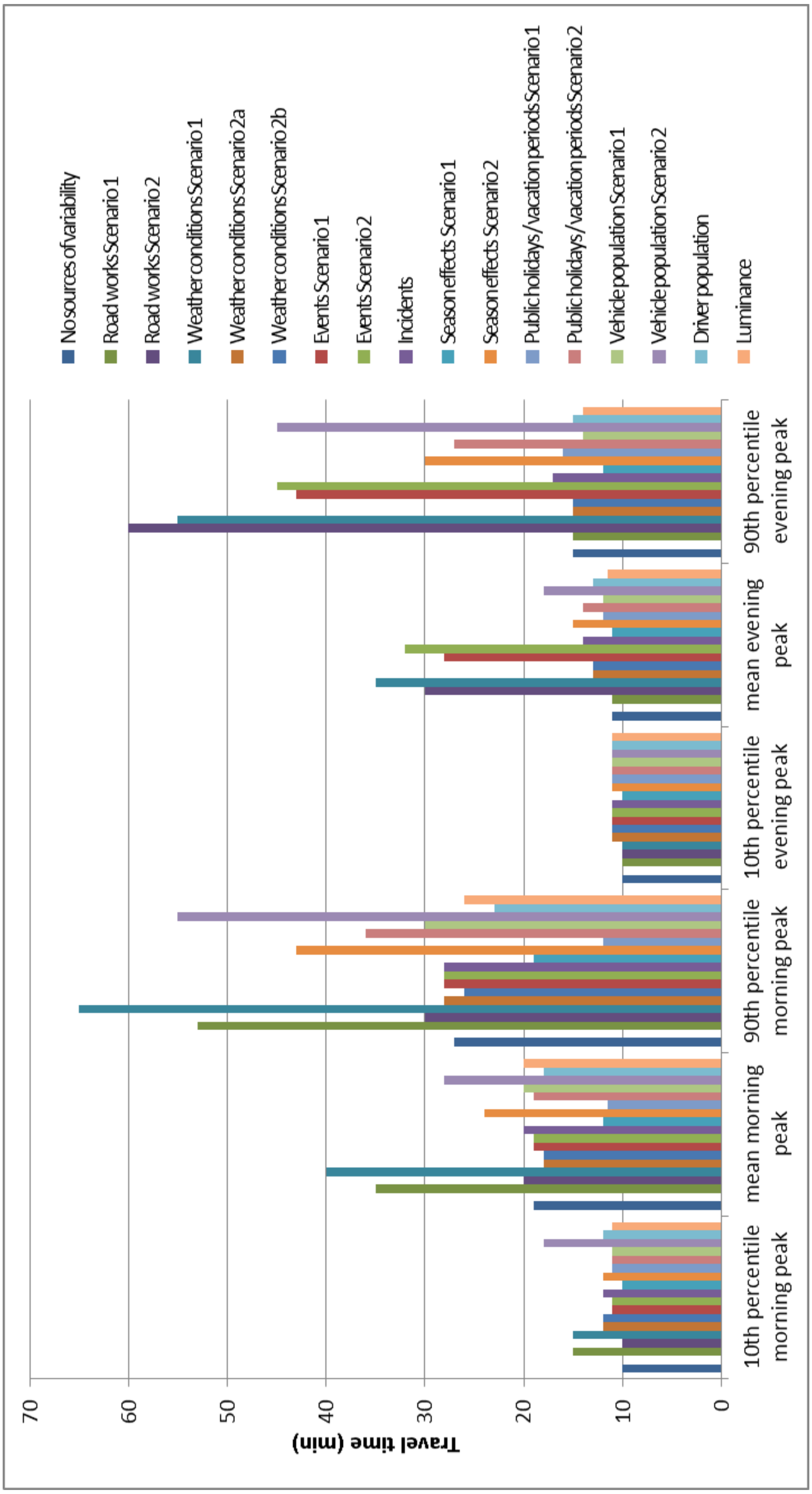


Table 6-3 shows the top and bottom outliers for each category.

Table 6-3: *Travel time outliers*

Category	Outliers to top	Outliers to bottom
10th percentile morning peak	- Road works Scenario 1 - Weather conditions Scenario 1 - Vehicle population Scenario 2	-
Mean morning peak	- Road works Scenario 1 - Weather conditions Scenario 1 - Season effects Scenario 2 - Vehicle population Scenario 2	- Season effects Scenario 1 - Public holidays / vacation periods Scenario 1
90th percentile morning peak	- Road works Scenario 1 - Weather conditions Scenario 1 - Season effects Scenario 2 - Public Holidays / vacation periods Scenario 2 - Vehicle population Scenario 2	- Season effects Scenario 1 - Public holidays / vacation periods Scenario 1
10th percentile evening peak	-	-
Mean evening peak	- Road works Scenario 2 - Weather conditions Scenario 1 - Events Scenario 1 - Events Scenario 2	-
90th percentile evening peak	- Road works Scenario 2 - Weather conditions Scenario 1 - Events Scenario 1 - Events Scenario 2 - Season effects Scenario 2 - Public holidays / vacation periods Scenario 2 - Vehicle population Scenario 2	-

The results without any sources of variability still show large uncertainties in travel times. Figure 6-22 shows that the travel time in the morning peak varies between 10 and 28 minutes. When the mean or median is then chosen as the ‘best guess’, the uncertainty in the travel time is quite large. Figure 6-2 shows that the reliability of this ‘best guess’ is approximately 25% when an error of 10% is accepted. This hints to the conclusion that there are bounds to the predictability of congestion.

Table 6-3 shows the travel time outliers from each of the categories in Figure 6-22. It stands out that both scenario 1 as scenario 2 from any case, have outliers. The most common cases are road works, weather conditions and events.

The formulated hypotheses will now be adopted or rejected.

1. *When more information about a certain influence factor is known, the prediction will be more accurate.*
   This hypothesis is adopted. When more information is available, the prediction will be more accurate. However, this does not mean that the size of the uncertainty bandwidth is also smaller. For example, travel time was much more uncertain on the short-term weather conditions case, than it was on the long-

term.

2. *Influence factors which have major effects on traffic demand or supply (such as road works, incidents or adverse weather conditions), ensure more uncertainty in the predictions.*
   This hypothesis is adopted. Road works and weather conditions caused many outliers in travel times according to Table 6-3. Incidents did not; this was probably due to their small probability of occurrence. Events did also turn op quite often. This is very case specific; because it highly depends on the size of the event, whether significantly more traffic is attracted.

3. *Influence factors which have limited effects on traffic demand or supply (luminance, driver population), also have limited effect on the reliability of the prediction.*
   This hypothesis is adopted. Luminance and driver population showed very similar results to the results with no sources of variability.

4. *When congestion is likely to set in, the travel time bandwidth will become larger.*
   This hypothesis is adopted. The prediction of the traffic conditions produced by the model is less reliable as traffic demand and traffic supply values are close to each other, than when traffic demand does not come near to traffic supply. This appeared in all cases. The travel time uncertainty around peak hours is found to be higher than in off peak hours. The difference between the 95th percentile and the 5th percentile in off peak hours is generally 2 minutes. In the peak hours, this varied from 1 to 50 minutes in all case studies.

7 Conclusions & Recommendations

In this research a methodology incorporated in a model has been developed, which is able to predict congestion on motorways. This model is able to take the variability of traffic into account and is substantiated with a solid theoretical framework relating the predictability of factors and their effects to traffic supply and demand. In this chapter the main findings, conclusions and further recommendations will be presented.

7.1 Main findings

The findings from this research are presented here as answers to the main research questions.

1. **To what extent can the different components of the variability in traffic be predicted?**

- The most important factors influencing traffic demand and traffic supply are: regular pattern of variation in human travel behavior over the day, over the days of the week and over the periods of the year; public holidays / vacation periods; events; weather conditions; road works; incidents; variations in vehicle population; variations in driver population; luminance; ‘intrinsic’ variations in driving behavior and ‘intrinsic’ variations in human travel behavior.
- Some of them have influence on traffic demand, while others relate to the traffic supply. For instance, events generally cause more traffic on the road, while incidents cause reductions in the traffic supply. Others have influence on both, for example rain might result in lower traffic demand, but has a negative effect on traffic supply as well, because drivers tend to increase distance to their predecessor. For the relations between factors and their effects on traffic demand and supply is referred to Chapter 4.
- The predictability of congestion is highly correlated to the predictability of the aforementioned influence factors. Factors like weather conditions and incidents cannot be predicted with full certainty. However, road works and events are factors that are planned in advance and could be predicted with very high certainties, if data is available. Incidents, on the other hand, are very hard to predict. The extent to which weather conditions can be predicted, clearly depends on the time horizon. Luminance, public holidays and vacation periods fully predictable.
- Especially for the factors which could be predicted with very high certainties (road works, events, variations in vehicle population etc.) it is key, that accurate data is available. When the data is not available or inaccurate, the prediction of the factor is also inaccurate or unreliable. Naturally this also holds for factors that are less predictable, but the gain in reliability is smaller. But of course, garbage in = garbage out.

2. How can the variability of traffic be incorporated in a congestion prediction model?

- When data of all identified factors is available to predict, the variability of traffic is governed by the intrinsic variability in traffic demand and traffic supply. That is, the variations in driving behavior and travel behavior. For example, if data of planned road works is instantly available, this factor can be ruled out or incorporated in the prediction.
- When the effects of all identified influence factors are known or calibrated, the resulting traffic demand and traffic supply variables can be derived. Using these two, travel times, or congestion can be predicted.
- To influence factors that are not fully predictable a probability function can be assigned. In the developed model, intelligent sampling has been used to generate predictions. For more information on the developed model, see Chapter 5.

3. What are the effects of incorporating the variability of traffic on congestion predictions?

- Based on the calibration results, the proposed methodology is found to be able to generate reliable output. However, the extent of the generic reliability of the developed model is inconclusive. The model has shown accuracy in the case study, but a larger number of case studies are required to validate the models overall reliability.
- The effects of the influence factors are in this research are fully adopted from literature. In this way, insight in the manner the influence factors affect predictions was provided.
- To be able to give accurate and reliable predictions, actual information about the identified influence factors is needed. Without this information, the variability of traffic cannot be accounted for accurately.
- When only the most probable traffic demand profile and traffic supply variables are used, the generated prediction lacks reliability. By adding uncertainty in traffic demand and traffic supply a more complete prediction can be generated. In this way the prediction provides a better reflection of reality. The presentation of the output can be achieved by displaying a travel time distribution using multiple percentiles instead of just a mean or median value.
- Another possibility for presenting the output has been used in this research as well. Here the median of the travel time prediction is provided, but next to this also the reliability of the prediction is used to indicate how ‘well’ the prediction is expected to be. In this way the quality of the provided information becomes more clear.

7.2 Conclusions

Here the final conclusions are presented and discussed.

1. **The model approach showed good performance, indicating the methodology behind the model is accurate.**
   An indirect macroscopic modeling approach was chosen in which traffic demand and traffic supply are combined to generate output (Chapter 3). In order to deal with the variability of traffic, the intelligent sampling technique Latin Hypercube Sampling was selected and successfully applied. This technique needs significantly less samples to converge, than the conventional random sampling techniques. The calibration of the model (Chapter 5) showed good results. The minimum mean absolute difference between recorded and modeled travel times was 0.38, while 80% of the modeled travel time distribution was found similar to the recorded distribution.

2. **The theoretical framework behind the model can be used to gain insight in the factors and effects influencing traffic demand and traffic supply.** For both the predictabilities and the effects of the influence factors a classification was made (Chapter 4). These were useful to systematically implement the influence factors in the model. Both the predictabilities and the effects of the influence factors were quantified. To the intrinsic variations in travel and driving behavior, special attention was given. For the traffic demand, the bandwidth was determined through a Poisson distribution. For the traffic supply a new approach was conceived (Chapter 4).

3. **The prediction of the traffic conditions produced by the model is less reliable as traffic demand and traffic supply values are close to each other, than when the traffic demand does not come near to the traffic supply.**
   The model showed very accurate free flow travel time estimation, however the bandwidth in the peak periods was much larger. When the traffic demand is generally close to the traffic supply, only small fluctuations in either traffic demand or traffic supply can result in congestion. The predicted total delay or travel time can differ significantly from the real total delay or travel time when congestion has or has not set in. These results were found through the case studies in Chapter 6. In off peak hours, the difference between the 95th and 5th percentile of the travel time distribution, was approximately 2 minutes. In the peak hours, this varied from 1 to 50 minutes.

4. **It is important to have reliable data sources regarding the identified influence factors.**
   To be able to produce accurate predictions, the data sources of the influence factors on traffic should be reliable. When these sources are unreliable or not even present, their effects on traffic demand or traffic supply cannot be taken into account accurately. Collecting data for the calibration of the model (Chapter 5) did not appear to be a straightforward task. For some of the influence factors also holds that not only the occurrence of the factor is available from data, but also their specific effects should be documented. For example knowledge of the occurrence of a certain event, does not directly

provides the extra traffic demand generated by this event. Of course an educated guess is possible, but to make the prediction most accurate, also indirect information should be provided.

5. **Next to the intrinsic variation also (major) events, road works, incidents and adverse weather conditions play an important role in the quality of the prediction.**
   In Chapter 6, it was found that influence factors which have major effects on traffic demand or traffic supply, also ensure more uncertainty in the predictions. The quality of the prediction is dependent of the availability of data. When data of a certain influence factor is not available, the occurrence of this influence factor can only be taken into account through its estimated probability of occurrence. However, this results in very high uncertainties in the prediction, especially with influence factors that have significant effects on traffic demand or supply. The mean or median prediction, which is in most cases used as the most important value, is then not to be trusted. So when knowledge of certain factors is not available, it is advised to leave this factor out of the prediction. The prediction then holds for a certain scenario (in which the occurrence of the concerned influence factor is neglected).

7.3 Recommendations

Next to the conclusions presented in the previous paragraph, this research also leads to recommendations concerning further research in this field and further development and implementation of the proposed methodology.

7.3.1 Further research in this field

For further research in this field, the following recommendations are stated.

- The estimation of traffic supply variables did not appear to be a straightforward task. Many sections of a motorway do not show congestion, which makes determining capacity very hard. However, not only involve free flow capacities or queue discharge rates, but also other traffic supply variables need to be determined. A reliable and easy method for determining the traffic supply variables is therefore recommended.
- The effects of influence factors on traffic supply are generally well known, however the effects of certain influence factors (weather conditions, road works) on traffic demand sometimes remain indistinct. This is also due to the fact that these effects can be different among different locations. However, a method to derive these effects for different locations or circumstances is recommended.
- To be able to do research on the effects or predictability of the identified influence factors, sufficient data should be available. During this research it became clear that data of for example events, but also incidents or road works cannot be easily retrieved or is not even collected. I would therefore recommend that data of important influence factors should be easily accessible in combination with traffic data.

- In this research the predictabilities and the effects of influence factors on traffic demand and traffic supply are quantified. However, more research is advised on the uncertainties of these predictabilities and effects.

7.3.2 Model development and use of the methodology

Next the recommendations concerning further model development and possible use of the methodology in practice.

- For operational use of the methodology, further analysis of the possibilities for extension of the model to larger networks (e.g. the Dutch motorway network) is recommended. With such an extension, possible hazards in the network can be identified and measures can be taken.
- The effects of the identified factors are incorporated using theoretical values. When the model is extended to a larger network, location dependent influence factors should be implemented more accurately. Especially demand effects may differ in different locations of the network.
- The implementation of a second order traffic flow theory model may lead to improvements in performance, assuming that the second order model operates in a robust way.
- A further evaluation of the developed model is recommended by doing multiple case studies to determine the generic reliability of the model.
- One of the model results was that prediction of the traffic conditions produced by the model is less reliable as traffic demand and traffic supply values are close to each other, even though the influence factors are fully predictable and accounted for. This is the result of the used methodology towards the intrinsic variations. To verify this statement, further research on this topic is desired.

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Appendix A: Main model code

The code in which the sampling takes place is shown here in a simplified form. Only a couple input variables are given here, also no corrections on probability functions within the loop are made here. It does however explain how the procedure works.

```
nsample = 200      %number of samples per variable * number of sampled variables

listofvariables =
{'roadwork';'event';'incident';'seasoneffects';'publicholidays';'weatherconditio
ns';'vehiclepop';'driverpop';'luminance';}

samples = lhs(nsample,size(listofvariables,1));

%%% CUMULATIVE PROB FUNC FOR EACH INPUT VARIABLE %%%
prob_roadwork = [0 100; false true]; %in this case a roadwork occurs
prob_event = [50 100; false true]; %in this case there is 50% chance on an event
prob_incident = [100 100; false true];
prob_seasoneffects = [100 100; false true];
prob_publicholidays = [100 100; false true];
prob_weatherconditions = [100 100; false true];
prob_vehiclepop = [100 100; false true];
prob_driverpop = [100 100; false true];
prob_luminance = [100 100; false true];


%%% THE BIG LOOP %%%
W = waitbar(0,'Please wait...');
for runs = 1:size(samples,1)

    %%% Here the values for the input variables are obtained using samples and
        the probability functions %%%
    for i = 1:size(listofvariables,1)
        eval(['sample_' listofvariables{i,1} '= samples(runs,i);']);
    end

    for i = 1:size(listofvariables,1)
        var = listofvariables{i,1};
        prob = eval(['prob_' listofvariables{i,1}]);
        sample = eval(['sample_' listofvariables{i,1}]);
        for n = 1:size(prob,2)
            if sample <= 0.01*prob(1,n)
                eval([var ' = prob(2,n);']);
                break;
            end
        end
    end

    %%% With the input variables (obtained above), the model parameters the
        effects on traffic demand and supply are accounted for and the traffic
        flow model will be runned %%%

    ModelParameters; TrafficDemand; TrafficSupply; TrafficFlowModel;
    %%% Variables are collected in an array (otherwise they would be overwritten
        in the next loop %%%


    input_weekday(:,:,runs)=weekday;
    input_roadwork(:,:,runs)=roadwork;
    input_event(:,:,runs)=event;
    input_incident(:,:,runs)=incident;
    input_seasoneffects(:,:,runs)=seasoneffects;
    case_Flow(runs,:)=Flow;
    case_qcrit(:,:,runs)=qcrit;
    case_kcrit(:,:,runs)=kcrit;
    case_ucrit(:,:,runs)=ucrit;
    case_ufree(:,:,runs)=ufree;
    case_qdisc(:,:,runs)=qdisc;
    case_kjam(:,:,runs)=kjam;
    case_lanes(:,:,runs)=lanes;
    output_q(:,:,runs)=q;
    output_k(:,:,runs)=k;
    output_u(:,:,runs)=u;
    output_tt(runs,:)=tt;
    output_queue(runs,:)=queue;
    output_vehiclesqueue(runs,:)=vehiclesqueue;
    output_delay(runs,:)=delay;
    output_totaldelay(runs,:)=totaldelay;
    output_timespent(runs,:)=timespent;

    waitbar(runs/size(samples,1))
end
close(W);

Plotting; %link to a script that plots several output indicators
```

Appendix B: Calibration results

Estimated traffic demand profiles (Monday – Sunday)

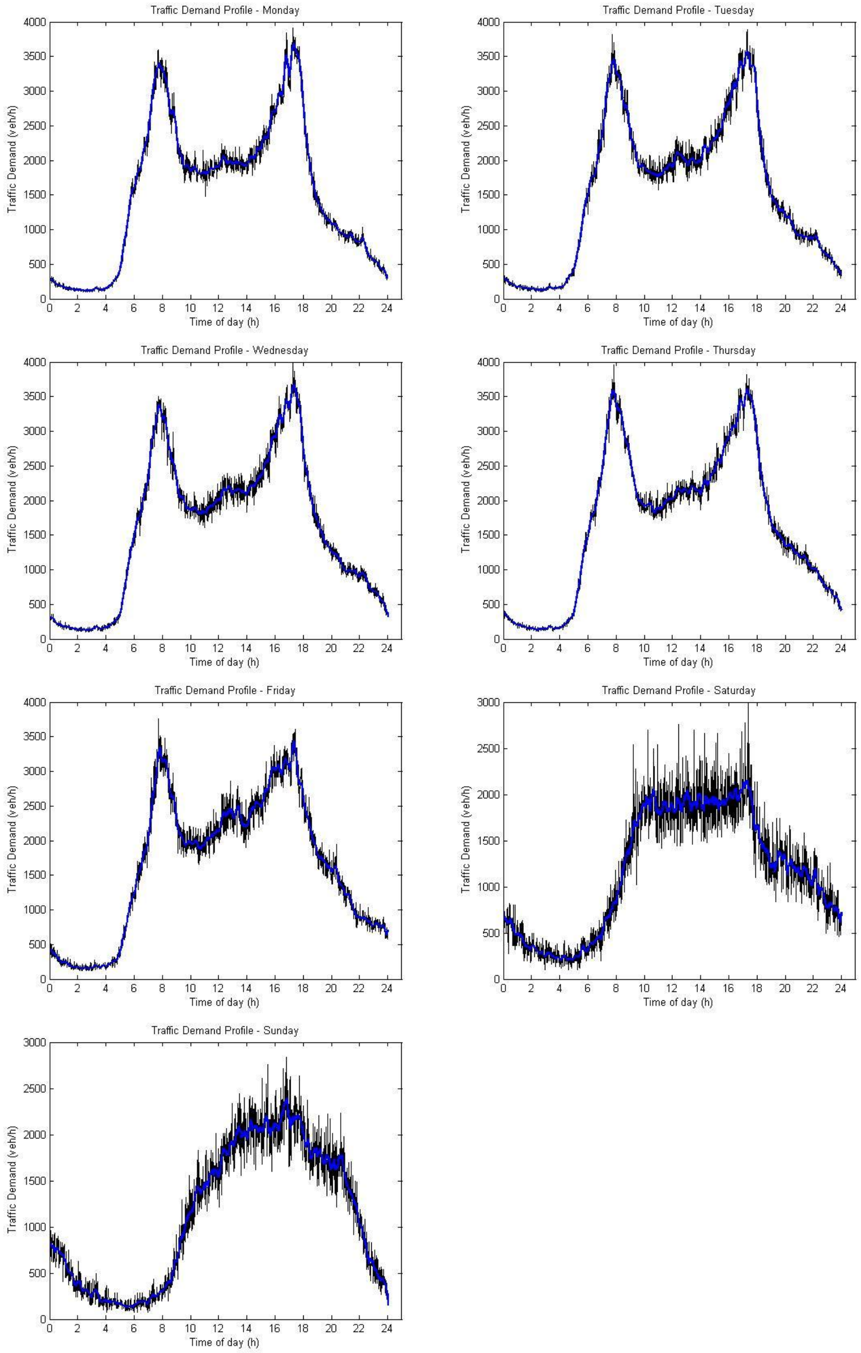


***Figure B-1:** Estimated traffic demand profiles (black: unsmoothed; blue: smoothed)*

Traffic Flow Model

Table B-1 and Table B-2 show the MAE and the MRE values for five days. The yellow marked cells indicate the lowest value of the row. The cells with bold values indicate the lowest value for the corresponding day. Clearly a 40% increase of the queue discharge rates and a capacity drop of 10%, provide the most accurate results. This 40% increase of the queue discharge rates seems rather high, indicating the method used to determine the queue discharge rates performed not very well. Note that the capacities were collected in an automated way. This could also have introduced some error. After several attempts to get better results from the data, it was decided to proceed with these calibrated queue discharge rates.

