Calibration of the IDM and METANET Traffic Flow Models

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**Calibration of the IDM and METANET Traffic Flow Models**

by

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Abstract

A common problem nowadays is the growing amount and severity of traffic jams on our freeways. First of all this can lead to economic loss since goods and employees are being delayed. However, emissions are becoming a problem more and more since in a traffic jam the engines will keep running and keep polluting the environment. Therefore, including emission models in the current Traffic Management Systems is proposed as a solution. This allows for a change on short-term rather than wait for the moment all vehicles are substituted with environmental friendly vehicles or wait for solutions like Intelligent Vehicles. In order to study the effects of using different traffic flow models combined with emissions models, a feedback structure is used. In this structure one part is microscopic and one part is macroscopic.

Before the proposed structure can be used there are two issues that need to be addressed. First, a conversion between the microscopic and macroscopic data and vice versa is necessary. The conversion from macroscopic data to microscopic data has three facets which are analysed one at a time. Furthermore, three methods for converting microscopic data back to macroscopic data are presented and analysed. The first method tries to mimic loop detectors, the second method is optimized for use in MATLAB and uses all information available, and the third method is inspired on the other two since it also tries to mimic loop detectors close however does this multiple times per segment. It is the secondary objective of this project to find a conversion method that is accurate but also computationally lightweight.

The second issue that needs to be addressed is the usage of accurate traffic flow models. The parameter values of the IDM model and the METANET model are optimized using numerical optimization techniques which minimizes the error between measurement data and simulation data based on an error measure. The resulting parameter values are compared to benchmark values from literature and are validated using different measurement data and calculating Theil’s inequality and the Variance-Accounted-For. It is the primary objective of this project to find parameter values that best reflect the behaviour of drivers on a specific freeway.
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In our daily businesses most of us use the freeways to travel between home, office, family and friends, holiday, leisure, and other destinations. We use the freeways extensively for commuting, for transporting goods, and for many more reasons. People have always wanted to travel around. Ever since the engine was invented, mobility of people and goods increased. Moreover, the economy has grown because a wider area was within reach to sell goods. This has led to more wealth and more people buying a vehicle. Unfortunately, this growing amount of cars has lead to more traffic jams, growing in frequency, in length, and in time needed to dissolve them [13, 23, 34]. A plurality of consequences exist for this increasing time that vehicles are standing still during congestion, most of the time with running engines. First of all, the commuters and goods being transported are delayed causing an economic loss. But a more acute problem is that the engines will most of the time keep running and keep producing emissions.

Road traffic is estimated to contribute for 45% to the pollutants of the U.S. [1, 18]. Smit et al. [35] show that congestion is an important source of emissions. They also show that the need for reduction of the emissions is urgent since the emissions of vehicles reduce the quality of the air that people breath. This applies especially to cities where vehicles have a lower average speed and traffic signals have as side effect that vehicles will have relatively high emission rates. This becomes even more critical in certain areas of cities where people live with an increased vulnerability to diseases, for example near hospitals or primary schools.

When thinking of solutions to reduce congestion there are several options. A rather improvident solution has the following philosophy: the amount of cars does not fit on the current roads, thus more roads are necessary. Building extra roads and extending existing roads cannot be continued for long. A lot of situations exist where this is already impossible simply because humans need space to live and/or building new roads is expensive. Furthermore, when using this strategy, using a car becomes more
attractive since there will be sufficient space to drive. This ultimately creates a vicious circle and certainly does not reduce emissions.

Other solutions to reduce congestion that will in addition be able to reduce emissions, address the drivers. For example, having the driver pay for using a congested road, having the human driver replaced by an automated driver, or using a Traffic Management System (TMS) with ramp-metering, speed limit signs, and/or route-guidance signs. Paying for using a road or paying per kilometre is already implemented in some countries and more intelligent techniques for detecting which road is used by who are being researched for some years now. This solution is however out of the scope of this project since only a few countries have such systems implemented.

Also, the research of intelligent vehicles is a developing field with great possibilities. Intelligent vehicles can be equipped with cameras and communication capabilities between cars and road-side devices in order to assist the driver or to take full control of the vehicle [4]. Unfortunately, this solution will take a long time to become reality for everyone. This means that the reduction of congestion and emissions will also be postponed. Therefore, this solution is excluded from the scope of this project as this project focusses on a solution for reducing emissions on the short term.

Since the necessity of reducing emissions is urgent [35], this thesis project focusses on improving and extending existing systems. Current TMSs use ramp metering, speed limits, and/or route guidance to manage the flow on the freeway. A lot of these devices are already installed alongside and above the road pavements. The most important part of this solution is to upgrade the control strategies in these TMSs. Current TMSs mainly focus on preventing congestion and dissolving congestion when it occurs. This can theoretically be extended with the ability to reduce emissions. Furthermore, in case a TMS uses a traffic flow model, the technique of reducing congestion can be improved by increasing the accuracy of the traffic flow model.

1-1 Overview of traffic flow models

To extend a TMS such that it will account for emissions is not straightforward. The results of a traffic flow model can be used by an emission model to calculate the emissions [34]. The first obstacle is that multiple types of traffic flow models exist with each a matching type of emission model. The two mainly used types of traffic flow models are microscopic and macroscopic. Table 1-1 summarizes the differences between the two types of traffic flow models.

It is advantageous to use a macroscopic traffic flow model in TMSs because the computational load is low and independent of the traffic density while the accuracy is good. When using microscopic traffic flow models, the total number of equations for the traffic system changes linearly with the number of vehicles. Since during rush hour the number of vehicles will increase by any means, the computational load of a TMS with a microscopic model will rise during periods the TMS is needed most. However, if emissions should be calculated it is more intuitive to use microscopic models because these models give the position, speed, and acceleration of each vehicle on the stretch of

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Table 1-1: Comparison of the two main categories in traffic flow models

<table>
<thead>
<tr>
<th></th>
<th>Microscopic</th>
<th>Macroscopic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level of detail</td>
<td>High, per vehicle</td>
<td>Low, per road segments</td>
</tr>
<tr>
<td>Computational load</td>
<td>High and dependent on number of vehicles</td>
<td>Low and independent on number of vehicles</td>
</tr>
<tr>
<td>Quantities</td>
<td>Position, speed &amp; acceleration</td>
<td>Flow, density &amp; average speed</td>
</tr>
<tr>
<td>Availability of measurement data</td>
<td>Low, sophisticated equipment necessary</td>
<td>Easy, equipment widely installed</td>
</tr>
</tbody>
</table>

freeway. Especially the acceleration is an important quantity for the emissions models. Unfortunately this quantity is missing from macroscopic traffic flow models since these models in general only compute the flow, density, and average speed per segment.

1-2 Improving a traffic management system

The dissonance between microscopic and macroscopic traffic flow models asks for a structure in which the strengths of both types of traffic flow models can be used. In Fig. 1-1 a structure is depicted with both a macroscopic model and a microscopic model. This structure is commonly referred to as a feedback structure and can be used for studying a new strategy for a TMS without interrupting a real-world freeway.