Table B-1: *MAE*

MAE		0%	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
Za 15-01-11	5%	1,70	1,25	1,10	0,99	0,89	0,80	0,72	0,64	0,56	0,49	0,43
Ma 14-02-11		20,83	13,61	9,17	5,90	3,88	2,50	1,54	1,49	0,79	0,50	0,41
Do 31-03-11		24,78	20,93	16,34	8,07	4,84	2,85	1,61	1,63	1,06	0,83	0,74
Di 05-09-11		20,19	13,23	8,89	5,85	3,90	2,68	1,99	2,01	1,59	1,35	1,24
Di 05-11-11		23,51	18,89	13,70	9,40	6,00	3,73	2,31	2,39	1,61	1,21	0,98
Za 15-01-11	10%	1,26	1,10	0,99	0,88	0,79	0,70	0,62	0,54	0,47	0,40	0,35
Ma 14-02-11		13,38	9,24	5,80	7,79	2,34	3,41	0,72	0,48	**0,38**	0,48	0,44
Do 31-03-11		20,28	15,59	7,88	16,56	2,64	4,37	0,97	0,73	**0,70**	0,86	0,89
Di 05-09-11		12,92	8,88	5,72	7,86	2,55	3,59	1,48	1,25	**1,16**	1,38	1,42
Di 05-11-11		18,35	13,18	9,28	14,13	3,48	5,51	1,42	1,04	0,99	1,19	1,42
Za 15-01-11	15%	1,13	0,99	0,88	0,79	0,69	0,61	0,53	0,45	0,39	0,33	**0,30**
Ma 14-02-11		12,29	8,12	5,06	3,20	1,95	1,06	0,55	0,41	0,40	0,46	0,54
Do 31-03-11		19,20	14,26	6,70	3,86	2,13	1,24	0,86	0,72	0,80	0,92	1,01
Di 05-09-11		11,75	7,85	5,05	3,29	2,27	1,71	1,37	1,22	1,23	1,41	1,56
Di 05-11-11		17,22	11,90	8,09	4,97	2,96	1,80	1,25	**0,97**	1,11	1,37	1,58

Table B-2: *MRE*

MRE		0%	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
Za 15-01-11	5%	0,12	0,10	0,09	0,08	0,08	0,07	0,06	0,06	0,05	0,04	0,04
Ma 14-02-11		0,45	0,35	0,27	0,21	0,17	0,13	0,09	0,09	0,06	0,04	0,04
Do 31-03-11		0,48	0,46	0,42	0,27	0,19	0,14	0,10	0,10	0,08	0,07	0,06
Di 05-09-11		0,44	0,35	0,27	0,21	0,17	0,14	0,12	0,13	0,11	0,11	0,10
Di 05-11-11		0,47	0,43	0,36	0,27	0,22	0,16	0,12	0,12	0,10	0,09	0,08
Za 15-01-11	10%	0,10	0,09	0,08	0,08	0,07	0,06	0,05	0,05	0,04	0,04	0,03
Ma 14-02-11		0,35	0,28	0,21	0,24	0,12	0,14	0,05	0,04	**0,03**	0,04	0,04
Do 31-03-11		0,45	0,41	0,27	0,42	0,13	0,17	0,07	0,06	**0,06**	0,07	0,08
Di 05-09-11		0,35	0,27	0,21	0,25	0,14	0,16	0,11	0,10	**0,10**	0,11	0,13
Di 05-11-11		0,42	0,35	0,27	0,36	0,16	0,20	0,09	0,08	0,08	0,09	0,12
Za 15-01-11	15%	0,09	0,08	0,08	0,07	0,06	0,05	0,05	0,04	0,04	0,03	**0,03**
Ma 14-02-11		0,33	0,25	0,19	0,14	0,10	0,07	0,04	0,04	0,04	0,04	0,05
Do 31-03-11		0,44	0,39	0,24	0,17	0,11	0,08	0,07	0,06	0,07	0,08	0,09
Di 05-09-11		0,33	0,25	0,20	0,16	0,13	0,11	0,10	0,10	0,11	0,12	0,14
Di 05-11-11		0,41	0,32	0,25	0,19	0,14	0,11	0,09	**0,08**	0,09	0,11	0,13

Next the calibration results for the five chosen days are shown. For each day an intensity contour plot, speed contour plot and travel time plot are presented from both the data and the model. The model contour plots are located in the upper area of the figures and the data contour plots are located in the middle of the figures. In the bottom a comparison of the measured and modeled travel time is made. The travel time obtained from data is indicated with red thick line, the modeled travel time is indicated with a blue line.

In general, the produced free travel times (no congestion) are almost an exact match. The location of the onset of the congestion is also very accurate. The start time and duration (size) of the congestion (and corresponding travel times) is also very much in line with the data, although to a lesser extent than the free flow travel times.

Figure B-2: *Calibration results Saturday 15-01-2011*

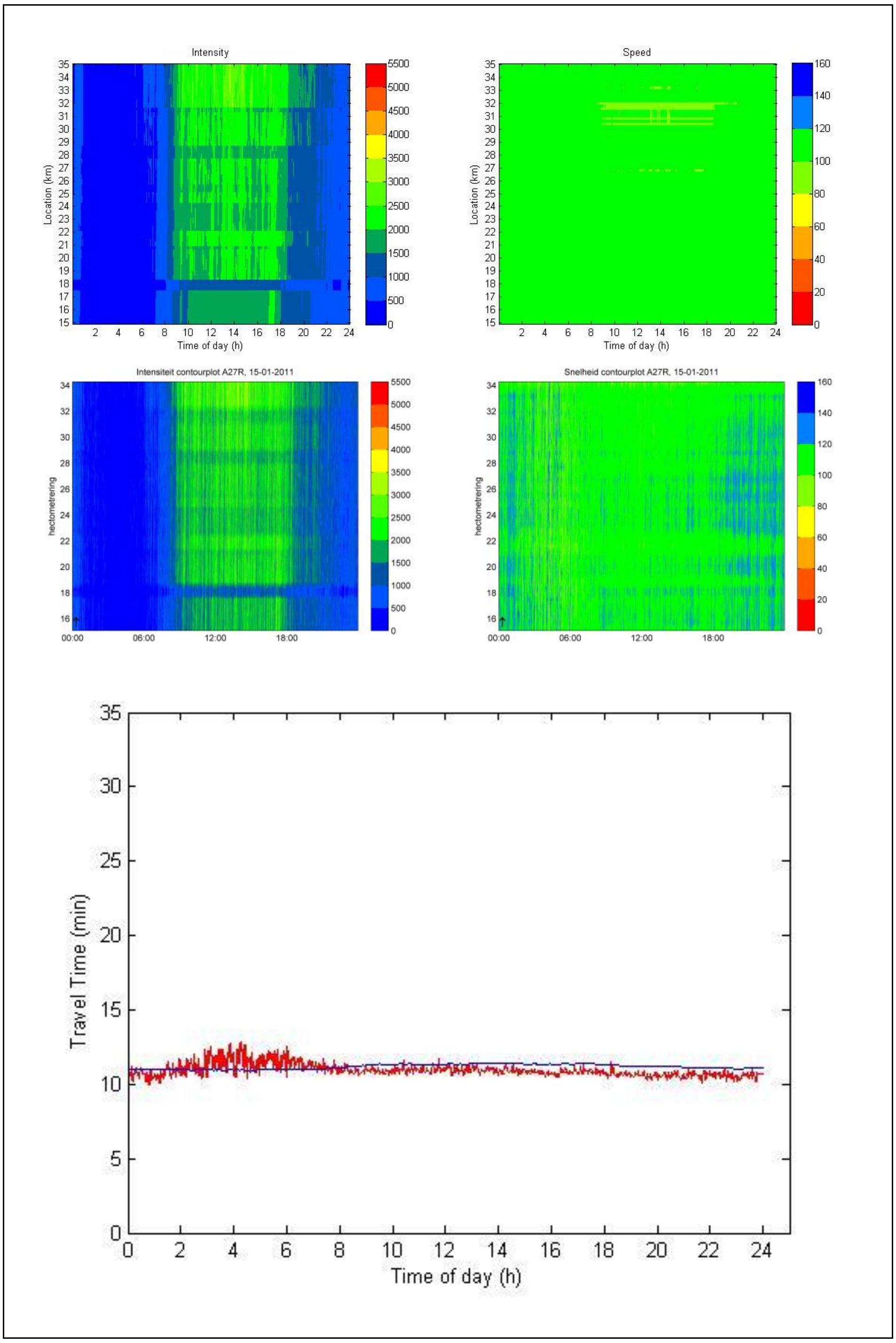


Figure B-3: *Calibration results Monday 14-02-2011*

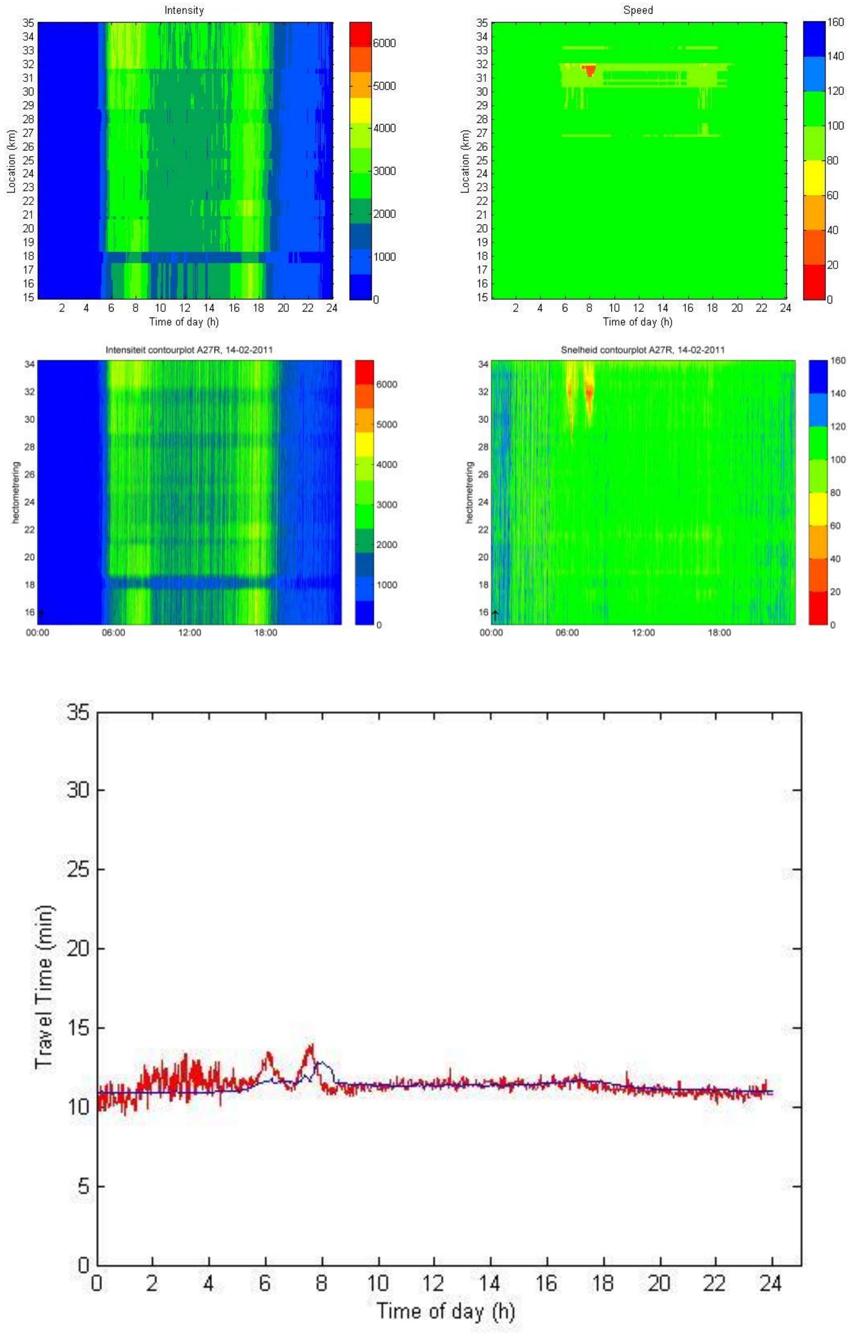


Figure B-4: *Calibration results Thursday 31-01-2011*

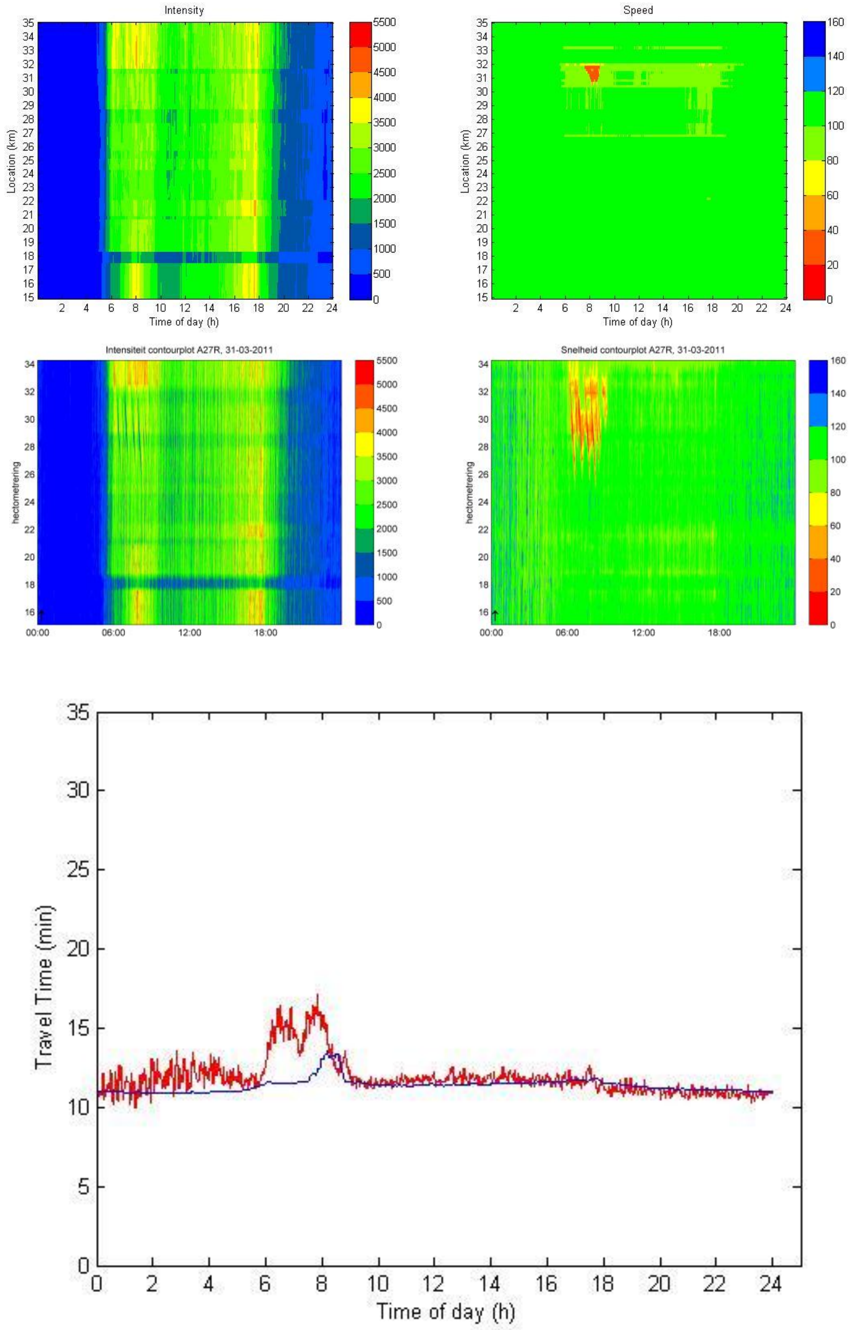


***Figure B-5:** Calibration results Tuesday 06-09-2011*

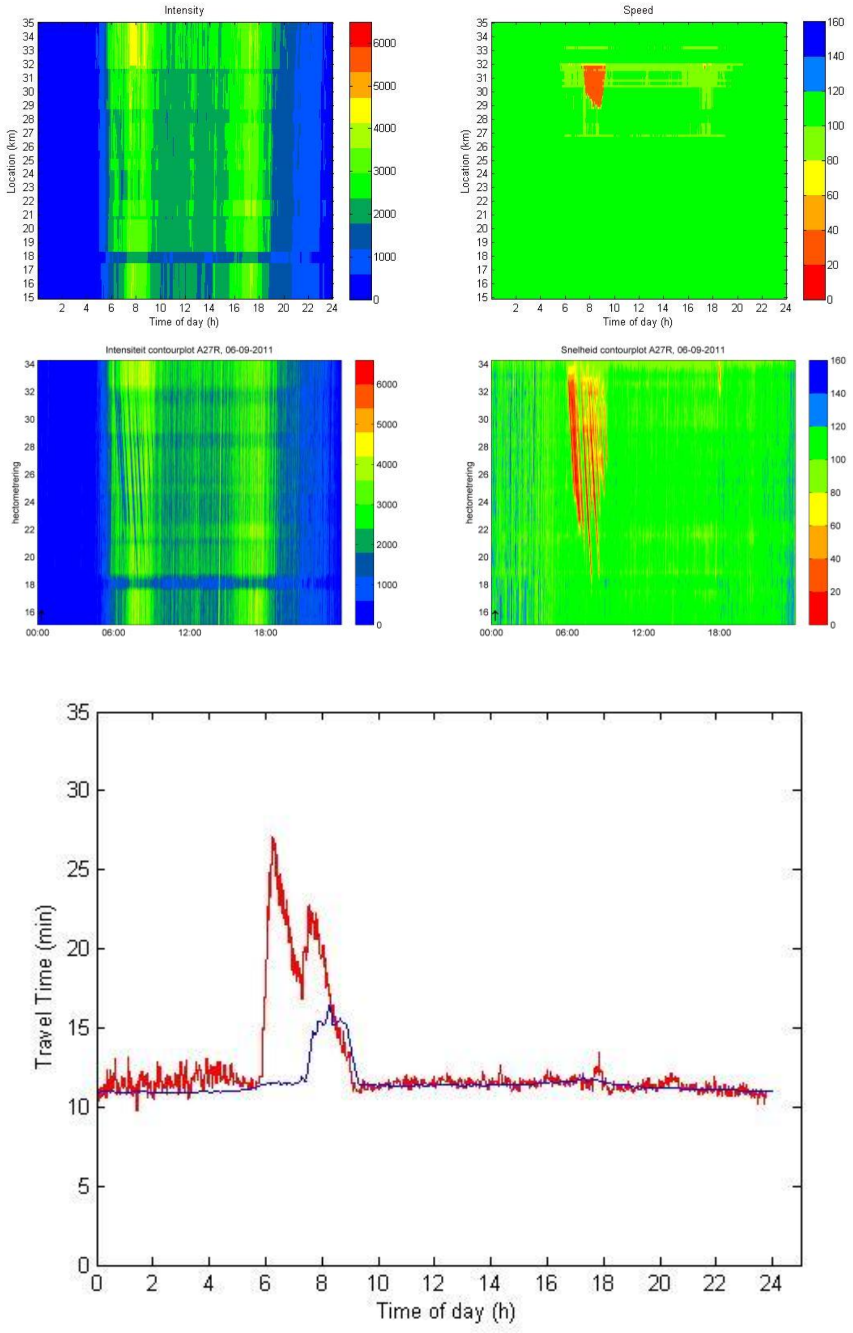
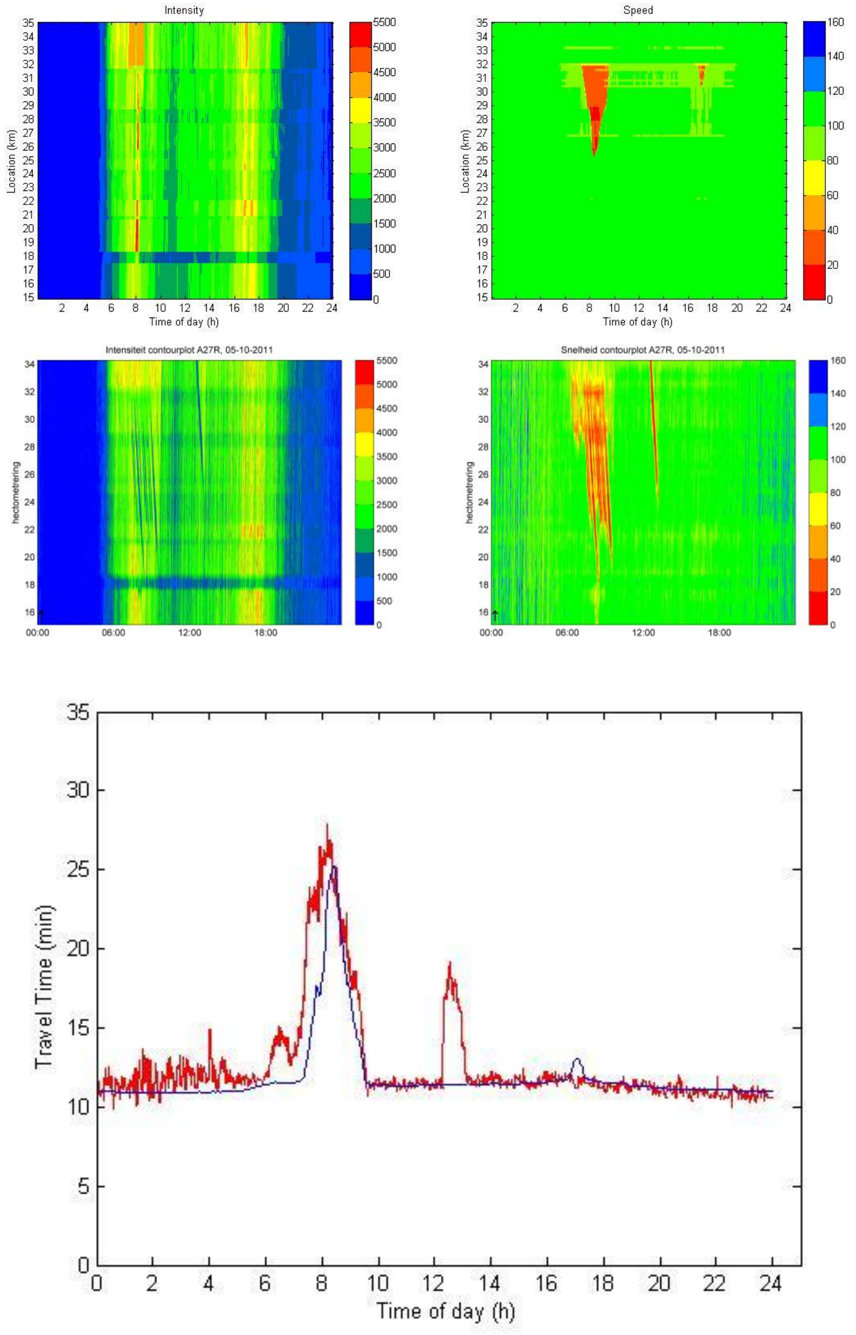


Figure B-6: *Calibration results Tuesday 05-10-2011*



Note the model was not able to reproduce the wide moving jam at approximately 12.30. This jam originated downstream of the modeled area, which makes it impossible for the model to reproduce it.

Intrinsic variability

Figure B-6 shows the obtained travel time distribution from the data. Table B-3 shows the model results for different bandwidths for the traffic supply variables. For each minute the modeled travel time distribution has been compared with data using the Kolmogorov-Smirnov test. The sum of minutes of which the result was positive (distributions are similar) was divided by the total number of minutes. In this way a percentage of succeeded tests was obtained. From Table B-4 it is clear that the bandwidth should be 92.5% - 112.5%. The corresponding figure (9th entry in table B-3) is indeed very similar to Figure B-7. One of the main differences is in the 95th percentile between 12.00 and 14.00. In the data a few outliers are observed here, while the model does not produce these. An explanation for this could be that on a number of days wide moving jams originating upstream were signaled at these time points.

***Figure B-7:** Travel time distribution from data (left)*

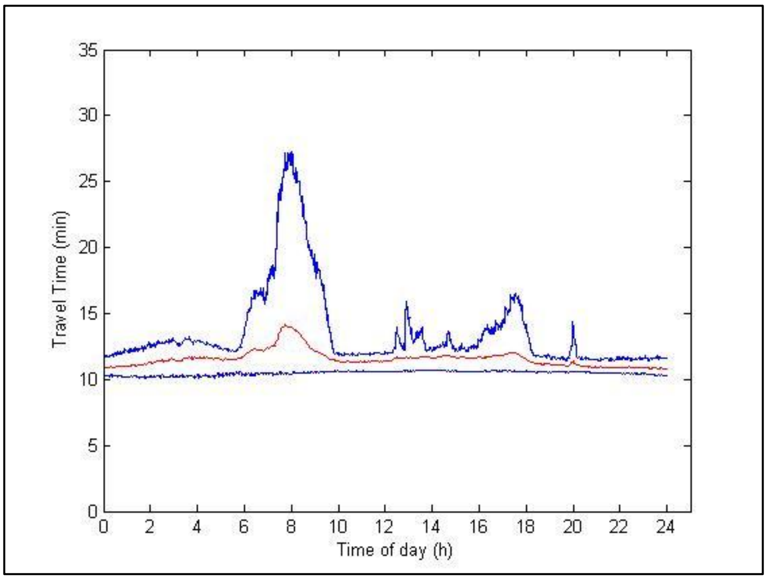
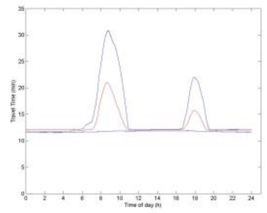
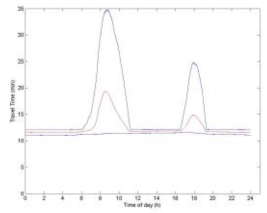
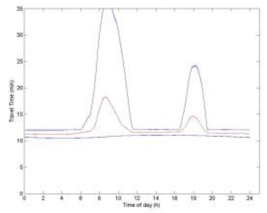
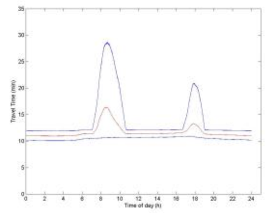
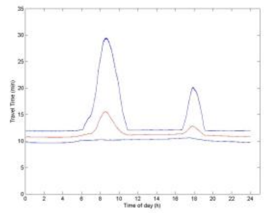
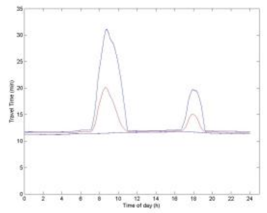
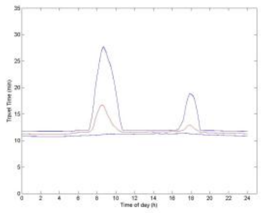
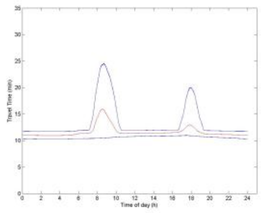


***Table B-3:** Effects of incidents upstream or downstream of the considered road stretch on the capacities*

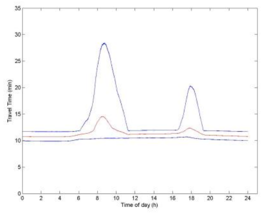
 b = 90%-95%, p = 0.000	 b = 90%-100%, p = 0.090	 b = 92.5%-97.5%, p = 0.474
 b = 90%-110%, p = 0.597	 b = 90%-115%, p = 0.794	 b = 92.5%-97.5%, p = 0.015



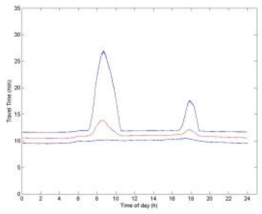
b = 92.5%-102.5%, p = 0.096



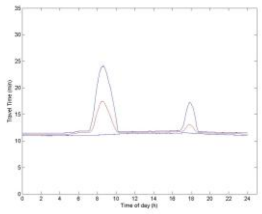
b = 92.5%-107.5%, p = 0.572



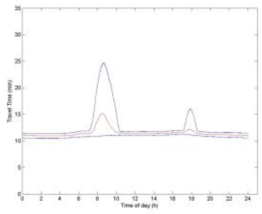
b = 92.5%-112.5%, p = 0.808



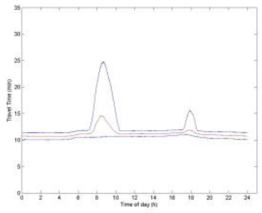
b = 92.5%-117.5%, p = 0.114



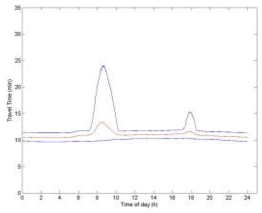
b = 95%-100%, p = 0.020



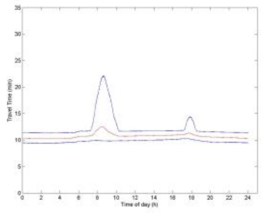
b = 95%-105%, p = 0.344



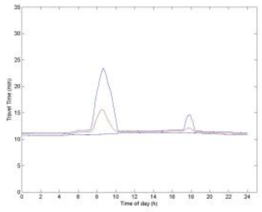
b = 95%-110%, p = 0.746



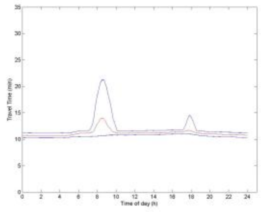
b = 95%-115%, p = 0.227



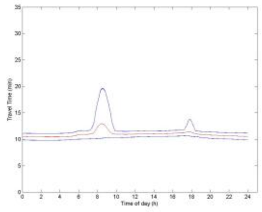
b = 95%-120%, p = 0.023



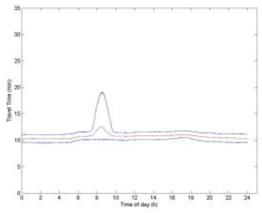
b = 97.5%-102.5%, p = 0.050



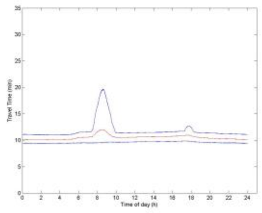
b = 97.5%-107.5%, p = 0.408



b = 97.5%-112.5%, p = 0.167



b = 97.5%-117.5%, p = 0.006



b = 97.5%-122.5%, p = 0.000

Table B-4: *Percentages of accepted Kolmogorov-Smirnov tests*

Bandwidth minimum / Size of bandwidth	90%	92,5%	95%	97,5%
5%	0,000	0,015	0,020	0,050
10%	0,090	0,096	0,344	0,408
15%	0,474	0,572	0,746	0,167
20%	0,597	**0,808**	0,227	0,006
25%	0,794	0,114	0,023	0,000

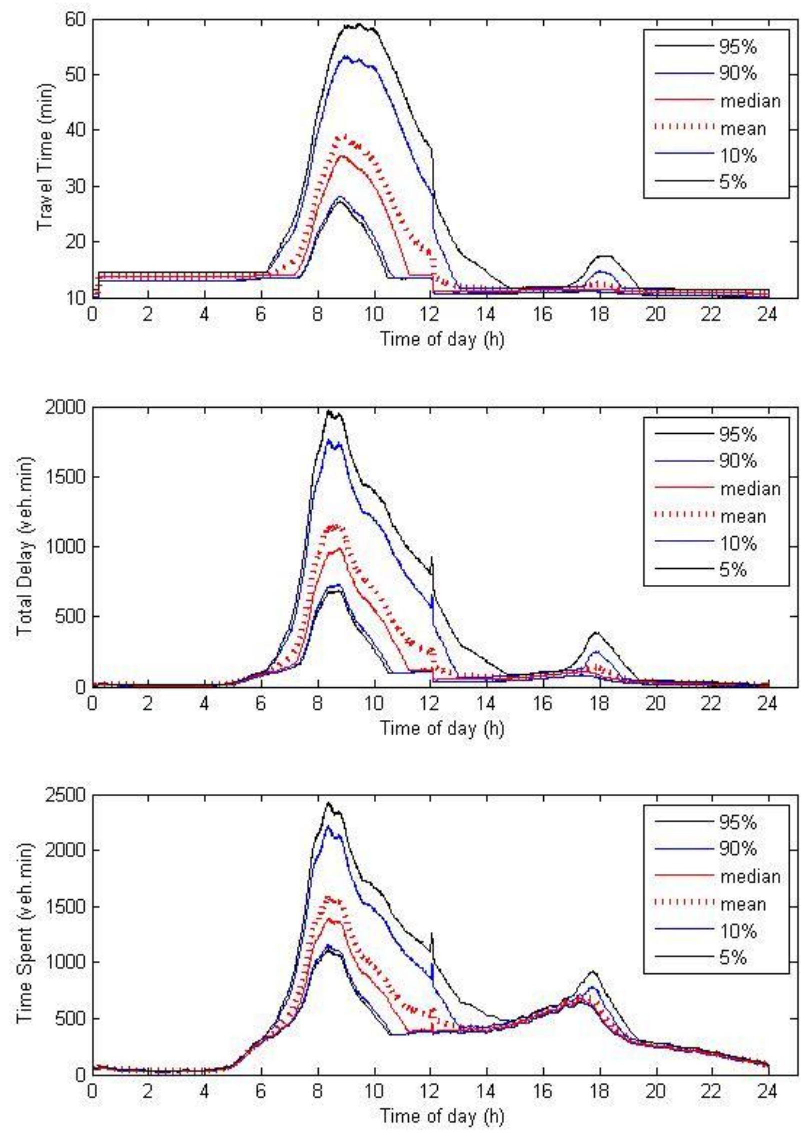
Appendix C: Model results

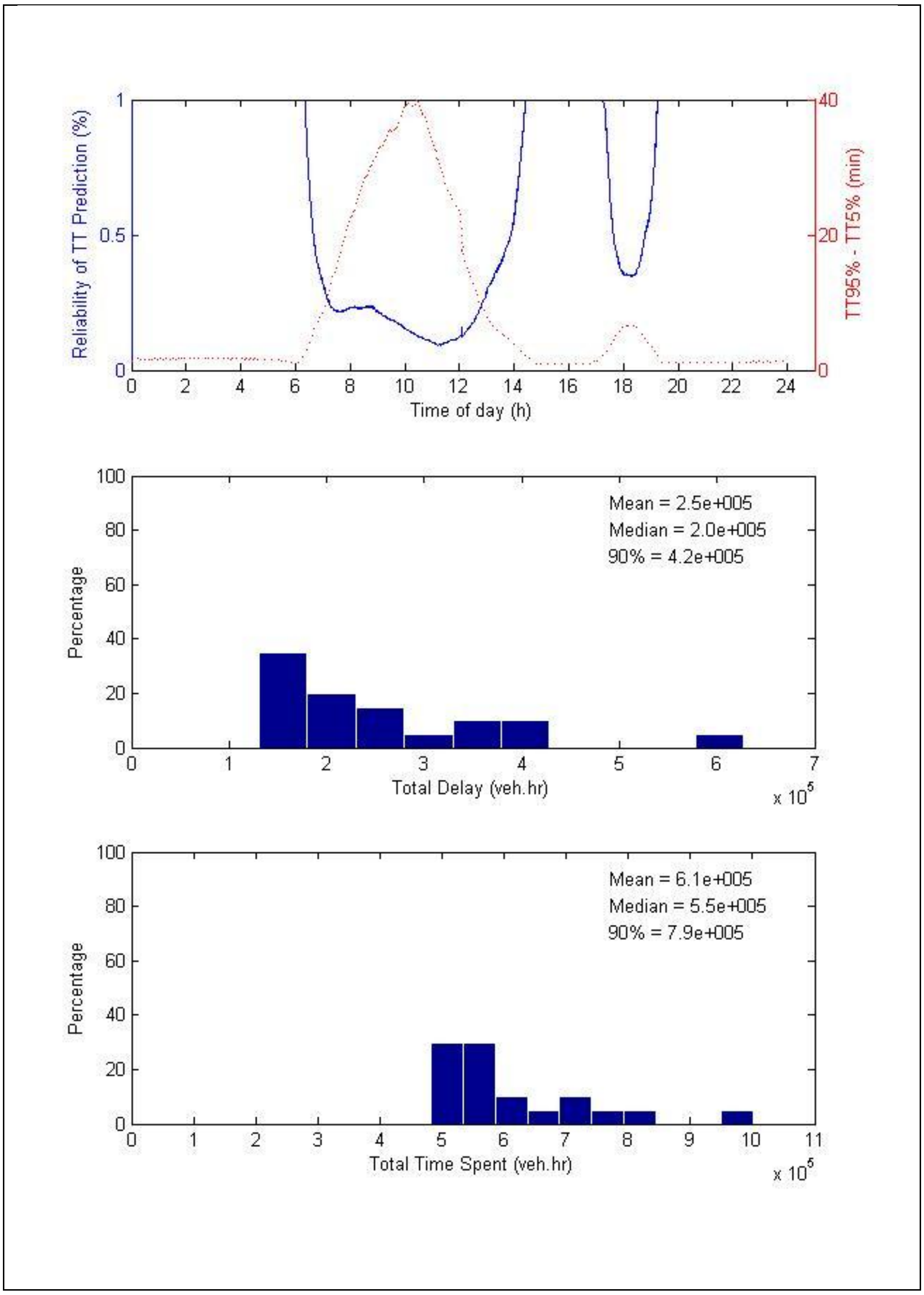
This appendix shows all case study results enlarged, for the observations and conclusions is referred to the corresponding chapters.