Figure 1-1: Feedback structure proposed for studying the reduction of emissions with a TMS

It is assumed that the new TMS will use a macroscopic model to compute a control strategy. The control strategy is imposed on the microscopic model, which acts as a surrogate of the real-world. The traffic conditions as simulated by the microscopic model are converted to macroscopic data and imitate the measurements that the TMS can use to compute a new control strategy. The strength of the microscopic model is the more accurate computation of the emission rate and the strength of the macroscopic model is the low computation load in the TMS.
Before using a model, the model must be calibrated so that accurate conclusions can be drawn. Both traffic flow models should react to traffic conditions as described by measurement data. For this, it is necessary that the measurement data is converted so that the models are calibrated using equivalent measurement data. And second, it is necessary to convert the results of either one of the models be able to compare the measurement data with the results of that model. Furthermore, conversion of data is needed in the feedback structure to facilitate the interaction between the two models.

1-3 Problem statement

The primary objective of this thesis is to calibrate the two traffic flow models. However, as stated above, this results in a secondary objective. That is, to find a way of converting the data between the macroscopic and microscopic variables. Since a decent conversion is mandatory for the calibration, the objective to find a method of conversion will have to be accomplished first.

The two objectives can be formally stated as follows:

1. Find a method of converting microscopic data to macroscopic data. The method should be computationally lightweight while still being accurate so that microscopic traffic models might be used in a TMS.

2. Find optimal parameter values for both the microscopic and the macroscopic traffic flow model to reflect the behaviour of drivers on a specific freeway which is described by measurement data.

That the conversion method should be computationally lightweight means that the time necessary to convert data should be as low as possible. When using a microscopic traffic flow model in a TMS it is most ideal if the microscopic model and the TMS itself use the largest portion of computation time available. Therefore, the computation time of the researched conversion methods should be compared.

However, a low computation time poses a trade-off with respect to the quality of the conversion. One can develop a conversion method that is very rapid yet gives very unreliable results and vice versa. The results of the researched conversion methods should therefore be examined to determine the accuracy.

The optimality of a set of parameter values is determined by the error measures used in the process of calibration and validation. A parameter value can be considered optimal if it is not possible to find another parameter value yielding a lower value for an error measure.

1-4 Research approach

This thesis project started with a literature study. Based on the information found in the literature, the path of research of the project was made up. After finishing the research part, all findings where described in this report.
During the literature study two models were chosen that will be used throughout the project. For the microscopic traffic flow model the IDM model by Messner and Papageorgiou [26] was chosen. This model was chosen because of its simplicity and intuitiveness. The macroscopic model that was used is the METANET model by Kotsialos et al. [23]. This was done because its good trade-off between accuracy and computational load. Note that these traffic flow are linkable with emission models [32, 41].

In the literature study no explicit description of a method for converting microscopic to macroscopic data was found. Therefore, no existing conversion methods was adopted for use in this thesis project. For converting macroscopic data to microscopic data, three methods were designed. Converting macroscopic data to microscopic data was done by distributing the vehicles evenly over each of the segments in which a freeway is divided.

The first method for converting microscopic vehicle position data to macroscopic flow data that was researched in this project is based on the functioning of the loop detectors as installed in the road pavements. By mimicking the loop detectors, presumably the best accuracy can be gained.

The second method that was researched in this project was designed with the way of structuring matrices in MATLAB keeping in mind the objective to be able to decrease the computation time. The vehicle position data is stored in a matrix with a column for each time step. It is therefore easy to calculate the density per time step. This resulted in the second method which was named the density averaging method.

Furthermore, a third method was designed to study the accuracy of both other methods. This last method was named the flow averaging method and calculates the flow based on multiple points in a segment. One can think of this as virtual detectors. The measurements of all virtual detectors in a segment are averaged to represent the measurement of the real detector.

In order to fulfil the primary objective of this project, optimization methods were used to fit the model to measurement data. The part of this freeway that is used is marked in Fig. 1-3. In this thesis project macroscopic measurement data from the freeway A12 in The Netherlands was available. The traffic flow models are initiated with a specific traffic condition given by measurement data, referred to as scenarios. As is depicted in Fig. 1-2, a scenario describes the demand flow with respect to time at the upstream boundary of the stretch of freeway, the density with respect to time at the downstream end and the initial traffic conditions for the first time step. Furthermore, it includes the measurement data to compare this with the results of one of the models.

For the IDM model these conditions must be converted from macroscopic to microscopic. The models are calibrated using numerical optimization methods with as objective the minimisation of the error between the measurement data and the result of the model. The key element in calibration is to define an error measure which can tell how well the simulation data fits to the measurement data. This error measure defines what the important aspects are that should be captured by the model. In this thesis project a normalized, quadratic measure was chosen. As stated, conversion of the microscopic data is necessary to be able to compute this error measure. Furthermore, this process
of optimization was also iterated itself with each iteration another starting point for the parameters, which is commonly referred to as multi-start optimization.

A subject closely related to calibration is validation. This is checking if the parameter values found through calibration also yields good results in situations other than the situation used for the calibration. Likewise as calibration, validation also uses a measure to compute the quality of the parameter values. In this project, multiple measures were used. First, a visual inspection was used to filter out parameter values with a large difference between the simulation data and the measurement data, especially to filter out parameter values that cannot reproduce a shock wave. Second, the parameter values were compared with alternative parameter values found in literature. Finally, another error measure than used for the calibration was used: Theil’s inequality. This measure gives a value between zero and one which represents the quality of the simulation result. With this definite value it is possible to compare data sets independent of size and content.

Figure 1-2: Visualization of a scenario. Each block represents a measurement point included in a scenario. Gray blocks represent traffic conditions used to determine the traffic conditions at the start of and during a simulation. White blocks represent traffic conditions that are used in the calculation of the error measure.

Figure 1-3: Map of the A12, the part marked with black was used in this thesis project. The lines perpendicular to the A12 point to the locations of the loop detectors.
1-5 Thesis outline

In the next chapter the IDM model and the METANET model will be described in detail. Also, the relation between both models is discussed. Chapter 3 will explain the conversion of macroscopic data to microscopic data and vice versa. In particular, the three researched methods of converting microscopic data to macroscopic data will be described. Chapter 3 concludes with a discussion on which conversion method should be used in the calibration process. The theory of calibration and validation is described in Chapter 4. The results of the calibration and validation of both traffic flow models are presented and discussed in Chapter 5. The thesis is closed with the conclusions and future research recommendations in Chapter 6.
Traffic flow models can be organized into several categories. The two main categories are macroscopic and microscopic [16]. Microscopic models have knowledge about each individual vehicle that enters the stretch of freeway under consideration [16]. This is the opposite of macroscopic models which more commonly operate with an average flow and density for a stretch of freeway. Both models have their own advantages and disadvantages, and therefore other models have been developed to overcome certain shortcomings such as mesoscopic models, which do not have exact knowledge about individual vehicles but model the probability that a vehicle has a certain velocity or that a segment has a certain density.

In this thesis project two models were calibrated for use in a traffic control system: a microscopic model and a macroscopic model. In this chapter both traffic flow models will be explained, starting with the macroscopic METANET model in Section 2-1. In the following section the microscopic IDM model will be explained. In Section 2-3 the relations between the two models will be described to point out the fact that there is an underlying system in traffic flow models.

2-1 the METANET model

In this project the Modèle d’Écoulement du Trafic Autoroutier: Network (METANET) model is used. The characteristic property of all macroscopic traffic flow models is that they operate with average speed, density, and flow or, in other words, aggregated information [16, 22]. In most macroscopic models a stretch of freeway is divided into segments. For each segment the flow, density, and/or speed are measured and used to calculate the average behaviour of the drivers in the traffic system. This gives macroscopic models a short computation time, because it is only needed to calculate three states for each segment in the stretch of freeway.
Also, Kotsialos et al. [23] state that macroscopic models are more suitable for designing a control system given their analytical nature. Furthermore, it is advantageous that the number of equations does not change if there is high or low density as is the case with microscopic models. This is advantageous because the set of model equations inside the Traffic Management System (TMS) does not have to be updated for each vehicle that enters or leaves the stretch of freeway.