Road works

Scenario 1: All information is present

Figure C-1: Results for road works scenario 1

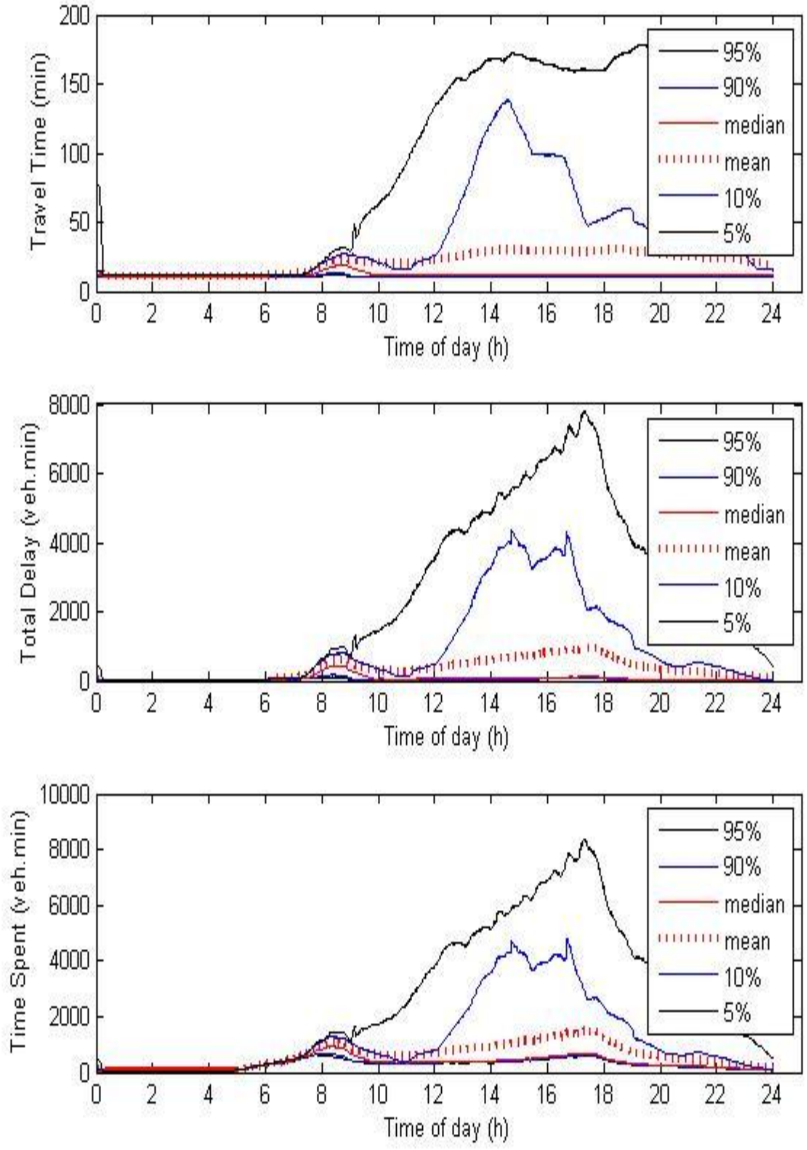


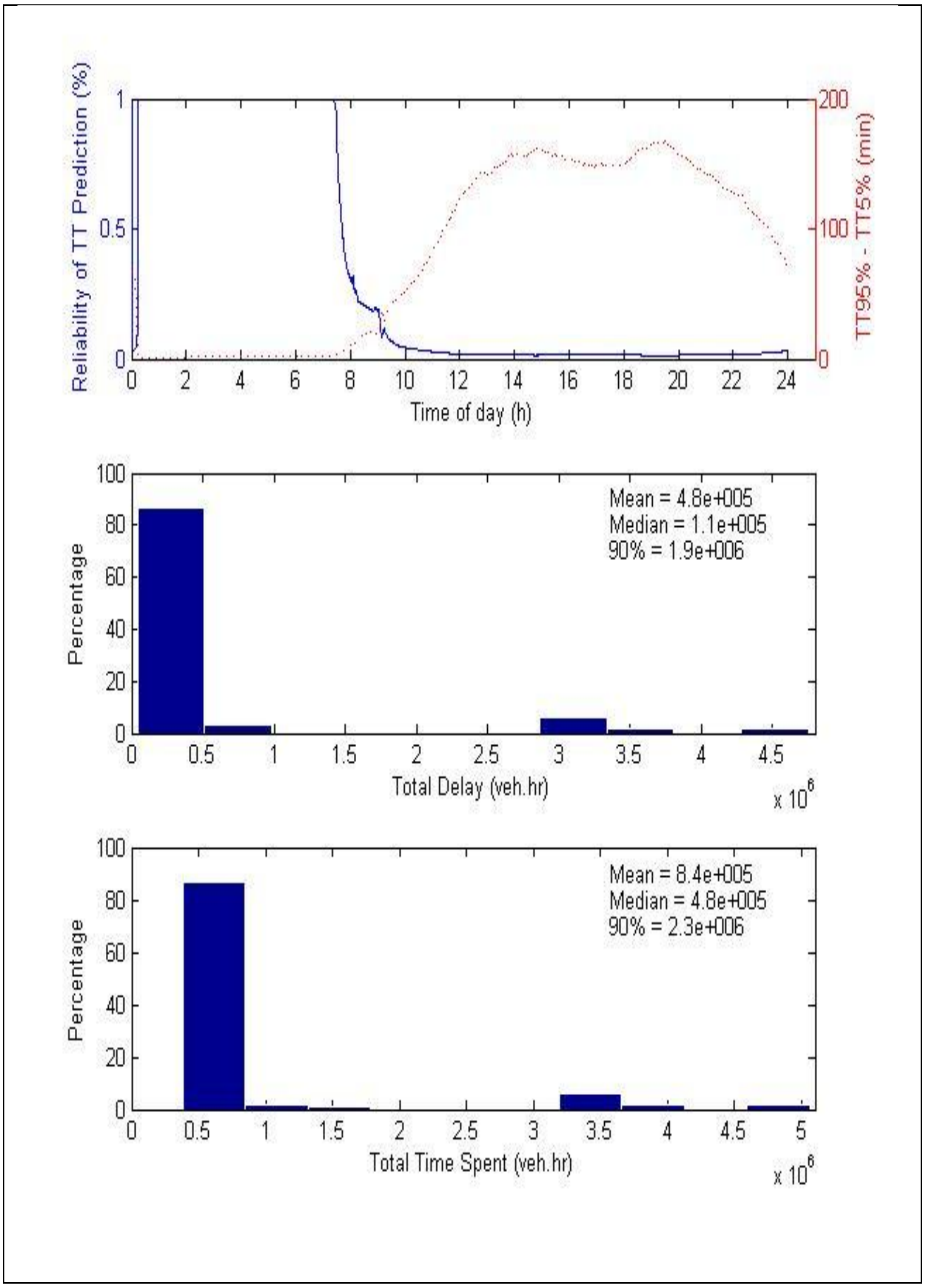


Reliability of TT Prediction (%)
TT95% - TT5% (min)
Time of day (h)
0
0.5
1
0
20
40
0
2
4
6
8
10
12
14
16
18
20
22
24
Mean = 2.5e+005
Median = 2.0e+005
90% = 4.2e+005
Percentage
Total Delay (veh.hr)
x 10^5
0
20
40
60
80
100
0
1
2
3
4
5
6
7
Mean = 6.1e+005
Median = 5.5e+005
90% = 7.9e+005
Percentage
Total Time Spent (veh.hr)
x 10^5
0
20
40
60
80
100
0
1
2
3
4
5
6
7
8
9
10
11

Scenario 2: No actual information is present

Figure C-2: *Results for road works scenario 2*

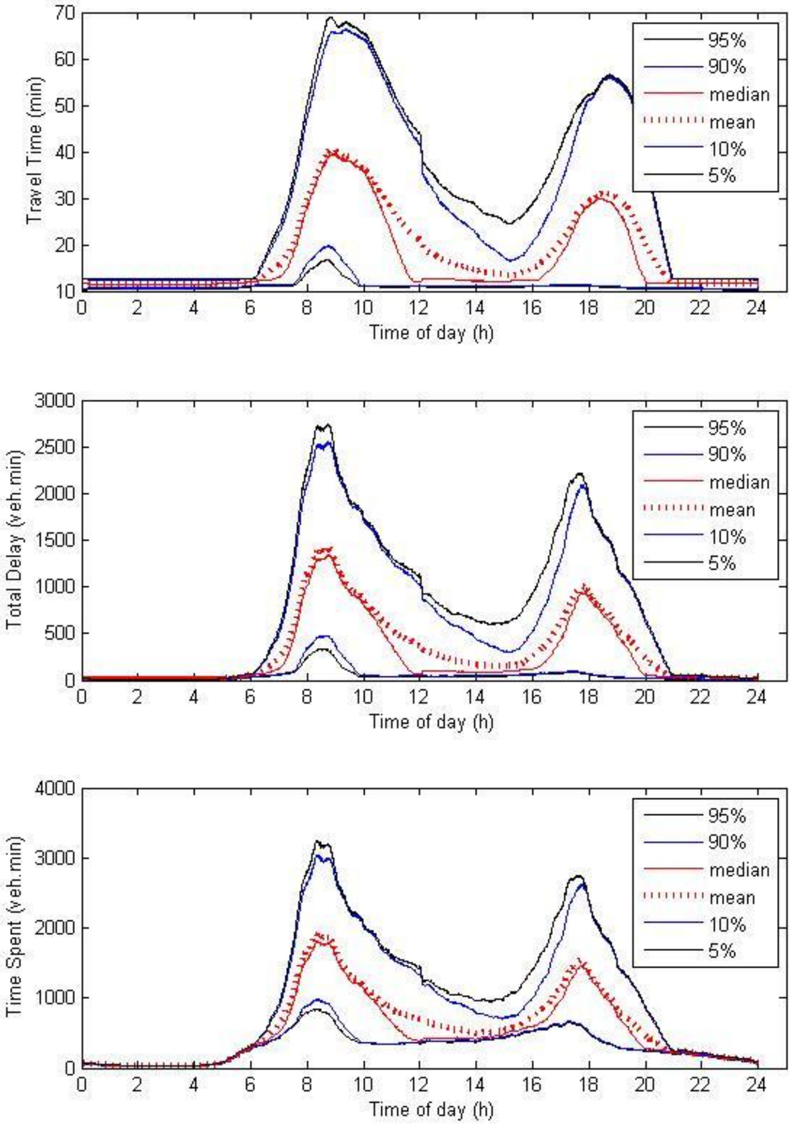


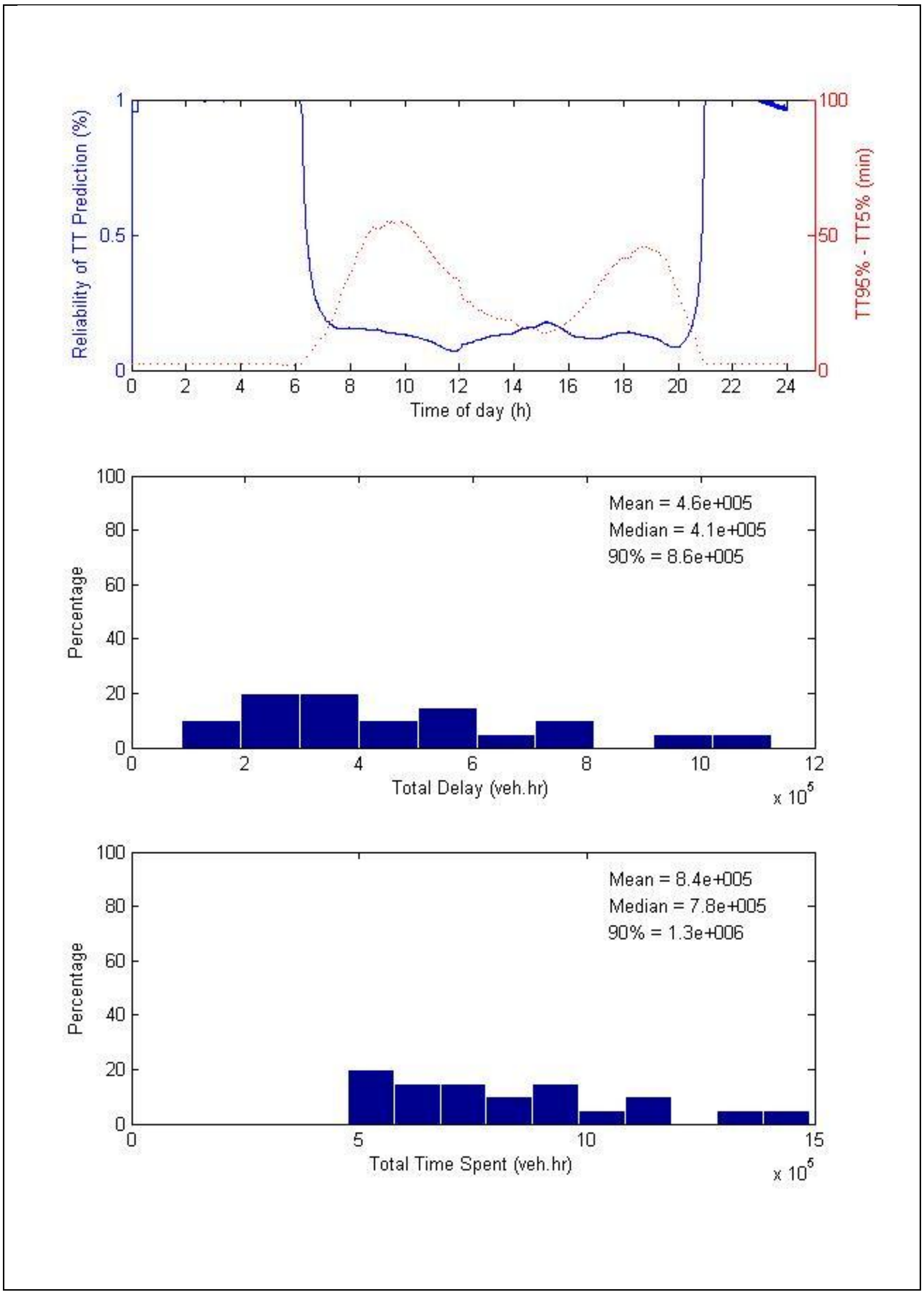

Reliability of TT Prediction (%)
1
0.5
0
0
2
4
6
8
10
12
14
16
18
20
22
24
Time of day (h)
200
100
0
TT95% - TT5% (min)
100
80
60
40
20
0
Percentage
Mean = 4.8e+005
Median = 1.1e+005
90% = 1.9e+006
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
Total Delay (veh.hr)
x 10^6
100
80
60
40
20
0
Percentage
Mean = 8.4e+005
Median = 4.8e+005
90% = 2.3e+006
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
Total Time Spent (veh.hr)
x 10^6

Weather conditions

Scenario 1: Short-term prediction

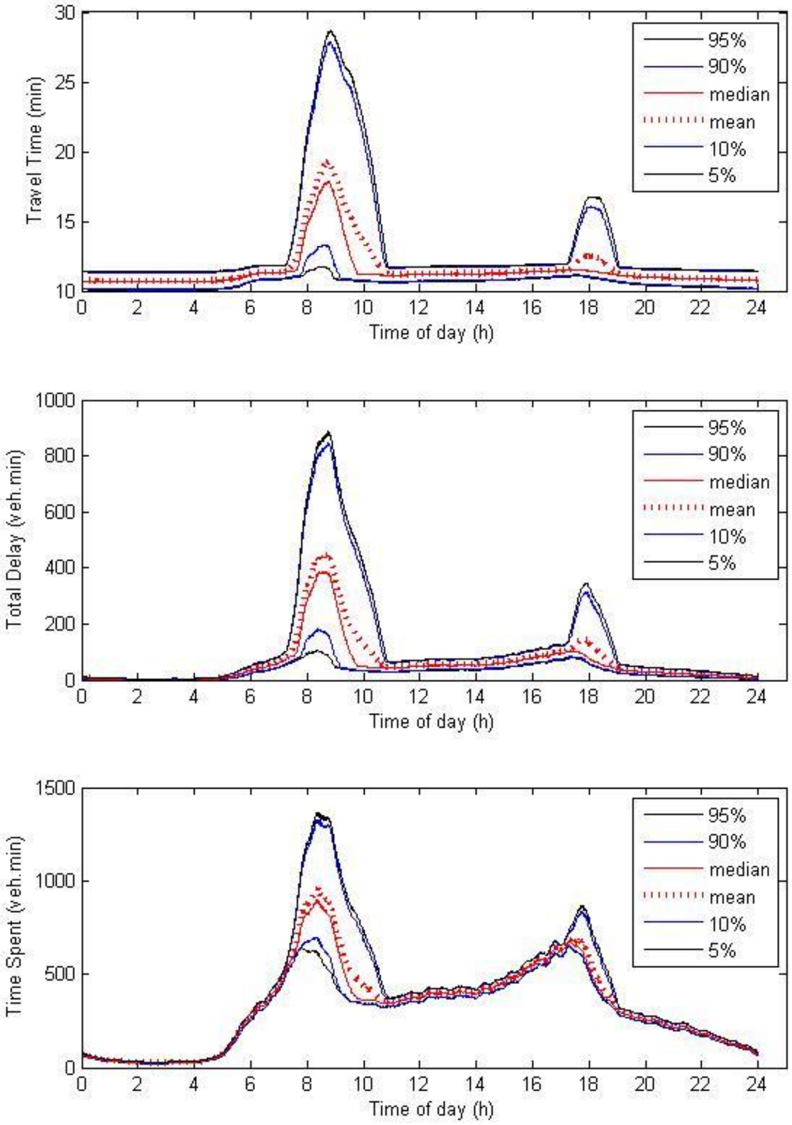
Figure C-3: *Results for weather conditions scenario 1*

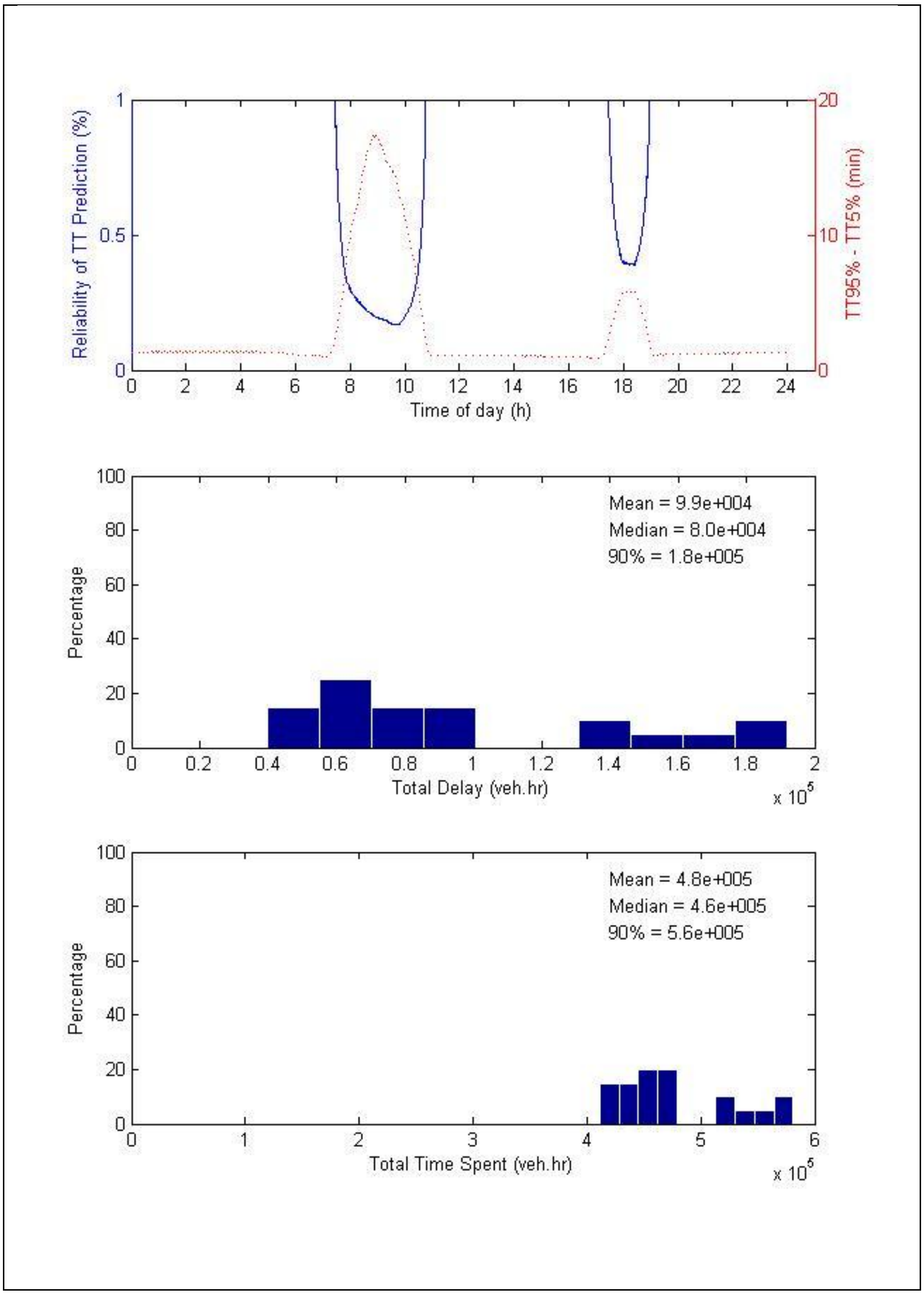



Reliability of TT Prediction (%)
TT95% - TT5% (min)
1
0.5
0
100
50
0
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of day (h)
Percentage
100
80
60
40
20
0
0 2 4 6 8 10 12
Total Delay (veh.hr)
x 10^5
Mean = 4.6e+005
Median = 4.1e+005
90% = 8.6e+005
Percentage
100
80
60
40
20
0
0 5 10 15
Total Time Spent (veh.hr)
x 10^5
Mean = 8.4e+005
Median = 7.8e+005
90% = 1.3e+006

Scenario 2a: Long-term prediction (January)