The three main quantities that macroscopic models describe are flow, speed, and density. The flow is the number of vehicles passing a specific point per unit of time similar to the flow of a fluid through a pipeline. This quantity is usually measured by counting the number of vehicles passing a loop detector in a period in the order of five minutes. The speed used by most macroscopic models is assumed to be the average of the vehicles passing this loop detector, which is referred to as the time-mean speed. The last quantity is the density which is the number of vehicles per unit of length. This quantity is rather difficult to measure with a loop detector since the loop detector is installed at one specific point. Fortunately, the density can be approximated by dividing the flow over the space mean speed and the number of lanes.

With these three main quantities a quite clear description can be made about whether the traffic system is stable or unstable [5]. There are mainly three regions of different stability, see Fig. 2-1. Below the critical density $\rho_{c_{r,m}}$, the traffic flow is stable and a perturbation will quickly dissolve. An example of a perturbation is a driver braking suddenly, below the critical density this will not cause a traffic jam because there is enough distance for the successor to react safely. Around the critical density, the traffic flow is metastable or marginally stable, and for larger density the traffic flow is unstable. In the metastable region, a small perturbation will be dissolved, but a big perturbation like an incident will lead to congestion. In the region above the critical density a perturbation, small or big, will always result in congestion.

If a model can accurately predict the interaction of flow, density, and speed in time and between segments, it is possible to predict a traffic break-down. The fundamental diagram in Fig. 2-1 shows a equilibrium curve which is common for the interactions between flow, density, and speed. For example, when the rush hour begins, the density is slowly increasing together with the flow. Around the critical density, the flow can not increase further while the density still increases. At this point a TMS should react to keep the traffic moving. If no TMS is used for that freeway, the flow will decrease as is shown in the figure. If the density keeps increasing, the speed on the freeway will decrease. If however, a TMS is installed and is able to manipulate these quantities with control measures such as ramp-metering, speed limits, and route guidance, it can prevent a traffic break-down.

A total prevention of all congestion is not yet shown to be possible, but during the literature study in this thesis project it was found relevant improvements have been realized [2, 5, 6, 12–14, 24, 28, 29, 42]. For example, Papageorgiou et al. were able to reduce the mean travel time with 19% with a single algorithm equation with one parameter [29]. Another example is that Kotsialos et al. were able to reduce the total time spent on a freeway with more than 30% [24].

The macroscopic traffic flow model that was selected to be used throughout this thesis
project is the Modèle d’Écoulement du Trafic Autoroutier: Network (METANET) [23]. This mode was selected for several reasons which will shortly be explained in this section. The first reason is that the model shows a good trade-off between accuracy and computation time [13]. In various studies the model has been calibrated with respect to measurements from traffic networks [4, 5, 23]. The results of these studies show that the model can predict traffic break-downs with good precision in size, time, and location while the computation time is very low. From [4] it is clear that the model can also capture shock waves in the network, which is a great advantage.

Another reason is that the model is easy to implement in a Model Predictive Controller (MPC) which is envisioned to be used as TMS in the feedback structure from Fig. 1-1. The equations of the model are discrete in time and in space [23], two properties that are convenient for the usage in an MPC. Please note that the usage of the METANET model is not implied by the choice for MPC; other models can also be used in the envisioned TMS in the feedback structure.

In the METANET model, a stretch of freeway is divided in parts as illustrated in Fig. 2-2.
A node is placed for each major change in the characteristics of the freeway. This can be an on-ramp, an off-ramp, a bifurcation, or even the start of a slope. Each consecutive node is connected via a link which contains one or more segments. The length of these segments should theoretically be equal within one link [23]. Though in practice it will never occur that three or more consecutive loop detectors are exactly evenly spaced. Therefore, in this thesis project a small modification is applied which implies that the length within one link does not have to be the same. This is equivalent to introducing a new link for each segment of different length, however this would result in an abundance of unnecessary equations for connecting the links.

A common length for the segments is 500–1000 m [5]. In [10] it is stated that the length of the segments divided by the length of a time step of the model should be higher than the maximum speed on the freeway. Otherwise a vehicle would be able to overpass a segment within one time step and the prediction of the traffic flow may become erroneous. This constraint is adequately met since the detectors are all more than 490 meters away from each other and the speed limit is 120 km/h.

Per segment the METANET model has two states, the density $\rho_{m,i}(k)$ in the segment and the mean speed $v_{m,i}(k)$ of the vehicles in the segment [23]. The density in a segment is described as

$$\rho_{m,i}(k+1) = \rho_{m,i}(k) + \frac{T}{L_{m,i} \cdot \lambda_m} \cdot \left[ q_{m,i-1}(k) - q_{m,i}(k) \right]$$

This equation states that the density $\rho_{m,i}(k)$ increases each time step as a result of the number of vehicles entering a segment minus the number of vehicles leaving the segment. The number of cars entering the segment is calculated by taking the flow out of the upstream segment $q_{m,i-1}(k)$ and multiplying it by the length of one time step, $T$. Since the same holds for the number of cars leaving the segment, both flows are grouped in parentheses. The density is calculated in vehicles per kilometre, therefore, the net change in number of cars should be divided by the length of the segment in kilometres, $L_{m,i}$, and the number of lanes, $\lambda_m$.

The change in average speed of a segment is described in four parts:

$$v_{m,i}(k+1) = v_{m,i}(k) + \frac{T}{\tau} \cdot \left[ V(\rho_{m,i}(k)) - v_{m,i}(k) \right]$$

$$+ \frac{T}{L_{m,i}} \cdot v_{m,i}(k) \cdot \left[ v_{m,i-1}(k) - v_{m,i}(k) \right]$$

$$- \frac{\eta_{m,i}(k) \cdot T}{\tau \cdot L_{m,i}} \cdot \frac{\rho_{m,i+1}(k) - \rho_{m,i}(k)}{\rho_{m,i}(k) + \kappa}$$

The first term is the speed in the previous time step which is updated to the speed in the new time step by adding and subtracting the other terms. These terms are all multiplied by the length of the time step, $T$, to have the right dimensions. These other terms are referred to as

1. the relaxation term,
2. the convection term and
3. the anticipation term.

The relaxation term takes care of drivers relaxing to the desired speed if the situation allows. In the equation this can be seen by the positive sign of this term. To be more precise, the desired velocity $V(\rho_{m,i}(k))$ depends on the density of the segment and the current speed limit $v_{\text{lim},m,i}(k)$. The speed limit is adjusted to reflect an imperfect compliance. The value for $\alpha$ is set to 0.1 which means that drivers will drive ten percent above the speed limit.

$$V(\rho_{m,i}(k)) = \min \left( v_{f,m} \cdot \exp \left[ -\frac{1}{\phi_m} \cdot \left( \frac{\rho_{m,i}(k)}{\rho_{\text{cr},m}} \right)^{\phi_m} \right], (1 + \alpha) \cdot v_{\text{lim},m,i}(k) \right)$$ (2-3)

The relation between the density and the desired speed given in Eq. (2-3) is depicted in Fig. 2-3.

![Figure 2-3: Relation between the density and the desired speed](image)

The third term in Eq. (2-2) is referred to as the convection term. The convection means that vehicles from segment $i - 1$ (upstream) entering segment $i$ will not adapt their speed $v_{m,i-1}(k)$ immediately but gradually change to the speed in segment $i$. This is of course logical as most of us are advised to not use the brake on the freeway. The difference between the speed of two consecutive segments is subtracted and multiplied by the speed in the current segment. This multiplication is because people will try harder to decelerate if the speed in the segment is higher. And on the other side, a bigger difference in speed will also lead to more deceleration which is deflected by the factor between brackets. The opposite is also true, if the segment ahead is empty, people will accelerate more. The result of the difference in speed multiplied by the speed in the current segment is divided over the length of the current segment, $L_{m,i}$, since the effect is smaller for long segments.
The last term in Eq. (2-2) is referred to as the density gradient or anticipation term. This term models the behaviour that drivers look ahead and estimate the density in segment $i + 1$ (downstream) denoted by $\rho_{m,i+1}(k)$. If the region ahead is dense with respect to the density in the current segment $\rho_{m,i}(k)$, the average driver will slow down which is denoted by a negative sign of this term [5]. The density in the current segment is subtracted from the density in the upstream segment. If the segment ahead is thus more dense this number will be positive. Also note that this number is divided over the length of the current segment. This is not because the driver is less anticipative if driving in a long segment – most drivers probably do not even know these segments exist – but because the density simulated a long distance ahead is of less importance since most drivers have a limited view.

The multiplication factor $\eta_{m,i}(k)$ in Eq. (2-2) is dependent on the gradient of the spatial density:

$$\eta_{m,i}(k) = \begin{cases} 
\eta_{\text{high}} & \text{if } \rho_{m,i+1}(k) > \rho_{m,i}(k), \\
\eta_{\text{low}} & \text{else} \end{cases}$$  \hspace{1cm} (2-4)

This separation was introduced in [13] because it gives a better representation of a phenomenon called capacity drop. In [13] it was found that the drivers leaving a jam will accelerate slower than the drivers that are approaching the jam will decelerate. This basically causes the jam to grow if nothing is done since more vehicles will be added to the jam than will run away from the jam.

With the two states $\rho_{m,i}(k)$ and $v_{m,i}(k)$ described, the flow $q_{m,i}(k)$ out of segment $i$ can also be calculated. Note that this is not exactly a state but more a extra variable which is written down apart for convenience. Also, perfectly spoken this is an approximation of the real flow [21].

$$q_{m,i}(k) = \rho_{m,i}(k) \cdot v_{m,i}(k) \cdot \lambda_m$$  \hspace{1cm} (2-5)

The low number of states gives the model a low complexity. Combined with the fact that the number of segments is lower than the number of cars gives macroscopic traffic flow models a relatively short computation time compared to microscopic models. Because of the short computation time the model can easily be used in on-line settings [5].

The adjustable parameters of the METANET model are $\tau$, $\eta_{\text{low}}$, $\eta_{\text{high}}$, $\phi_m$, $v_{l,m}$, $\rho_{ct,m}$, $\kappa$, and $\alpha$ [23]. These parameters reflect the characteristic properties of the traffic system. The parameters $\phi_m$, $v_{l,m}$ and $\rho_{ct,m}$ can even be adjusted on the level of links since these can depend on the geometry of the freeway and the behaviour of the drivers at the specific link. The parameters will be adjusted during the calibration, which is the subject of Chapter 4.

**Bifurcations:** At a bifurcation node, the speed of the vehicles and the density of the segment can change because of the speed or density in the next link. Per node two set are defined, $I_n$ consisting of all incoming links to node $n$ and $O_n$ consisting of all outgoing links from node $n$. The number of segments in link $m$ is denoted by $N_m$, thus
$q_{m,N_m}(k)$ denotes the last segment in link $m$. For the anticipation term in Eq. (2-2) it is necessary to introduce a virtual segment $N_m + 1$ downstream, with a density

$$\rho_{m,N_m+1}(k) = \frac{\sum_{\mu \in O_n} (\rho_{\mu,1}(k))^2}{\sum_{\mu \in O_n} \rho_{\mu,1}(k)} \quad \forall m \in I_n$$

(2-6)

In this equation the density in the first segment of each outgoing link, $\rho_{\mu,1}(k)$, is squared. This way, links with a high density add more to the density of the virtual segment than links with a lower density. This is to reflect the fact that the links with high density will block the incoming links so the flow out of all links in $I_n$ will be lower. The newly calculated density is copied to all the virtual segments of the incoming links and then used in the calculation of the new average speed in Eq. (2-2).

For the convection term it is necessary to introduce a virtual segment 0 before the beginning of each link, with speed

$$v_{m,0}(k) = \frac{\sum_{\mu \in I_n} v_{\mu,N_\mu}(k) \cdot q_{\mu,N_\mu}(k)}{\sum_{\mu \in I_n} q_{\mu,N_\mu}(k)} \quad \forall m \in O_n$$

(2-7)

This equation is in fact a weighted average for the average speed in the virtual segment at the beginning of a link. When one of the incoming links $\mu$ in set $I_n$ has a high flow, it will have more weight in the average speed of the virtual segment. A link with only a few vehicles per hour coming in will not change anything to the average speed because these vehicles can only adapt their speed to the mainstream. The newly calculated average speed is used for the virtual segments at the beginning of all outgoing links of node $n$ and will then be used in the calculations for the next state. Thus, the speed will not be the same for the first real segment in all outgoing links.

![Figure 2-4: The representation of bifurcation with the aid of virtual segments](image)

Another advantage of the METANET model is its ability to operate in a destination oriented mode. This gives the model the ability to account for dynamic splitting rates at bifurcations. These splitting rates can be calculated by a traffic assignment method.
and enhance the model of the traffic network. Since this feature was not used during the thesis project, it will also remain uncovered in this report. For detailed information one can see [23].

In this thesis project the METANET model was used in the non-destination oriented mode. For each node the model sums up the incoming traffic flows in $Q_n(k)$ and distributes the total traffic flow over the outgoing links with predefined splitting rates. The splitting rate $\beta_{n,m}(k)$ is multiplied by the total incoming flow of node $n$ to get the outgoing flow $q_{m,0}(k)$ per link $m$:

$$Q_n(k) = \sum_{\mu \in I_n} q_{\mu,N_n}(k) \quad \forall n$$  \hspace{1cm} (2-8)

$$q_{m,0}(k) = \beta_{n,m}(k) \cdot Q_n(k) \quad \forall m \in O_n$$  \hspace{1cm} (2-9)

**Boundary conditions:** The METANET model further has equations to describe the behaviour at origins and on-ramps. Origins and on-ramps are modelled as a separate link that is treated as all other links in a bifurcation. Origins and on-ramps receive a demand flow $d_o(k)$, which can be measured by loop-detectors or user-specified, and forward it to the network. For each on-ramp a queuing model is used [23], see Eq. (2-10) – (2-12). The out-flow $q_o(k)$ of origin or on-ramp $o$ is dependent on the density in the first segment of the main-stream link $m$, on the length of the waiting queue $w_o(k)$ and on the capacity, i.e., the maximum flow of the on-ramp or origin link $Q_{\text{max},o}$:

$$q_o(k) = r_o(k) \cdot \min \left( d_o(k) + \frac{w_o(k)}{T}, q_{\text{max},o}(k) \right)$$  \hspace{1cm} (2-10)

$$q_{\text{max},o}(k) = \begin{cases} Q_{\text{max},o} & \text{if } \rho_{m,1}(k) \leq \rho_{cr,m} \\ Q_{\text{max},o} \cdot \frac{\rho_{\text{max},m} - \rho_{m,1}(k)}{\rho_{\text{max},m} - \rho_{cr,m}} & \text{else} \end{cases}$$  \hspace{1cm} (2-11)