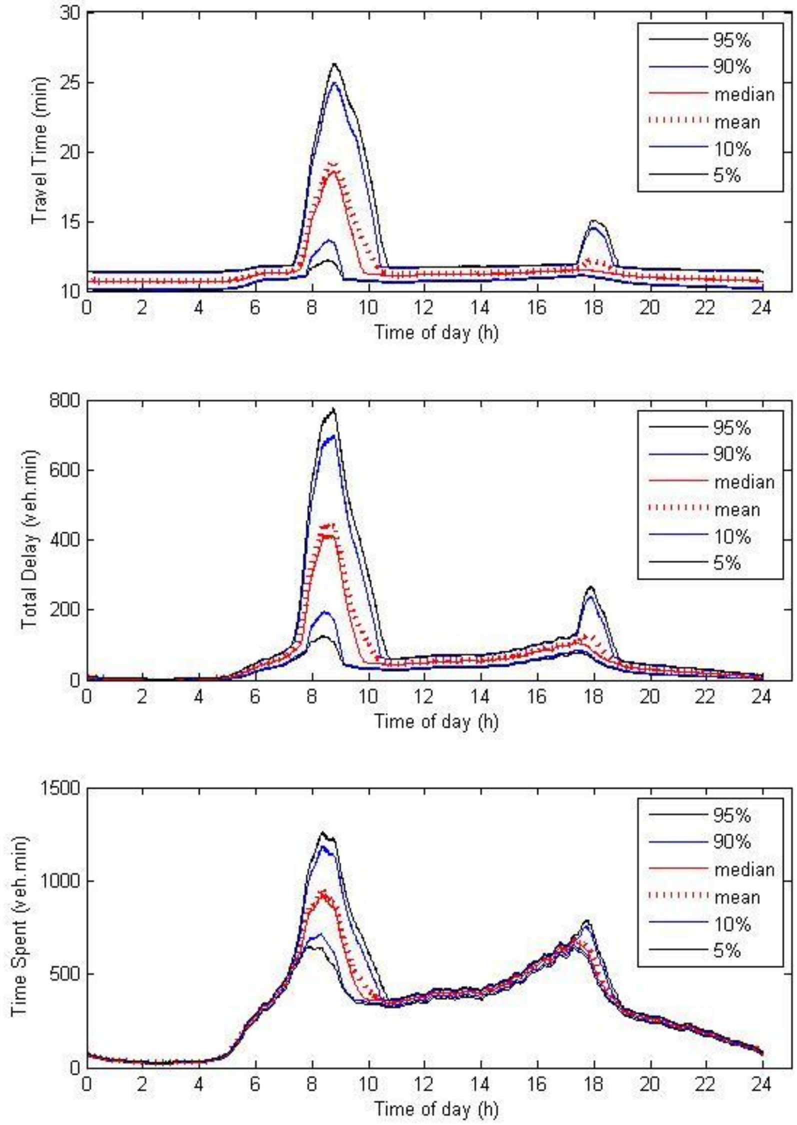
Figure C-4: *Results for weather conditions scenario 2b*

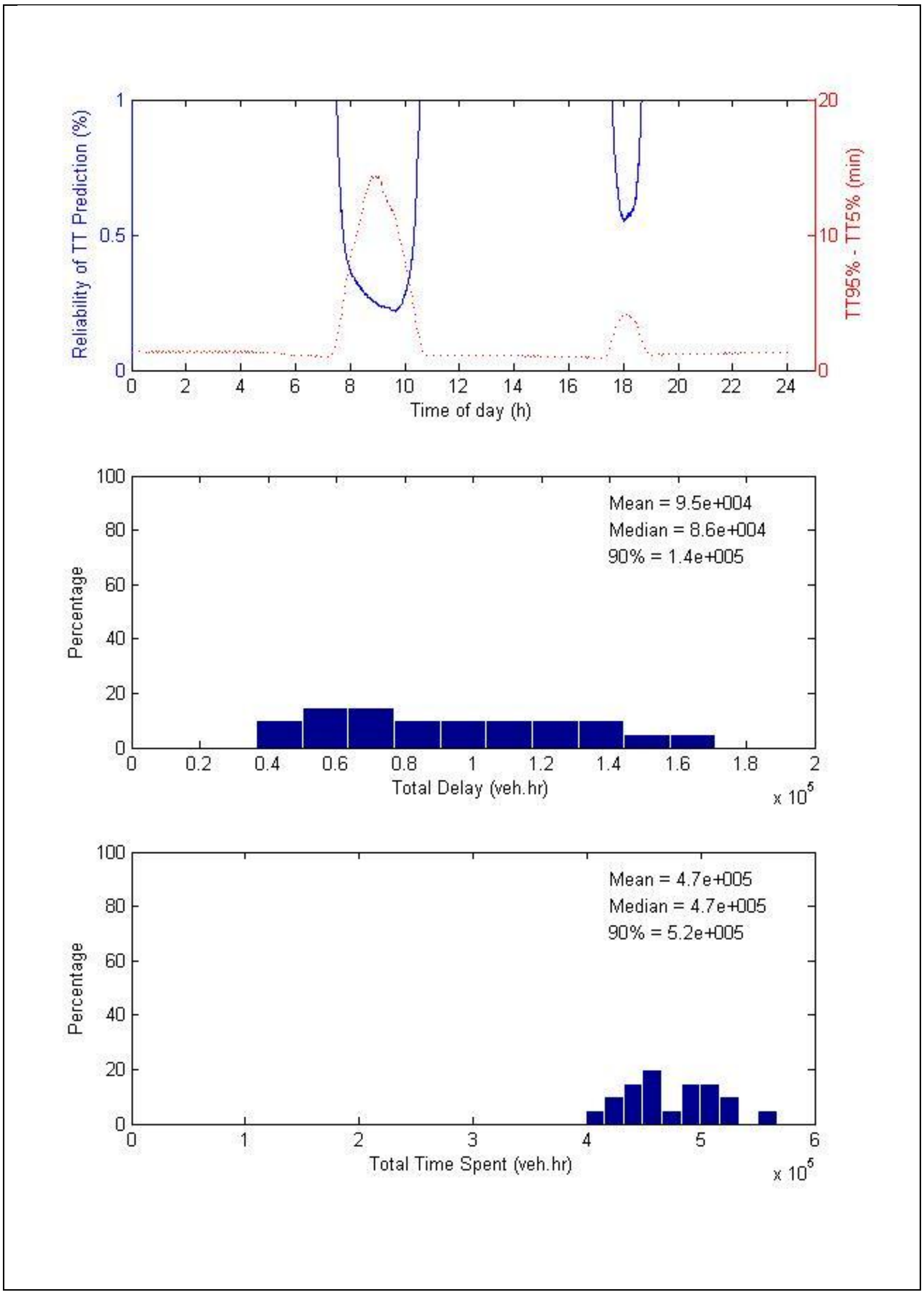



Reliability of TT Prediction (%)
TT95% - TT5% (min)
1
0.5
0
20
10
0
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of day (h)
Percentage
100 80 60 40 20 0
Mean = 9.9e+004
Median = 8.0e+004
90% = 1.8e+005
0 0.2 0.4 0.6 0.8 1 1.2 1.4 1.6 1.8 2
Total Delay (veh.hr)
x 10^5
Percentage
100 80 60 40 20 0
Mean = 4.8e+005
Median = 4.6e+005
90% = 5.6e+005
0 1 2 3 4 5 6
Total Time Spent (veh.hr)
x 10^5

Scenario 2b: Long-term prediction (July)

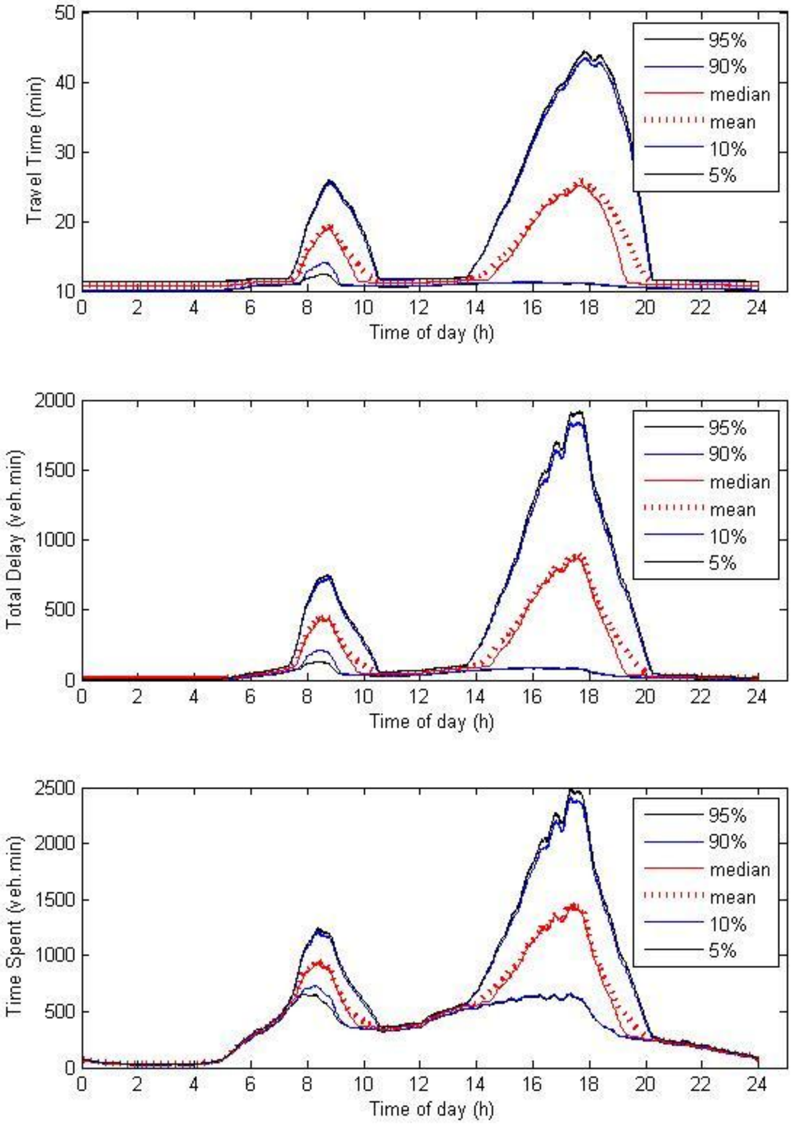
Figure C-5: *Results for weather conditions scenario 2a*

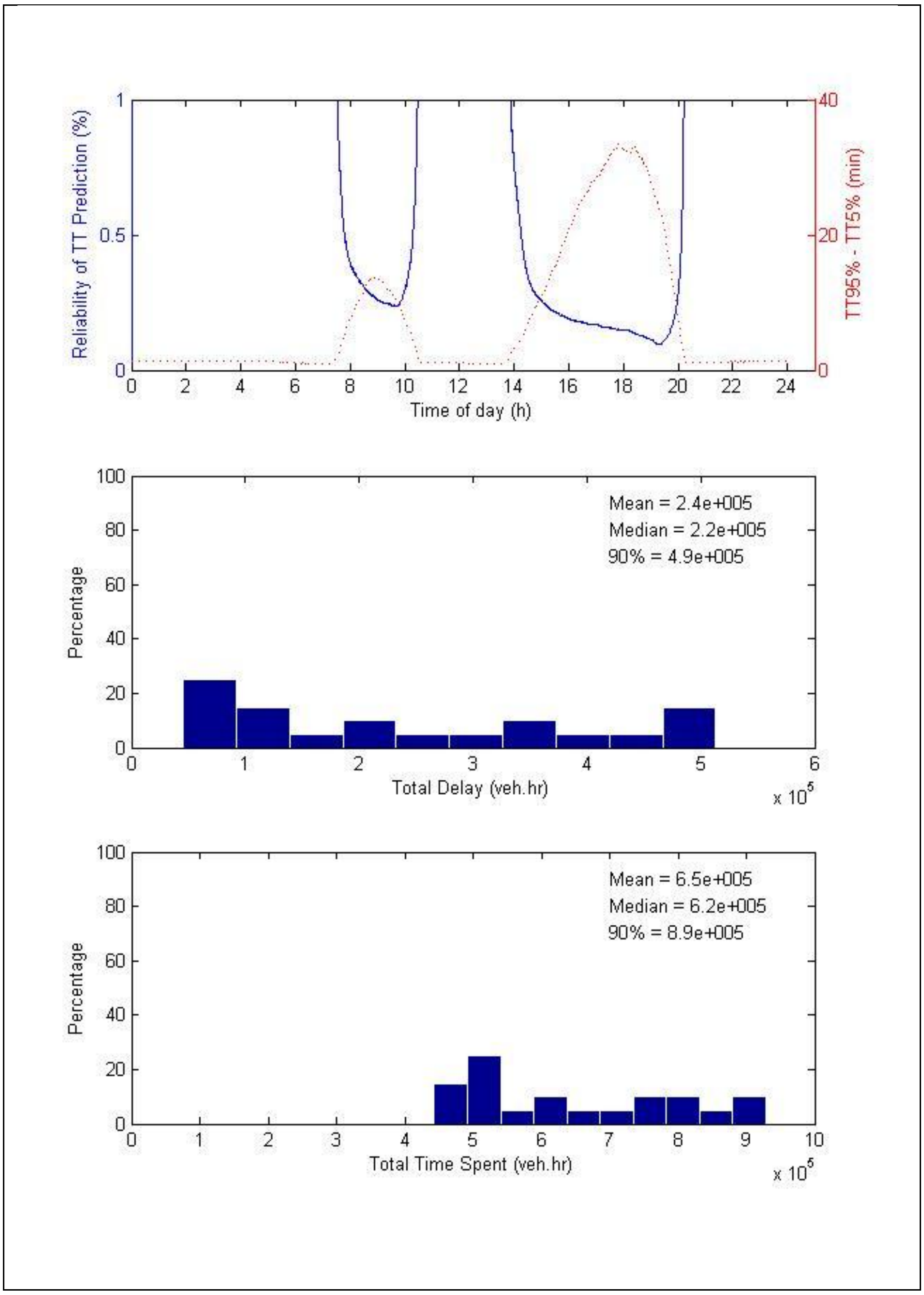



Reliability of TT Prediction (%)
1
0.5
0
TT95% - TT5% (min)
20
10
0
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of day (h)
Percentage
100 80 60 40 20 0
Mean = 9.5e+004
Median = 8.6e+004
90% = 1.4e+005
0 0.2 0.4 0.6 0.8 1 1.2 1.4 1.6 1.8 2
Total Delay (veh.hr)
x 10^5
Percentage
100 80 60 40 20 0
Mean = 4.7e+005
Median = 4.7e+005
90% = 5.2e+005
0 1 2 3 4 5 6
Total Time Spent (veh.hr)
x 10^5

Events

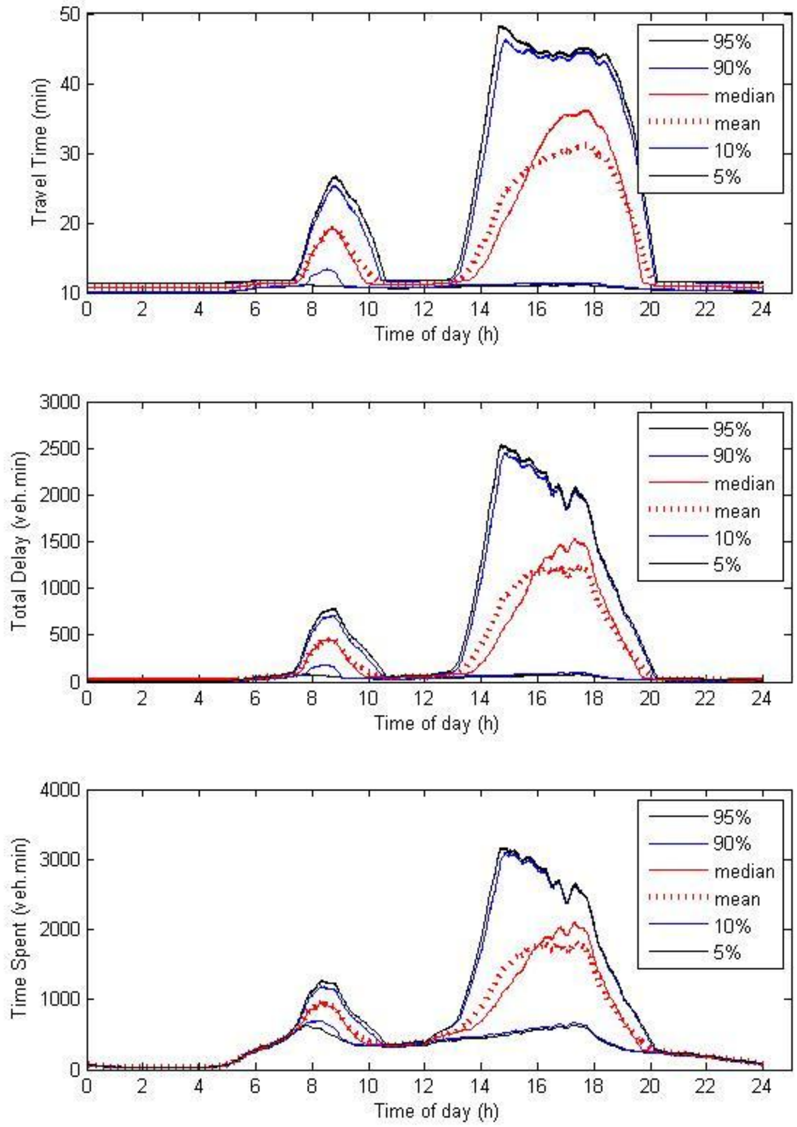
***Figure C-6:** Results for events scenario 1*

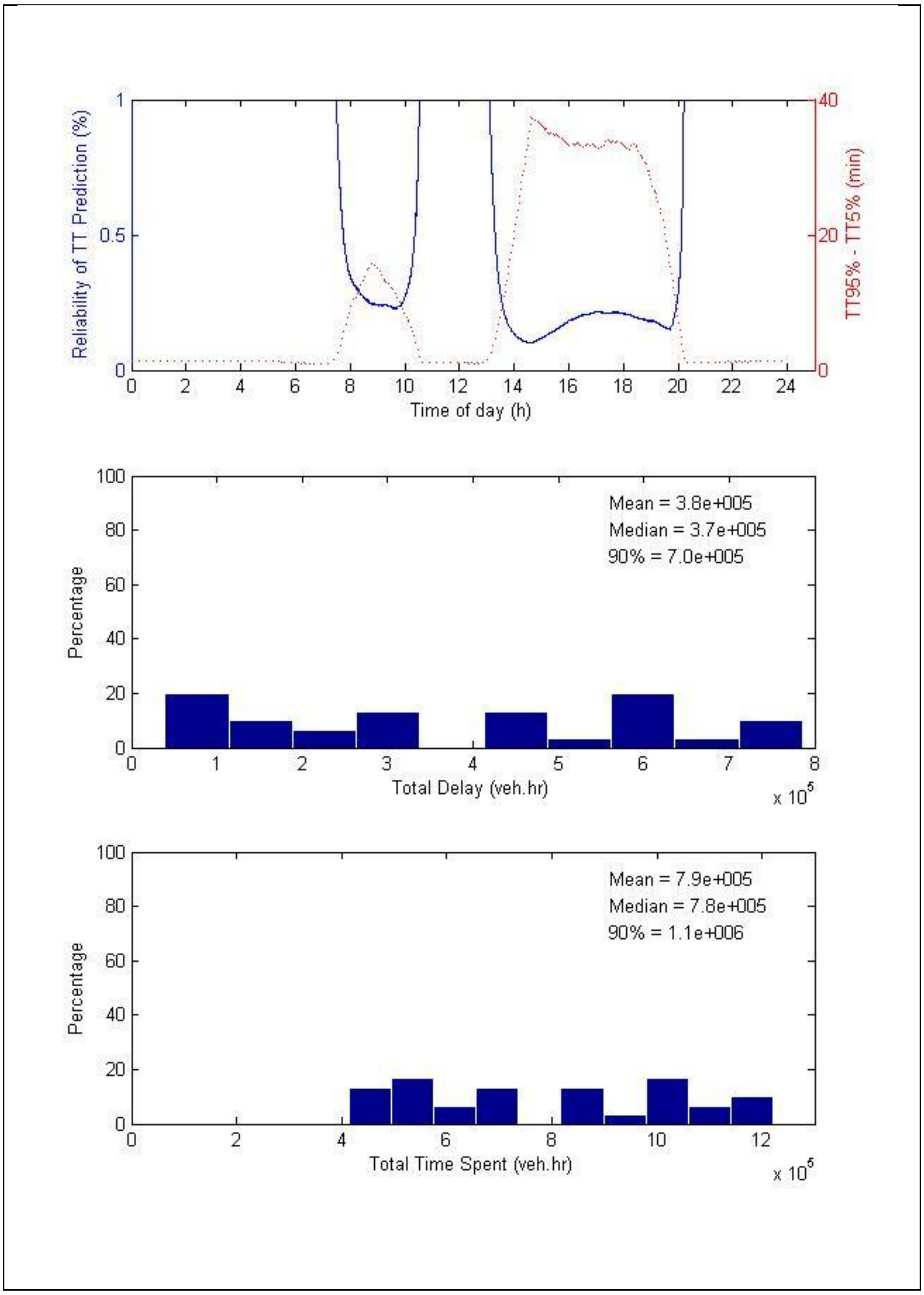



Reliability of TT Prediction (%)
1
0.5
0
TT95% - TT5% (min)
40
20
0
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of day (h)
Percentage
100 80 60 40 20 0
Mean = 2.4e+005
Median = 2.2e+005
90% = 4.9e+005
0 1 2 3 4 5 6
Total Delay (veh.hr)
x 10^5
Percentage
100 80 60 40 20 0
Mean = 6.5e+005
Median = 6.2e+005
90% = 8.9e+005
0 1 2 3 4 5 6 7 8 9 10
Total Time Spent (veh.hr)
x 10^5

Scenario 2:

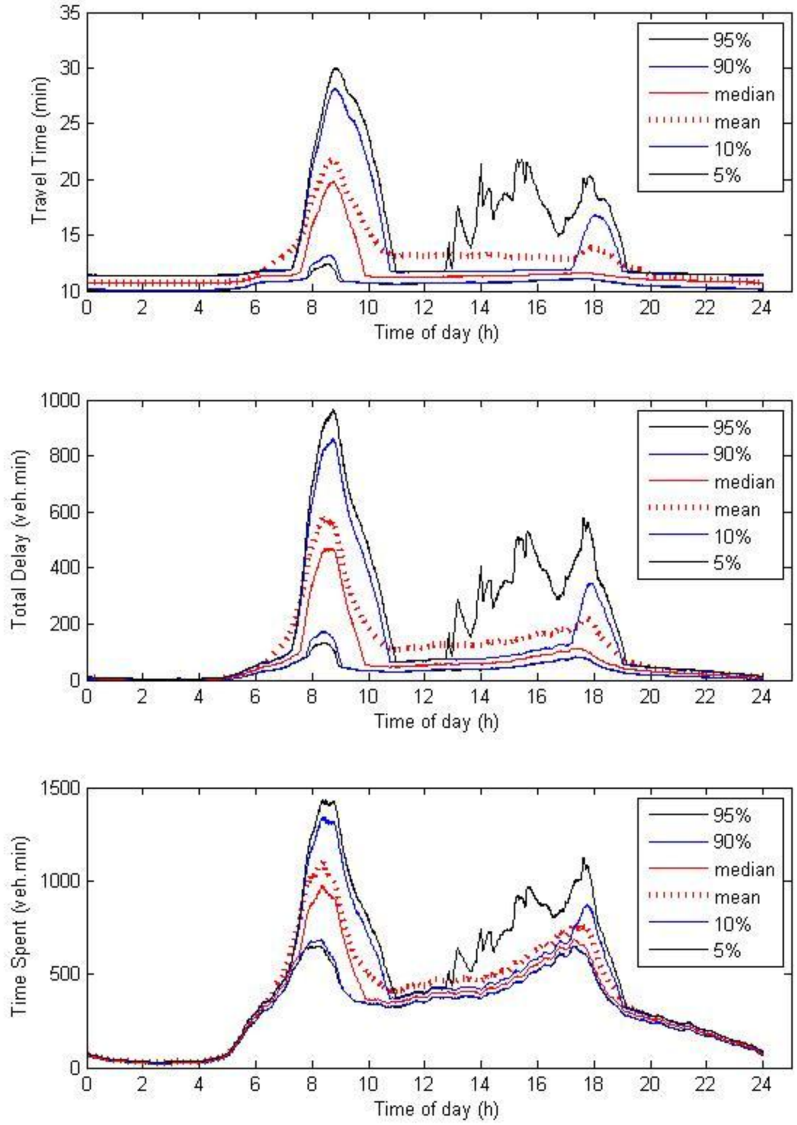
Figure C-7: *Results for events scenario 2*

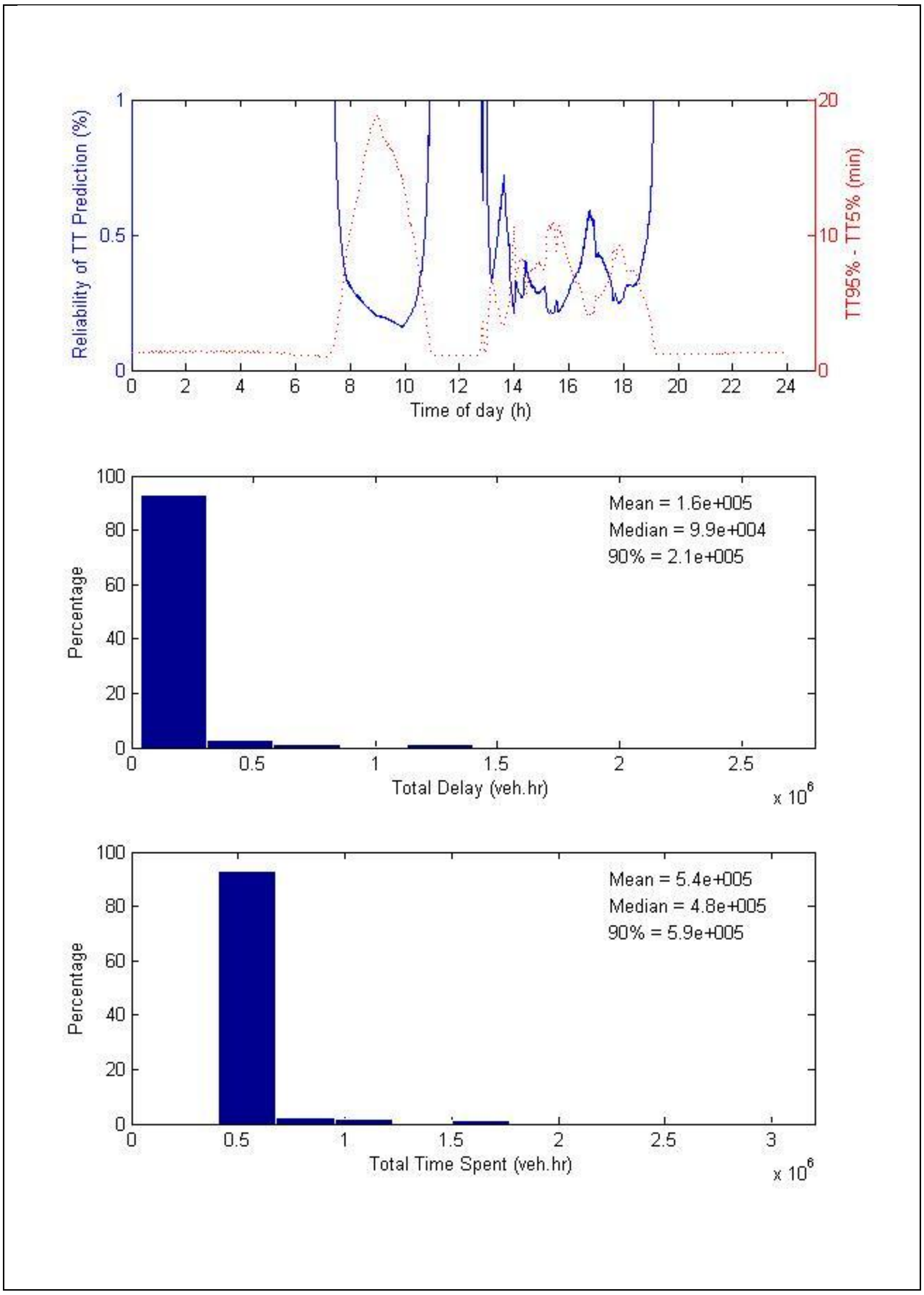



Reliability of TT Prediction (%)
TT95% - TT5% (min)
1
0.5
0
40
20
0
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of day (h)
Percentage
100 80 60 40 20 0
Mean = 3.8e+005
Median = 3.7e+005
90% = 7.0e+005
0 1 2 3 4 5 6 7 8
Total Delay (veh.hr)
x 10^5
Percentage
100 80 60 40 20 0
Mean = 7.9e+005
Median = 7.8e+005
90% = 1.1e+006
0 2 4 6 8 10 12
Total Time Spent (veh.hr)
x 10^5

Incidents

Figure C-8: *Results for incidents*

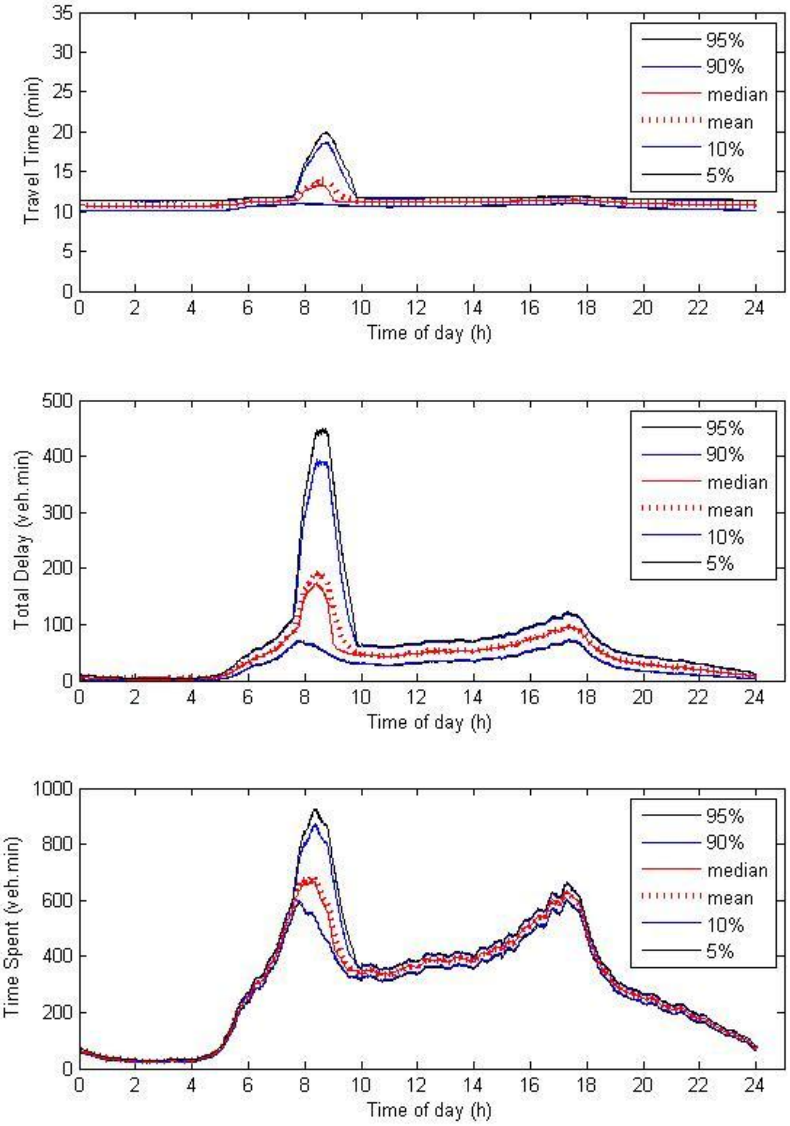


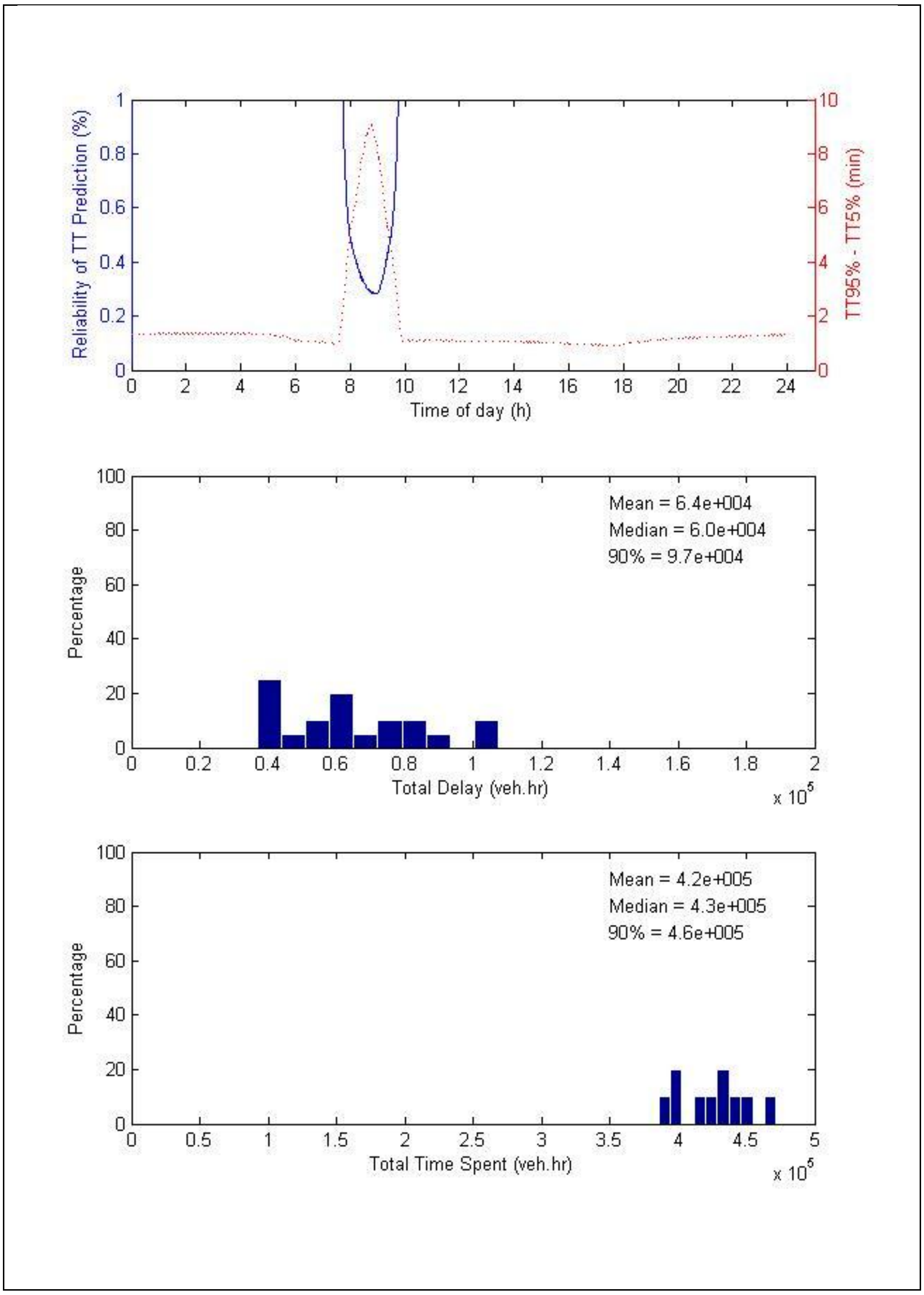

Reliability of TT Prediction (%)
TT95% - TT5% (min)
1
0.5
0
20
10
0
0 2 4 6 8 10 12 14 16 18 20 22 24
Time of day (h)
Percentage
100
80
60
40
20
0
Mean = 1.6e+005
Median = 9.9e+004
90% = 2.1e+005
0 0.5 1 1.5 2 2.5
Total Delay (veh.hr)
x 10^6
Percentage
100
80
60
40
20
0
Mean = 5.4e+005
Median = 4.8e+005
90% = 5.9e+005
0 0.5 1 1.5 2 2.5 3
Total Time Spent (veh.hr)
x 10^6

Season effects

Scenario 1: All information is present

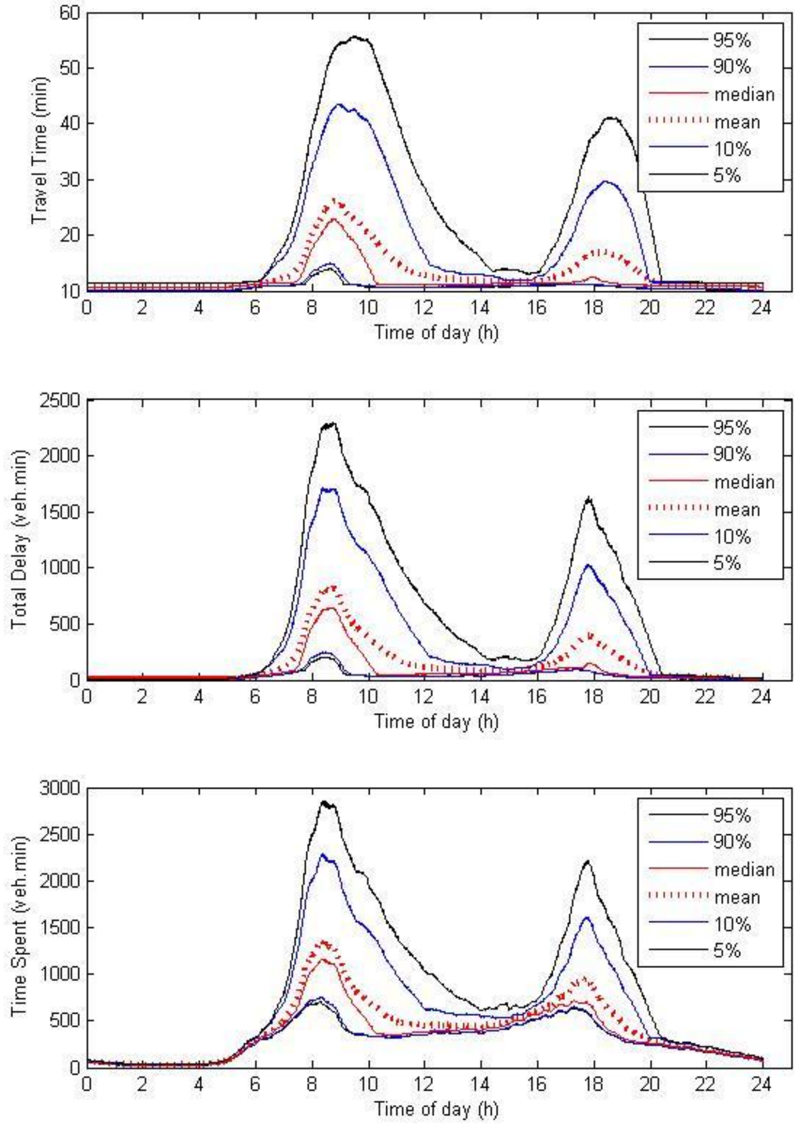
Figure C-9: *Results for season effects scenario 1*

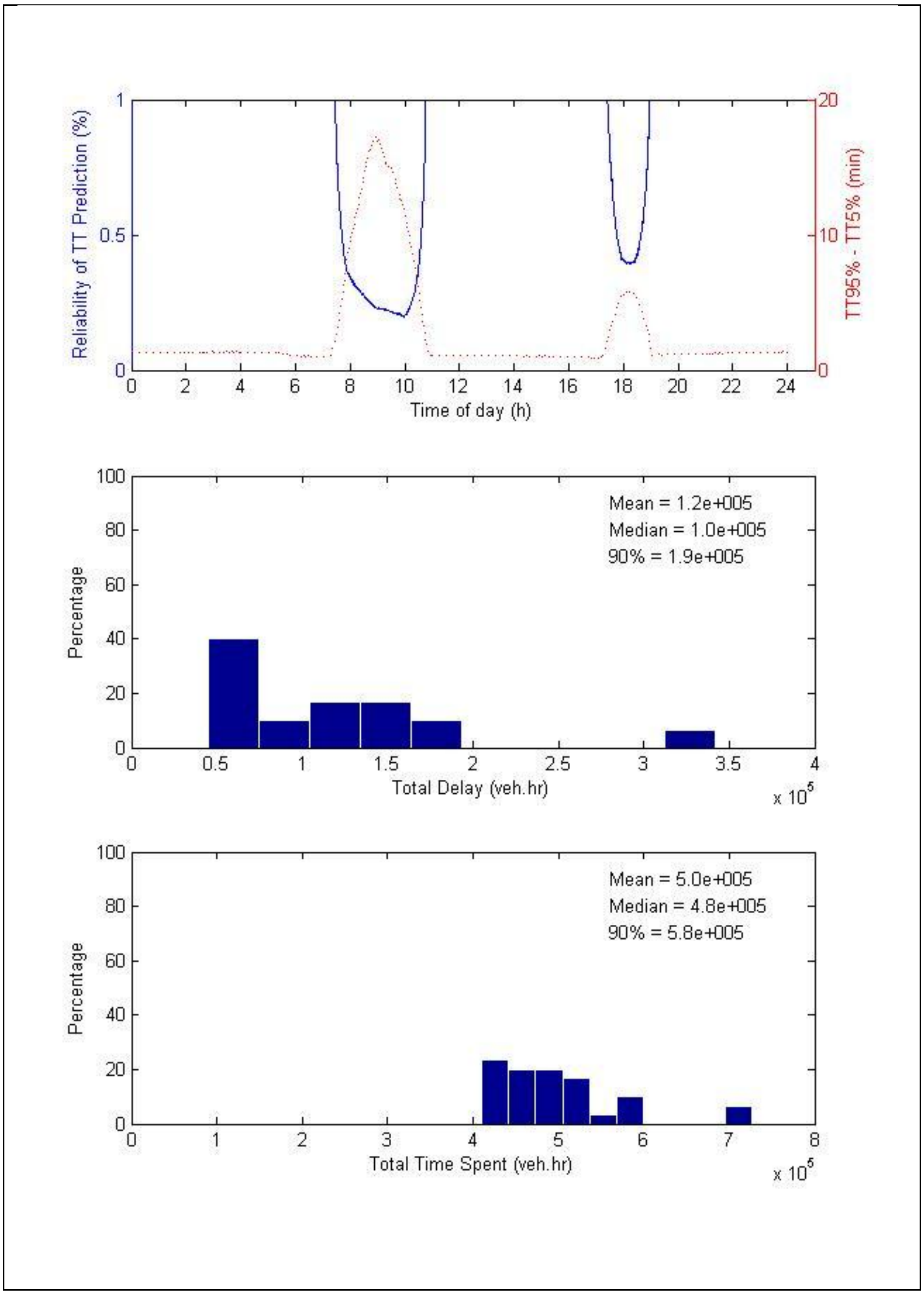



Reliability of TT Prediction (%)
TT95% - TT5% (min)
Time of day (h)
Percentage
Total Delay (veh.hr)
x 10^5
Mean = 6.4e+004
Median = 6.0e+004
90% = 9.7e+004
Percentage
Total Time Spent (veh.hr)
x 10^5
Mean = 4.2e+005
Median = 4.3e+005
90% = 4.6e+005