Here, $\rho_{\text{max},m}$ is the maximum density possible in link $m$. Eq. (2-10) also holds for origin links without ramp metering, then $r_o(k)$ should be taken equal to 1. Per origin and on-ramp a new state is added, namely the length of the queue

$$w_o(k + 1) = w_o(k) + T \cdot [d_o(k) - q_o(k)]$$  \hspace{1cm} (2-12)

The difference between the incoming demand $d_o(k)$ and the outgoing flow $q_o(k)$ gives the change in the length of the queue. It is obvious that the waiting queue builds up if the ramp metering is limiting the flow, that is, if $r_o(k)$ is lower than 1 or if the demand is higher than the maximum flow $q_{\text{max},o}(k)$. The ramp metering rate $r_o(k)$ should be changed by a central controller. During the calibration this is impossible because it is necessary to have the same amount of vehicles entering the freeway for each iteration to be able to see progression in the calibration. In other words, if a different amount of vehicles is let in, it is impossible to know if a different amount of vehicles in a certain segment is the result of different parameters or the result of less incoming vehicles. It
therefore adds an unwanted degree of freedom, hence ramp metering is disabled during the calibrations by setting \( r_o(k) \) to 1. A recommendation for future research is to use the same ramp metering rate as is actually used on the freeway during the measurement period. Unfortunately, in this project this information was unavailable.

The beginning and the end of the stretch of freeway under consideration also needs boundary conditions. This is not explicitly described in [23], Kotsialos et al. use a queue model for all type of origins. In this thesis project this was done by defining a node at the beginning and at the end of the stretch of freeway and connecting an incoming or outgoing link to this node with one segment. This segment gets assigned the values for the density, speed, and flow that where measured. This means that there is no queue at the beginning of the stretch of freeway which is more accurate since the traffic conditions should be modelled equal to the real-world situation. If there would be a jam on that particular point, it would also be measured and hence be reflected in the simulations.

Although enough reasons exist to use this model, there are also some disadvantages [5]. First, the model does not take into account the effects of multi-lane roads such as overtaking. In [39] an example is given with two trucks, the first overtaking the other, this obviously leads to a temporary bottleneck. Though this example is a little extreme, a car overtaking another car happens much more frequently. This example also touches a second lack in the model, it is originally a single-class model. Deo et al. [11] have extended the METANET model to take account of multiple classes. Nevertheless, it is assumed that the parameters of the original METANET model can be tuned to overcome these shortcomings. It is, however, an advise to future research to incorporate the mentioned extension to the METANET model.

### 2-2 The IDM model

As opposed to macroscopic models, microscopic models operate with data with a high level of detail. That is, the model has knowledge of each individual vehicle within the freeway under consideration. For some models, this knowledge sometimes only consists of the distance to the predecessor and the velocity of the vehicle. Other models include the approach rate with respect to the predecessor, which is the difference in speed of the two vehicles, or the lane on which the vehicles is.

In this thesis project, the Intelligent Driver Model (IDM) was used [38]. This model is developed with the thought that a model should be as simple as possible but without missing important properties. Furthermore the parameters should be intuitive and relevant. Another important aspect is that a macroscopic version of the model is known. In [38] the results of the model are compared to a gas-kinetic traffic model, which is a macroscopic model. Furthermore, Treiber et al. [38] describe a concurrent use of a macroscopic model and the IDM model, which is useful within the scope of this thesis project.

The model consists of a non-linear differential equation for the speed \( v_\alpha \) of vehicle \( \alpha \). This is in fact the acceleration \( \dot{v}_\alpha \) and it is a function of the speed of vehicle \( \alpha \), the
distance $s_\alpha$ to predecessor vehicle $\alpha - 1$, and the approach rate $\Delta v_\alpha$ to the vehicle in front:

$$\dot{v}_\alpha = a_\alpha \cdot \left[ 1 - \left( \frac{v_\alpha}{v_\alpha^*} \right)^{\delta_\alpha} - \left( \frac{s_\alpha^*(v_\alpha, \Delta v_\alpha)}{s_\alpha} \right)^2 \right]$$  \hspace{1cm} (2-13)

In this equation a few of the model parameters are used. The acceleration parameter, $a_\alpha$, gives the maximum possible value of acceleration since the terms in the brackets will normally add up to be equal to or lower than one.

The desired speed, $v_\alpha^*$, is used to calculate the amount of acceleration or deceleration necessary to converge to the desired speed. This is similar to the relaxation term in the METANET model, therefore this name will also be used for the IDM model. The ratio between the actual speed and the desired speed is raised to the power of $\delta_\alpha$. A higher value makes that the drivers try more intensively to converge to the desired speed, or, in other words, more aggressively. If the speed is lower than the desired speed the ratio of the speed and the desired speed becomes less than one, raising this to the power with a $\delta_\alpha$ higher than one will give a number close to zero whereby the acceleration will be high. A value lower than one will result in low acceleration as well as low deceleration in case the actual speed is higher than the desired speed.

The last term within the brackets is the ratio between the desired distance to the predecessor vehicle and the actual distance. When the actual distance is lower than the desired distance, this ratio will be higher than one resulting in a deceleration. The desired distance is calculated as

$$s_\alpha^*(v_\alpha, \Delta v_\alpha) = d_{0,\alpha} + d_{1,\alpha} \cdot \sqrt{\frac{v_\alpha}{v_\alpha^*}} + T_\alpha \cdot v_\alpha + \frac{v_\alpha \cdot \Delta v_\alpha}{2 \sqrt{a_\alpha \cdot b_\alpha}}$$  \hspace{1cm} (2-14)

For the sake of readability the terms in Eq. (2-14) are given names:

1. minimal distance term
2. comfortable distance term
3. safe time headway term
4. anticipation term

The function of the minimal distance term is to bias the desired distance with a constant minimum, $d_{0,\alpha}$ in meters. This term has the most influence when standing still as can be seen in Fig. 2-5.

The second term is dependent on the speed of the vehicle in a way that it adds some comfort to driving. By adding some extra distance to the desired distance the driver has more time to react to changes in the speed of the predecessor, the driver can react more cautiously and thus more comfortably. The jam distance parameter $d_{1,\alpha}$ together with the ratio of actual speed and desired speed determines how much extra distance is added.
As opposed to the comfortable distance term, the safe time headway is the absolute minimal distance necessary to come to a stand still if the predecessor suddenly breaks. This distance becomes larger for higher speeds by multiplying the speed with $T_\alpha$, which is referred to as the safe time headway parameter.

Similar to the METANET model, the anticipation term is necessary to model the behaviour that drivers look ahead and respond to changing densities. However, a difference exists between the METANET model and the IDM model because the different level of detail. In the IDM model a driver only looks to the first vehicle ahead. If this predecessor is coming closer to the current driver, he will respond by releasing the gas pedal or braking. In the IDM model this is modelled by setting a higher desired distance. The approach rate will in this case be positive since it is calculated as the speed of vehicle $\alpha$ minus the speed of the leading vehicle:

$$\Delta v_\alpha = v_\alpha - v_{\alpha-1}$$  \hspace{1cm} (2-15)

The anticipation term also contains the deceleration parameter, $b_\alpha$, which is used to weaken the deceleration from the anticipation. Note however, that the deceleration is theoretically not limited as opposed to the acceleration.

For each vehicle the acceleration is integrated over time to get the velocity and the velocity is again integrated over time to get the position $x_\alpha$.

$$\dot{x}_\alpha = v_\alpha$$  \hspace{1cm} (2-16)

Here, $t$ is the length of a time step in the IDM model, given in seconds.

The actual distance to the predecessor is calculated by taking the position of the leading vehicle $\alpha - 1$ and subtracting the position of vehicle $\alpha$ and subtracting the length of a vehicle $l_\alpha$, which is a parameter of the model:

$$s_\alpha = x_{\alpha-1} - x_\alpha - l_\alpha$$  \hspace{1cm} (2-17)

The states of the IDM model are the speeds and locations of all the vehicles combined. These values plus the accelerations for each vehicle have to be stored so that they can be used by emission models or the conversion method.

During the calibration process the next constants will be altered in search for the optimal parameter set which most accurately predicts the behaviour of the traffic flows on the stretch of freeway under consideration: $d_{0,\alpha}$, $d_{1,\alpha}$, $\delta_\alpha$, $v^*_\alpha$, $a_\alpha$, $b_\alpha$, $T_\alpha$, $l_\alpha$.

The constants $\delta_\alpha$, $d_{0,\alpha}$, $d_{1,\alpha}$, $\Delta v_\alpha$ and $T_\alpha$ are parameters that change the shape of the fundamental diagram. When $\delta_\alpha = \infty$ the shape of the fundamental diagram is a triangle as shown by the dashed line in Fig. 2-6. This is a very aggressive configuration which is reflected in the relaxation term in Eq. (2-13): it is either zero or infinity. Decreasing $\delta_\alpha$ makes the fundamental diagram smoother as shown by the blue line. However, the shape of the fundamental diagram of the IDM model will not match the shape of the fundamental diagram of the METANET model since another structure for the equations is used.
Figure 2-5: Effect of velocity on the desired gap

Figure 2-6: Fundamental diagram of traffic flow and density for the IDM model

The other parameters, $a_\alpha$ and $b_\alpha$ together with $T_\alpha$ have effect on the stability of the traffic flows. This gives the IDM model the possibility to be calibrated with measurements of stable and unstable traffic flows for all the parameters except $a_\alpha$, $b_\alpha$, and $T_\alpha$. Recall that unstable traffic flows result in congestion, even with a small perturbation while stable traffic flows will be able to overcome even large perturbations.

In [39] the IDM model is calibrated with data from several freeways in The Netherlands and Germany. The results show that the model is able to reproduce multiple types of traffic jams, from jams located at a certain point (in [39] referred to as pinned) or moving jams and oscillating or homogeneous congestion.
A disadvantage of the IDM model is that it cannot model bifurcations and joints, because the model is a single-lane model. This means that the model does not account for lane changing and weaving. A solution proposed in [15] is to model such segments with a macroscopic model. For this, it is needed to link the IDM model with a macroscopic model, which is not a trivial task. In this project this situation was circumvented by only considering a stretch of freeway without on/off-ramps and focus on the conversion of microscopic and macroscopic data. Nevertheless, the overtaking and lane changing is still not modelled in the version of the IDM model used in this thesis project. Kesting et al. propose a lane changing model which should be considered in future research [19].

2-3 Relation between IDM and METANET

Although the METANET and IDM models are of different levels of detail, some parallels can be drawn. In this section these parallels will be discussed to point out the fact that there is an underlying system in traffic flow models and to ensure that the conversion carried out in this project is valid.

The first evident link is the parameter for free flow speed in both of the models. The implementation of the parameter is however not the same for both models. This comes from the fact that the METANET model focuses on the desired speed of drivers while the IDM model focuses on the desired distance to the predecessor. The METANET model uses the free flow speed parameter directly in the calculation of the desired speed. The parameter is multiplied by a exponent to take account of the sensitivity of drivers to the density on a free way.

The IDM model does also take account of the free flow speed and the sensitivity of drivers to the density but separates these two. The acceleration as calculated in Eq. (2-13) is divided into a term which takes account of the distance to the predecessor and a term that takes account of drivers wanting to drive the free flow speed. These two terms have to compete each other while in the METANET model the average distance to the predecessor is incorporated in the equation for the desired speed. But, when assuming enough space on the freeway both models predict a similar speed profile with high acceleration for standing still and decreasing acceleration when approaching the free flow speed as shown in Fig. 2-7. An important note here is that the IDM model shows a limitation in the acceleration whereas the METANET does not. This limit is of course a realistic feature, however also the IDM model does not have a limit for the deceleration.

In the IDM model the sensitivity to changing densities is parametrized by the jam distance $d_{0,\alpha}$ and $d_{1,\alpha}$. The first jam distance $d_{0,\alpha}$ gives the minimum distance between cars if standing still. Adding the length of the cars $l_{\alpha}$ gives the inverse of the maximum density. At this density there is theoretically no movement on the freeway because the cars are too close to each other to comfortably drive. In Fig. 2-6 this is indicated by the curve going to the horizontal axis and becoming zero. As can be seen in Fig. 2-1, the curve for the METANET model also decreases; though, it will never be zero because of the exponent in the equation for the desired velocity.
The comfortable distance term in Eq. (2-14) with the second jam distance $d_{1,\alpha}$ is an addition to the safe time headway term with the $T_\alpha$ parameter. The safe time headway is the time needed to safely come to a stand still if the vehicle in front suddenly stops. In order to have a more comfortable ride, the comfortable distance term adds some extra distance for higher speed. This is not directly seen in the METANET model because this is incorporated in the desired speed function $V(\rho_{m,i}(k))$. Namely, the shape of the fundamental diagram of METANET as seen in Fig. 2-1 is similar to the shape of the fundamental diagram of IDM as seen in Fig. 2-6 where the blue line is the equilibrium curve when the jam distance $d_{1,\alpha}$ is set to a value higher than zero. If $d_{1,\alpha}$ is set to zero the fundamental diagram of IDM becomes more like a triangle, especially the right part of the curve is more straight.

Now the last term in Eq. (2-14), the anticipation term, is needed to model the fact that subsequent vehicles do not have to drive at the same speed, especially in the case of a shock wave. By adding this term to the model, a predecessor with lower speed will result in a higher desired distance (the approach rate $\Delta v_\alpha$ is calculated by subtracting the predecessors speed from the vehicles own speed).

When looking at the METANET model we can see a similar modelling; however, it comes in twofold. First, the METANET model has the convection term and second, the model has the anticipation term. The convection term is needed to model the difference in speed for vehicles coming into segment $i$. The anticipation term is needed to model the difference in density between the current segment and the next segment, however this also includes speed as $V(\rho_{m,i}(k))$ is density dependent. This is obviously the difference between macroscopic and microscopic models. In the microscopic IDM model and most other microscopic models cars only look to information about the car itself and the predecessor. On the other hand, macroscopic models are based on the segmentation of a freeway and thus each segment is influenced by the situation in adjacent segments. It is therefore not surprising that the anticipation term in Eq. (2-14) has a link to both the convection and the anticipation term. Both a dense region ahead and a different speed...
per segment is reflected in the last term of Eq. (2-14) and the fact that $s_\alpha$ becomes smaller in both cases.