Scenario 2: Month is unknown

Figure C-10: *Results for season effects scenario 2*



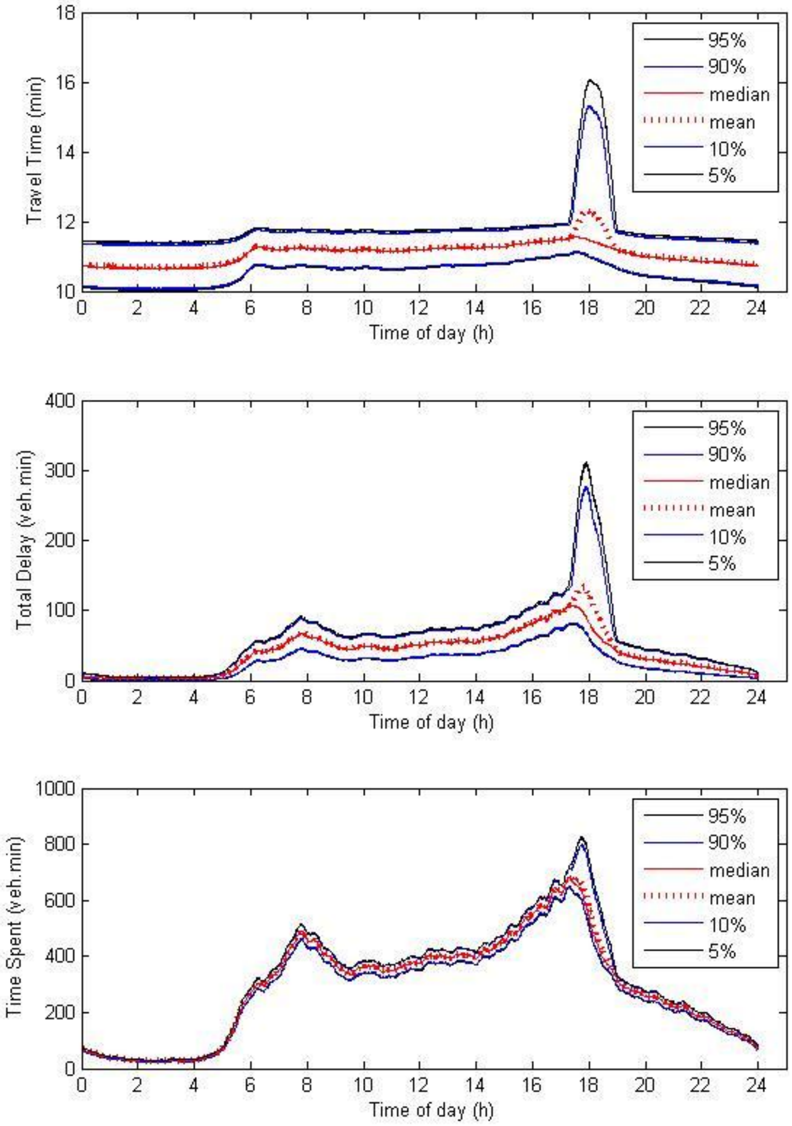


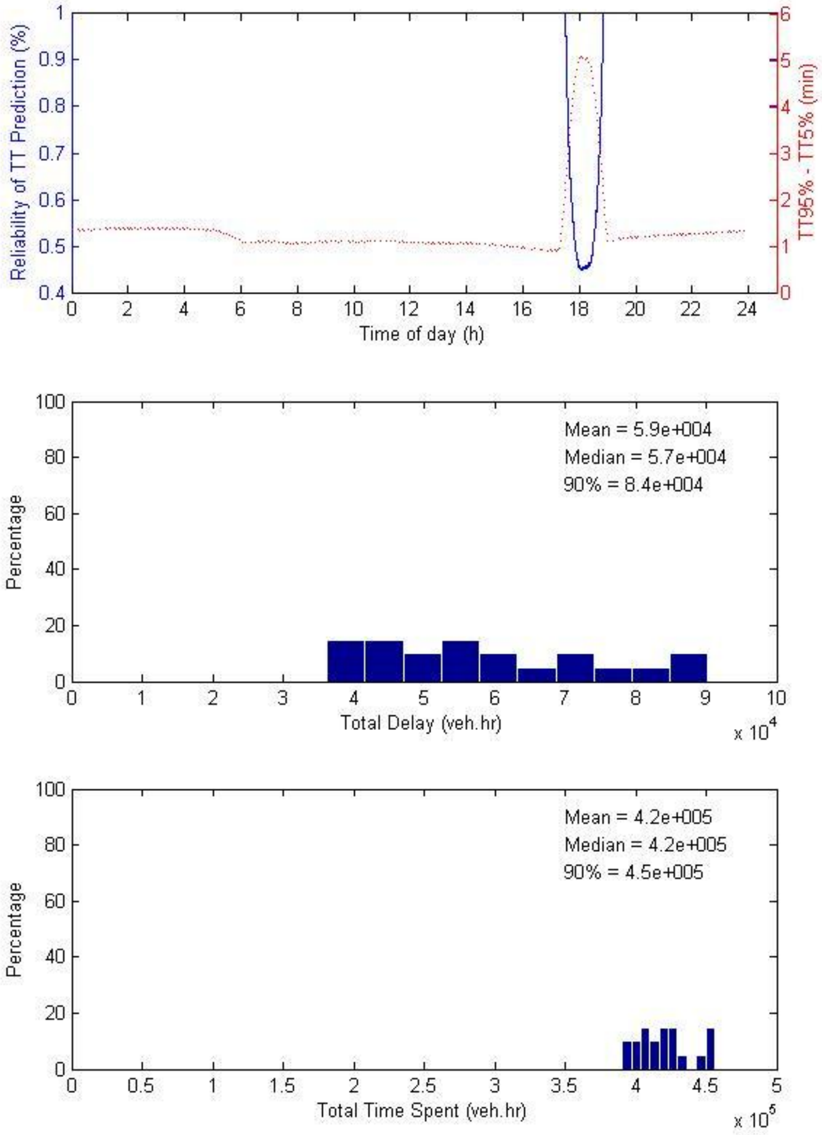
Reliability of TT Prediction (%)
TT95% - TT5% (min)
Time of day (h)
1
0.5
0
20
10
0
0 2 4 6 8 10 12 14 16 18 20 22 24
Percentage
Total Delay (veh.hr)
x 10^5
Mean = 1.2e+005
Median = 1.0e+005
90% = 1.9e+005
0 0.5 1 1.5 2 2.5 3 3.5 4
0 20 40 60 80 100
Percentage
Total Time Spent (veh.hr)
x 10^5
Mean = 5.0e+005
Median = 4.8e+005
90% = 5.8e+005
0 1 2 3 4 5 6 7 8
0 20 40 60 80 100

Public holidays / vacation periods

Scenario 1: All information is present (category)

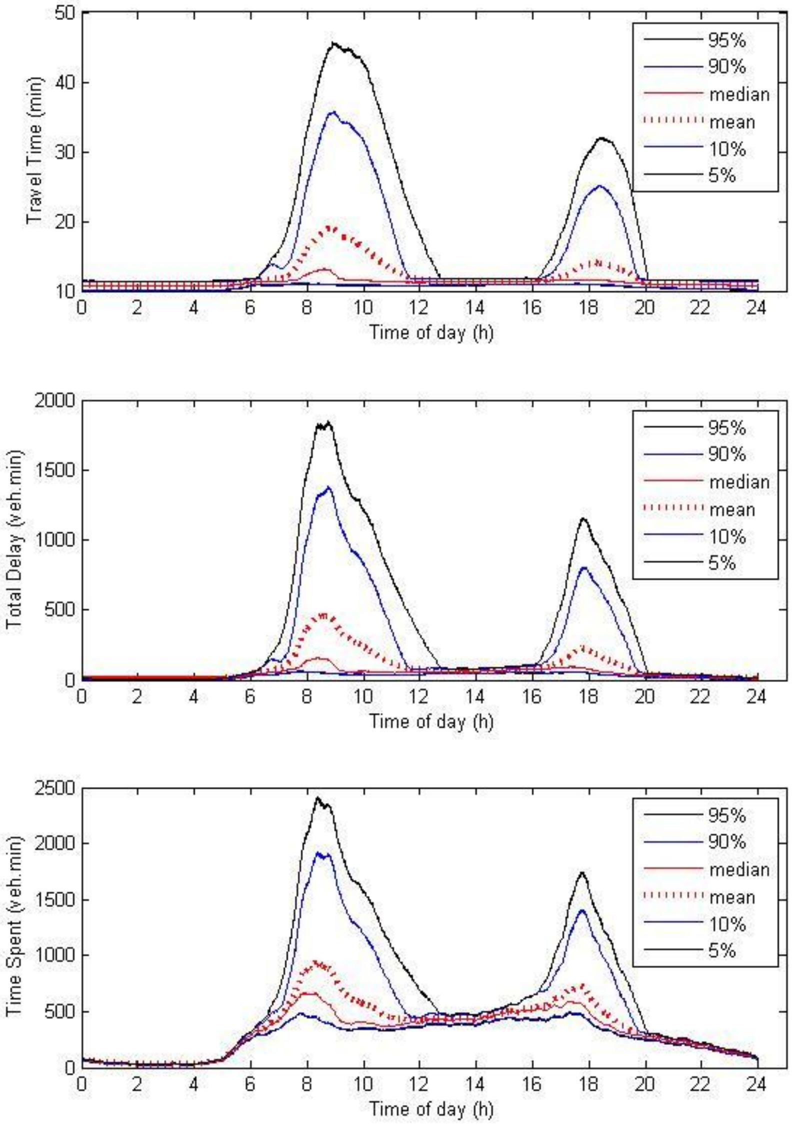
Figure C-11: *Results for public holidays scenario 1*

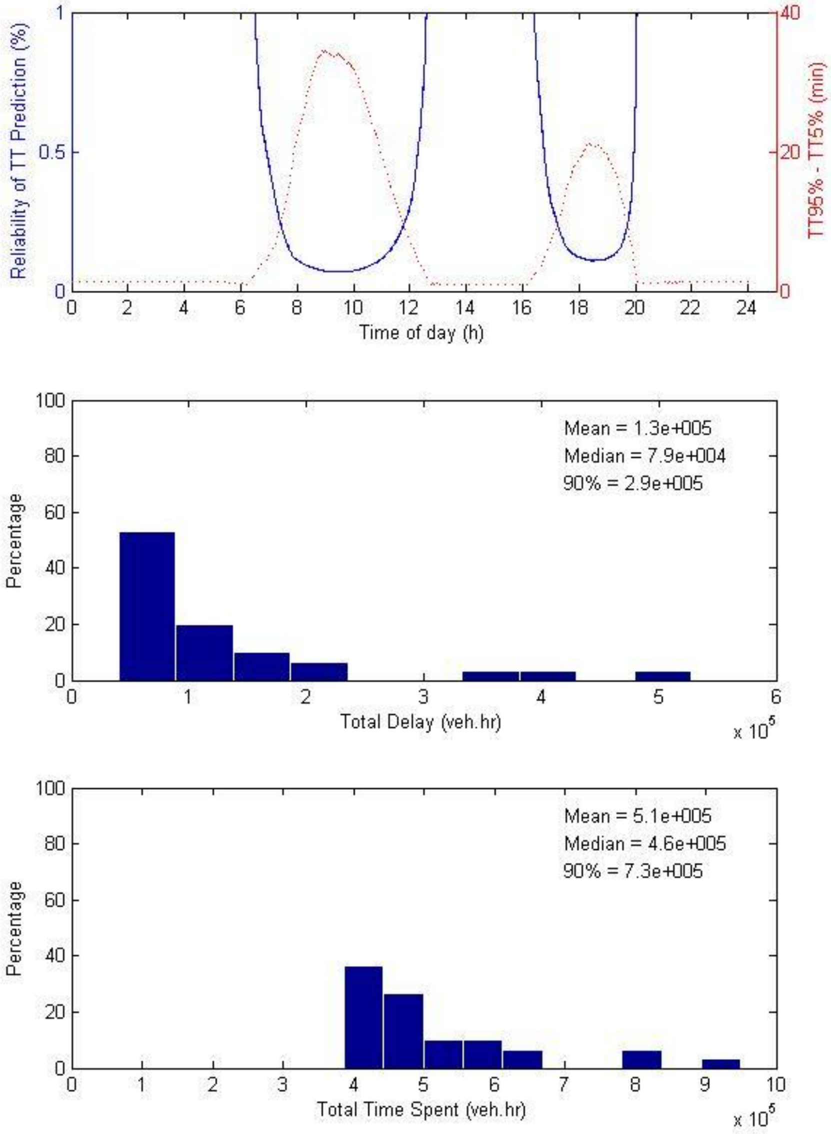



Reliability of TT Prediction (%)
1
0.9
0.8
0.7
0.6
0.5
0.4
TT95% - TT5% (min)
6
5
4
3
2
1
0
0
2
4
6
8
10
12
14
16
18
20
22
24
Time of day (h)
Mean = 5.9e+004
Median = 5.7e+004
90% = 8.4e+004
Percentage
100
80
60
40
20
0
0
1
2
3
4
5
6
7
8
9
10
Total Delay (veh.hr)
x 10^4
Mean = 4.2e+005
Median = 4.2e+005
90% = 4.5e+005
Percentage
100
80
60
40
20
0
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
Total Time Spent (veh.hr)
x 10^5

Scenario 2:

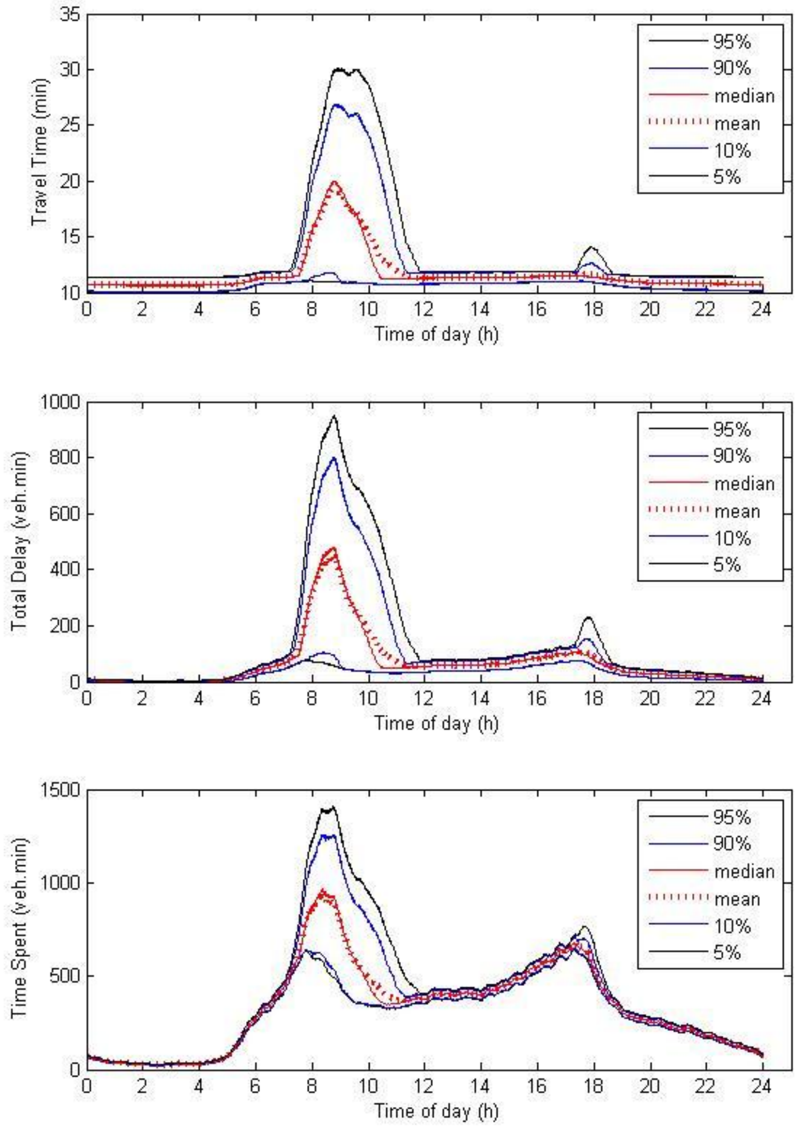
Figure C-12: *Results for public holidays scenario 2*




Reliability of TT Prediction (%)
TT95% - TT5% (min)
Time of day (h)
0
0.5
1
0
20
40
0
2
4
6
8
10
12
14
16
18
20
22
24
Percentage
Total Delay (veh.hr)
x 10^5
Mean = 1.3e+005
Median = 7.9e+004
90% = 2.9e+005
0
20
40
60
80
100
0
1
2
3
4
5
6
Percentage
Total Time Spent (veh.hr)
x 10^5
Mean = 5.1e+005
Median = 4.6e+005
90% = 7.3e+005
0
20
40
60
80
100
0
1
2
3
4
5
6
7
8
9
10

Vehicle population

Figure C-13: *Results for vehicle population; mean truck fraction 15%*



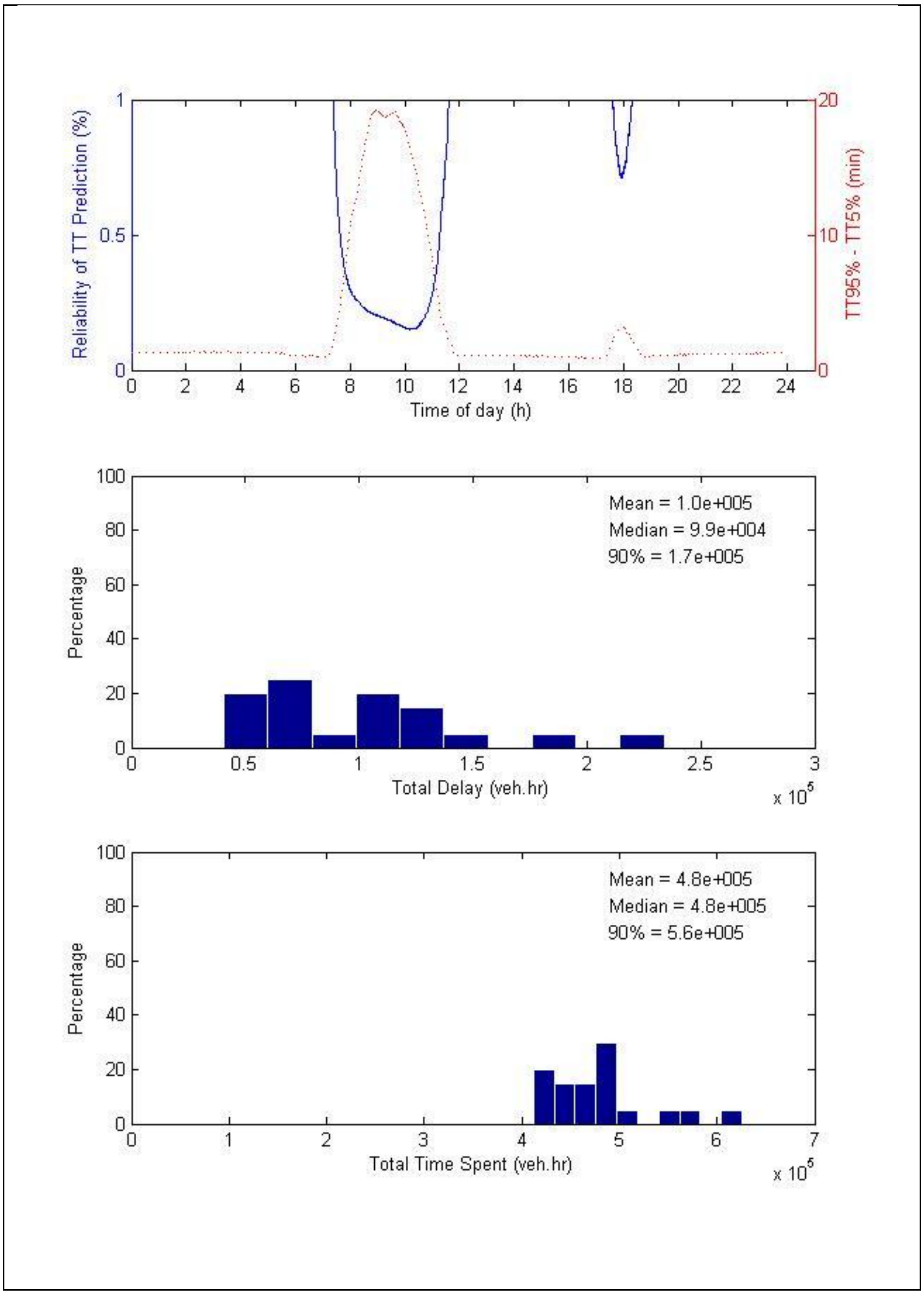
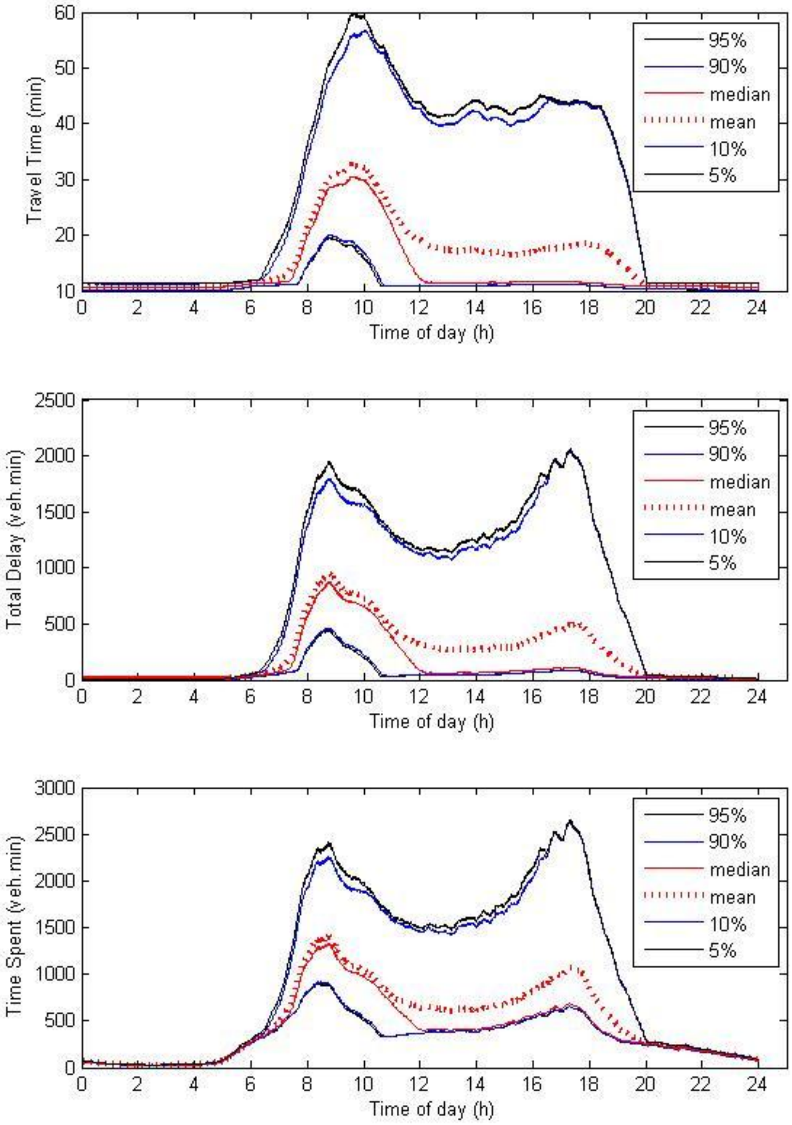
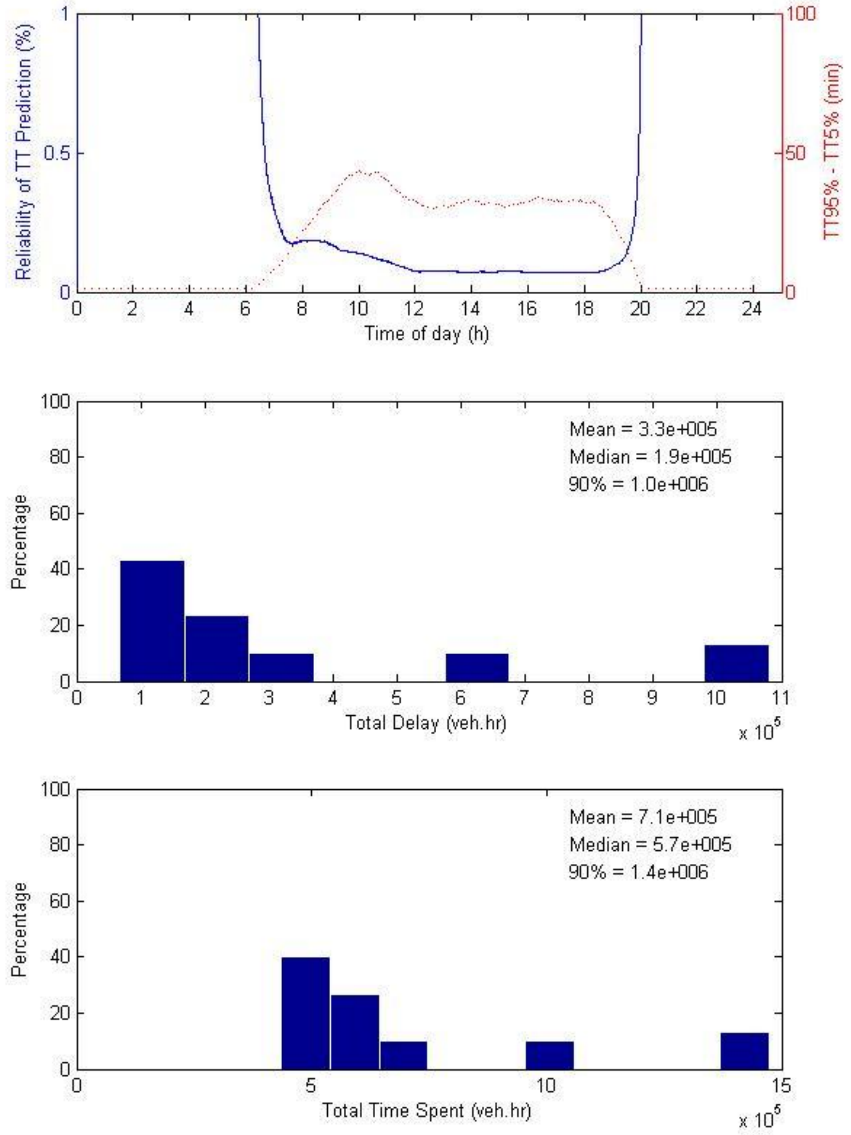

Reliability of TT Prediction (%)
TT95% - TT5% (min)
Time of day (h)
0 2 4 6 8 10 12 14 16 18 20 22 24
Percentage
Mean = 1.0e+005
Median = 9.9e+004
90% = 1.7e+005
Total Delay (veh.hr)
x 10^5
Percentage
Mean = 4.8e+005
Median = 4.8e+005
90% = 5.6e+005
Total Time Spent (veh.hr)
x 10^5

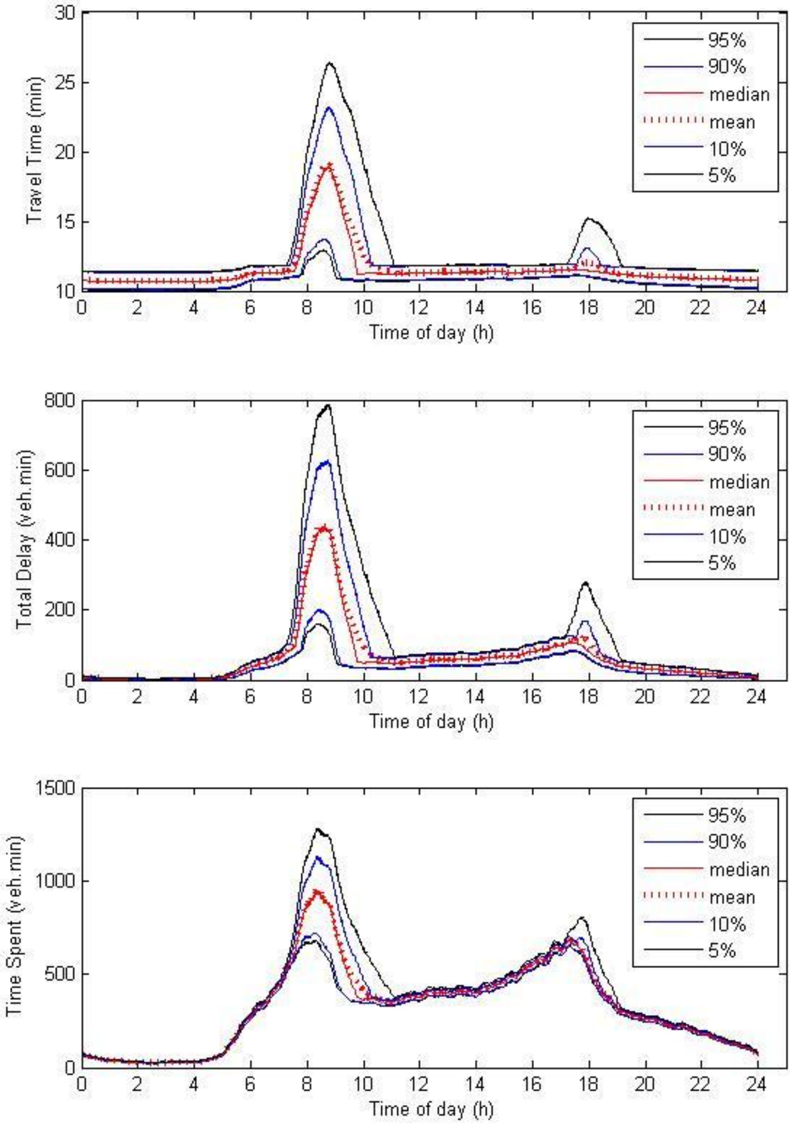
Figure C-14: *Results for vehicle population; mean truck fraction 25%*

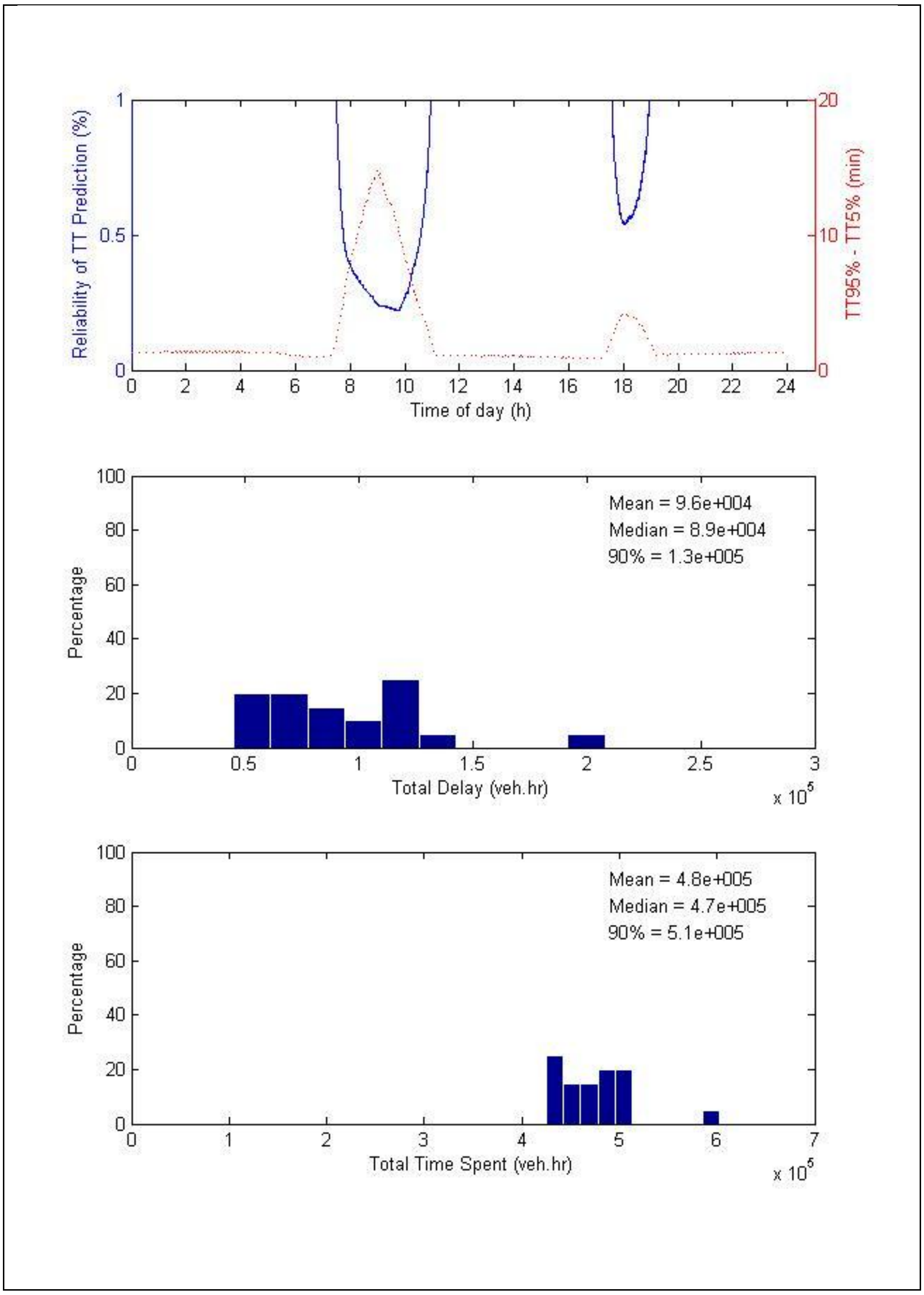



Reliability of TT Prediction (%)
TT95% - TT5% (min)
Time of day (h)
0
0.5
1
0
50
100
0 2 4 6 8 10 12 14 16 18 20 22 24
Percentage
Total Delay (veh.hr)
x 10^5
0 1 2 3 4 5 6 7 8 9 10 11
0 20 40 60 80 100
Mean = 3.3e+005
Median = 1.9e+005
90% = 1.0e+006
Percentage
Total Time Spent (veh.hr)
x 10^5
0 5 10 15
0 20 40 60 80 100
Mean = 7.1e+005
Median = 5.7e+005
90% = 1.4e+006

Driver population

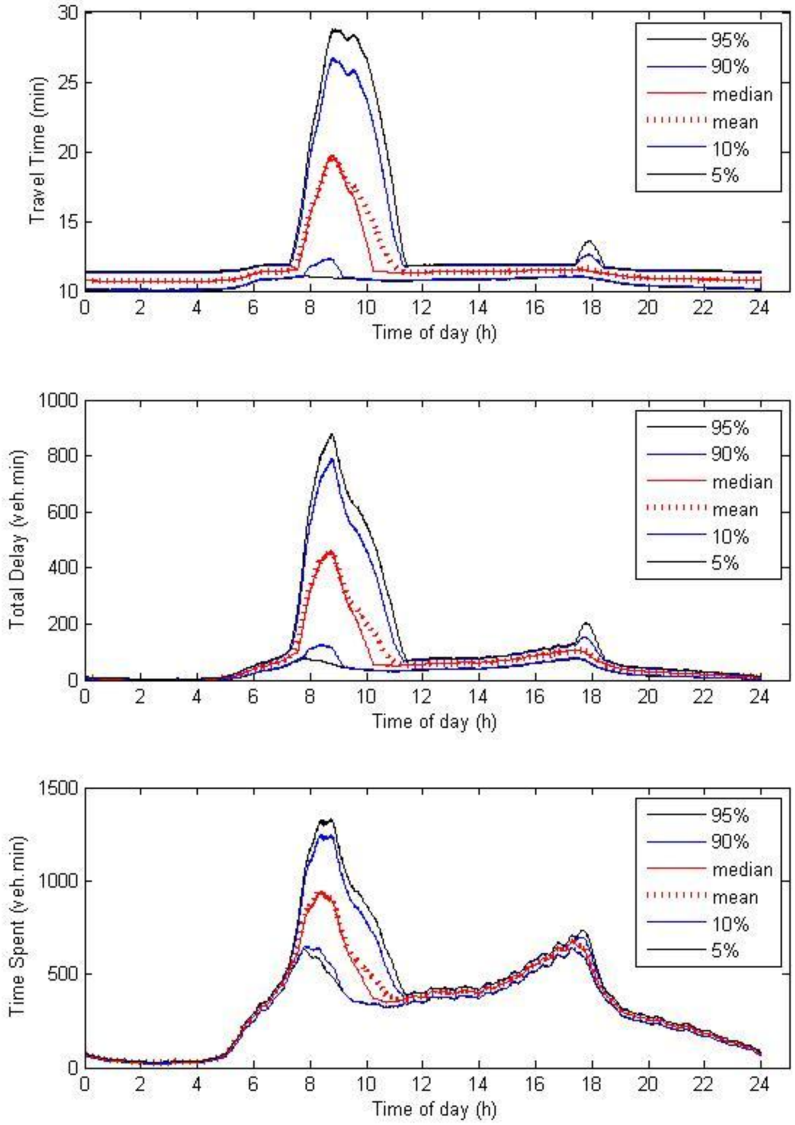
Figure C-15: *Results for driver population*

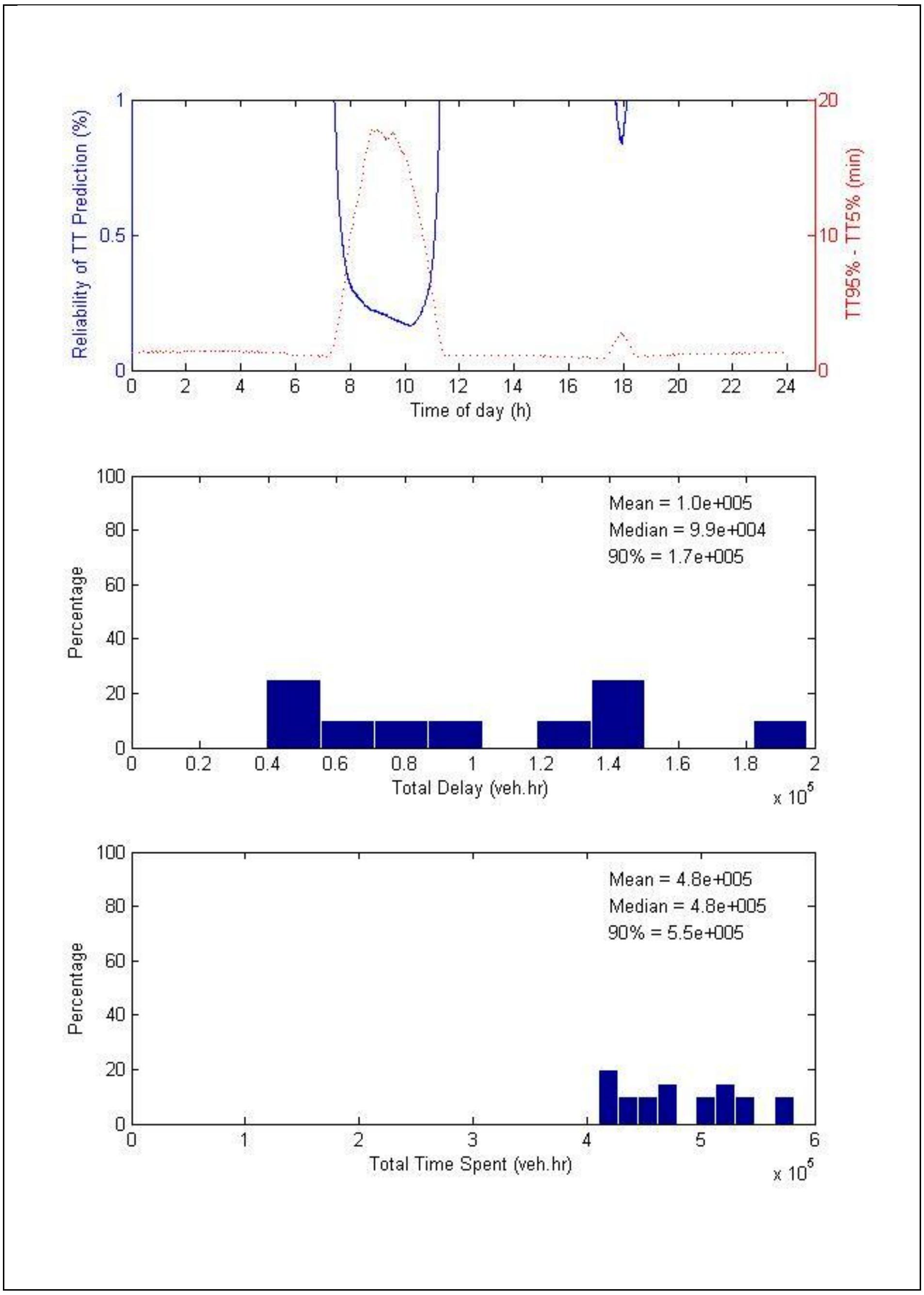



Reliability of TT Prediction (%)
TT95% - TT5% (min)
Time of day (h)
0
0.5
1
0
10
20
0 2 4 6 8 10 12 14 16 18 20 22 24
Percentage
Total Delay (veh.hr)
x 10^5
0 0.5 1 1.5 2 2.5 3
0 20 40 60 80 100
Mean = 9.6e+004
Median = 8.9e+004
90% = 1.3e+005
Percentage
Total Time Spent (veh.hr)
x 10^5
0 1 2 3 4 5 6 7
0 20 40 60 80 100
Mean = 4.8e+005
Median = 4.7e+005
90% = 5.1e+005

Luminance

***Figure C-16:** Results for luminance*




Reliability of TT Prediction (%)
TT95% - TT5% (min)
Time of day (h)
0
0.5
1
0
10
20
0
2
4
6
8
10
12
14
16
18
20
22
24
Percentage
Total Delay (veh.hr)
x 10^5
Mean = 1.0e+005
Median = 9.9e+004
90% = 1.7e+005
0
20
40
60
80
100
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
Percentage
Total Time Spent (veh.hr)
x 10^5
Mean = 4.8e+005
Median = 4.8e+005
90% = 5.5e+005
0
20
40
60
80
100
0
1
2
3
4
5
6