2-4 Conclusions

The METANET models was described as it was used in the rest of this project. The METANET model was extended to account for segments of different length within a link and also to be able to simulate an origin in a traffic network without the queue model as used by Kotsialos et al. [23]. The IDM model was described as it is proposed by its authors [38] without adding extensions. It is recommended that both models be extended for multi-lane.

Section 2-3 relates the METANET and the IDM model by pointing out to differences and similarities in the equations of both models and discussing how several aspects of traffic flow models are modelled. Both models have a parameter for the free-flow speed, however, it is used in different fashions. Also, the parametrizing of the critical density is done in a very different way. The result is a different speed profile for both models. Furthermore, in both models a mechanism for anticipation can be found, however, the major difference between macroscopic and microscopic is found to be the usage of information from the next segment against the usage of information about the predecessor.
Chapter 3

Traffic data conversion

The two traffic flow models that are used in this thesis project operate on two different levels of detail. There is the IDM model with knowledge of each individual vehicle and there is the METANET model, which only needs information on the level of segments. As indicated both models should be calibrated for the use in a traffic management system. For this it is first needed to have data available from a real-world freeway. Measurement data of a part the A12 in the Netherlands of three month in 2009 (September, October, and November) was provided by the Dutch Governmental Department for Infrastructure and Environment (RWS). This data was collected by loop detectors installed in the road pavement, giving the flow in vehicles per hour and the average speed in kilometres per hour for each consecutive minute.

The measurement data to calibrate the macroscopic METANET model are directly used in the calculations. Note that the average speed data should be converted from time-mean to space-mean speed [31, 40]. However, the equations that Rakha and Zhang and Knoop et al. propose need microscopic data which is not available from the measurements. Therefore, in this thesis project the time-mean is used. However, further research should be carried out to find a method of converting macroscopic time-mean to space-mean without the necessity of microscopic speed data.

From the available data, the correct data has to be selected for use in the boundary conditions and for use in the calibration and validation. However, the calibration of the microscopic IDM model requires significantly more work. Apart from the aforementioned data selection, the data should be converted so that the IDM model can be simulated in the correct manner, that is with correct initial conditions. The methods for data conversion used in this thesis project will be described in Section 3-1. Secondly, the microscopic data resulting from a simulation should be converted back to be able to see the error between the data and the simulation. For this, several methods can be proposed which will be described and discussed in Section 3-2.

An important type of congestion is the shock wave phenomenon. A shock wave is a moving jam that travels in the opposite direction of the vehicles. Since it travels in the
opposite direction, it can startle unsuspecting drivers leading to impulsive reactions. It is therefore important to eliminate these types of congestion or at least dissolve them as soon as possible upon detection. Therefore, the ability to properly describe a shock wave jam is a good criteria to validate a model.

3-1 From macroscopic to microscopic

The conversion of the traffic conditions measured in macroscopic variables to microscopic variables can be separated in three parts. At the beginning of the simulation, the whole stretch of freeway should be filled with vehicles according to the measurements. Then, after the simulation is started and as each time step passes by, the upstream and downstream boundary conditions must be calculated. The upstream boundary conditions are necessary to let in the same amount of vehicles as measured. The downstream boundary conditions are necessary to let vehicles out at a rate which is limited by the density as measured.

Initial conditions

Before the IDM model can be run to simulate a stretch of freeway, some vehicles should be positioned on the freeway as is measured by the loop detectors on the real freeway. Almost none of the scenarios in this project started with an empty freeway, all the more since some scenarios sometimes began halfway through a day. The number of vehicles to be positioned can easily be calculated by multiplying the density in a segment by the length of the segment. In this thesis project, all vehicles were spaced evenly in each segment according to the density in the segment. Since the density was not available from the data, it was calculated by dividing the flow by the speed. A recommendation for future research would be to research the effect of different types of distribution.

Upstream boundary conditions

Another issue is to let cars in into the freeway during the simulation. From the available data, the flow and average speed measured by the first upstream detector in the freeway can be used to let cars in into the freeway.

The first possible method for this is to invert the flow so that the time between each vehicle is known. From this, the time for each vehicle to come into the simulation can be calculated. If a new vehicle is to be let in, the vehicle gets assigned the speed that is measured by the mentioned loop detector. However, in this thesis project it was found that this method is incorrect. If too many vehicles are let in, all excessive vehicles pile up at the beginning of the simulation. The speed of the loop detector is assigned to the vehicle, however, in some cases the desired distance is much higher than the actual distance and the vehicles break very hard. The criterion should be extended by calculating if the vehicle has sufficient distance to the predecessor on the moment it should be let in.
The second possible method is thus an extension of the first method. The extension is a check if the vehicle to be let in has sufficient distance to the predecessor. Using Eq. (2-14) with the speed of the predecessor and an approach rate of zero, the desired distance is calculated. If the available distance is less than the desired distance, the vehicle will not be let in. In the following time step the procedure is repeated until the vehicle has sufficient space and can be let in. After a vehicle is let in, the moment of the next inlet is calculated and the above procedure is repeated.

Note this is method is neither ideal since in the real situation there is no queue either. However, as mentioned, without this criteria the vehicles will pile up at the upstream end of the stretch of freeway. Ideally the parameters are tuned such that the vehicles entering the freeway have sufficient space. However, when starting a calibration it can be assumed the parameters are far from ideal and will almost always result in congestion at the upstream end of the stretch of freeway. In this thesis project it was found this effectively forms a barrier in finding optimal parameter values even when using a multi-start approach.

**Downstream boundary conditions**

As stated above, a shock wave is an important phenomenon which travels in the opposite direction of the traffic flow and thus visits the downstream end of the stretch under consideration earlier than the upstream end. The measurable effects of a shock wave are a lower outflow, a lower speed, and a higher density. Despite being measurable, the outflow is not used in this project for the downstream boundary condition in this project. First, the flow is a result of the situation on the freeway. A certain flow can be accompanied with different levels of density as can be seen in the fundamental diagram in Fig. 2-1. It is more conclusive to use the speed or the density since the density is related to average speed with a one-to-one equations, which is visualized in Fig. 3-2. Second, because the implementation is rather cumbersome and intervening the role of a traffic flow model. Using the outflow, would mean a vehicle somehow has to be slowed down or stopped until sufficient time has passed matching the outflow. Such a mechanism is intervening the role of the traffic flow model since the model in combination with the parameter values determines what the speed of a vehicle should be. The traffic flow model should be calibrated such that correct parameter values yield the correct outflow. Density and speed can however be used in a way that the role of the traffic flow model is not undermined by representing the density and average speed ahead of the most downstream vehicle for microscopic models and the most downstream segment for macroscopic models. Unfortunately, the other two quantities, density and average speed, can be used in several ways. In this thesis project two methods were explored.

In Fig. 3-1(a) a graphical representation of the first method is given. The density from the measurements is converted to the distance to the predecessor. This distance is directly used in Eq. (2-13) for the most downstream vehicle within the simulation, in the figure this is the length of the arrow. Secondly, the measured speed can also be used to calculate an approach rate independent of the actual approach rate to the virtual vehicle. As is clear in Fig. 3-1(a) the actual approach rate will always be zero.
since the distance of the virtual vehicles is kept constant. Although the conversion of the density to a distance might seem adequate, the overall result of this method is wrong. It is important to realize that the distance to the predecessor has to change in subsequent time steps if the vehicles in the next segment (outside the simulation) have a different speed and thus come closer or move away each time step. With this method, the distance stays the same since the density stays the same. Hence, a simulated shock wave is not as intense as is really measured and free flow might be higher.

The second method consists of only using the speed and neglecting the density. This is depicted in Fig. 3-1(b). Each vehicle that crosses the last downstream detector is given the average speed that was measured by that detector during the concerning time step. These vehicles are treated as so-called virtual vehicles, they exist for the successor but are not updated via the model equations. The positions of the virtual vehicles are updated by keeping the speed equal to the speed measured in the segment each virtual vehicle is in. In this way the vehicles that did not yet cross the detector but have a virtual vehicle in front of them will react as usual on the traffic conditions imposed by the measurements. In case of a shock wave the following vehicles will be approaching the virtual vehicles quickly. This also means that the density becomes higher just like measured during shock waves or jams.

A possible, however mistaken, counterargument of this method is that the speed of the vehicle suddenly changes when a vehicle crosses the detector and becomes a virtual vehicle. The argumentation is that this can have erroneous effects on vehicles that are following. However, if the vehicles are so close to each other that a sudden change in speed would lead to errors in the simulation, the speed of the vehicles will already be quite low as prescribed by Eq. (2-13). This can be underlined by examining Fig. 3-2. If the density is high, which is analogous to little distance between vehicles, the average speed of the vehicles will also be low and changes in the speed will be negligible. On the other side of the spectrum when density is low and vehicles are moving fast, changes in the speed will also be absorbed since the distance between vehicles is large.
3-2 From microscopic to macroscopic

After a microscopic simulation is run, the position and speed data of each vehicle over time has to be converted back to flow, density, and speed data. This comprises the detection of the segment a car is in for each macroscopic time step of which the length in the measurement data is ten seconds.

The conversion can be seen from both dimensions of a simulation, time and space. When assuming a fixed time and varying space, the density at a particular time step can be calculated from the number or positions of the cars in a segment. On the other hand, when assuming space fixed and varying time, the flow can be calculated by looking at the number of vehicles crossing a detector or the time of crossing, where the detector has a fixed position. The latter is based on the functioning of loop detectors, while the first is not since it would require many loop detectors in one segment or sophisticated hardware. Furthermore, the density calculation approach is easier to implement in MATLAB. In this thesis project three variations of these principles were explored and will be explained in Sections 3-2-1 to 3-2-3. Furthermore, in Section 3-2-4 the three methods will be discussed in order to select a method which will be used in the calibration process.

3-2-1 Mimicking detectors

This first method is mostly based on the functioning of loop detectors as installed in the road pavements. These devices detect how many vehicles drive over a double inductive loop. A specific algorithm used to calculate the flow is the following: each minute the number of vehicles is multiplied by sixty to get the number of vehicles per hour. Since the time step of the measurements is ten seconds, the method of counting cars is less...
accurate if applied to the data of the simulation\footnote{Please note that the simulation is split up in parts because of memory issues. A macroscopic time step is ten seconds long and comprises multiple microscopic time steps which are one second or shorter. Every macroscopic time step a conversion is carried out and all the unnecessary microscopic position data is thrown away with the exception of the last microscopic time step, in order to guarantee a continuous path for the simulated vehicles.} since the number of vehicles in the last ten seconds has to be multiplied by 360.

Therefore, the time between two adjacent vehicles crossing detector \( d \) is used. In Fig. 3-3(a) this is denoted by \( \hat{h}_c \), where \( c \) denotes the index of the vehicle that crosses the detector in the current time step. The time headway of all the vehicles that crossed the detector in the last ten seconds is illustrated in Fig. 3-3(a) with the blue discs. The amount of vehicles that crossed the detector is given by \( N_{\text{cross}, d} \). The average of time between two adjacent cars can then be used to calculate the flow \( \bar{q}_d \) as

\[
\bar{q}_d = \frac{N_{\text{cross}, d} - 1}{\sum_{c=1}^{N_{\text{cross}, d} - 1} \hat{h}_c} \tag{3-1}
\]

When the number of vehicles that crossed the detector is lower than two, it is obviously impossible to calculate the time between the vehicles. Therefore, the resulting flow of the conversion is defined to be 360 veh/h/lane when a single vehicle passed the detector in the last ten seconds. This is the flow that would be calculated if vehicles crossed the detector every ten seconds. A flow of zero veh/h will be given if no vehicle passed the detector.

The speed of each vehicle is also measured by the loop detectors, with the help of two loops that are placed with a known distance between them. When simulating the IDM model, the speed of all vehicles is already known and can easily be averaged over the macroscopic time step, which is given by

\[
\bar{v}_d = \frac{1}{N_{\text{cross}, d} - 1} \sum_{c=1}^{N_{\text{cross}, d} - 1} v_c \tag{3-2}
\]

Here, \( v_c \) is the speed of each individual vehicle that crosses the location of the detector.

The IDM model is implemented by discretizing time and keeping space continuous. The result of a simulation is a matrix with a column per time step and a row for each vehicle. The values of the elements of the matrix represent the position on the freeway. For this conversion method, which mimics a detector, it is necessary to detect when a vehicle crosses a detector. Since the model is implemented with discrete time steps, the crossing can also happen between two time steps. Thus, for each macroscopic time step it has to be checked which of the cars is positioned before a detector in one of the microscopic time steps and is positioned after that same detector in the next microscopic time step. In Fig. 3-3(a) this can be seen by a black line for which one of the black dots is below a blue thick line and the next dot is above the blue line. From this, the time of crossing the detector can be calculated by comparing the position at the two time steps with the position of the detector. To do so in MATLAB, multiple
Figure 3-3: Conversion of position data to macroscopic data with three methods. For each method the position-time samples are marked with a circle, and samples that are being used in the computation are marked with a filled circle. The horizontal, thick blue lines are the placements of loop detectors. The vertical, thick red lines are the macroscopic time steps were a measurement is available. The vertical, thin red lines are microscopic time steps of the IDM model. The vertical, thin blue lines represent virtual loop detectors.

(a) Detector mimicking

(b) Density averaging

(c) Flow averaging
columns must be read since a macroscopic time step spans multiple microscopic time steps. To convert a scenario consisting of 6 segments and 7000 seconds takes 21 seconds on a average desktop computer with an Intel® Pentium® D CPU running at 2.8 GHz and 1 Gb available RAM memory.

### 3-2-2 Average density

The second conversion method is based on the average density and average speed in the totality of the segment and not just on the density around the place of the loop detector or the flow passing the detector divided by the average speed. This can be seen by looking at Fig. 3-3(b), where the discs that mark the use of a data point are spread throughout the whole segment, while in Fig. 3-3(a) only data points located on the blue line are marked for use.

For each of the microscopic time steps within the last macroscopic time step, the density is calculated by counting the number of vehicles in the segment $d$ and dividing over the distance to the next detector, $L_d$. This is illustrated in Fig. 3-3(b) by the red circles along the thin red lines.

$$\rho_d(k) = \frac{N_{\text{seg},d}(k)}{L_d} \quad (3-3)$$

Also, the speed of these vehicles, $v_c$, is averaged in $v_d(k)$ for each microscopic time step $k$:

$$v_d(k) = \frac{1}{N_{\text{seg},d}(k)} \sum_{c=1}^{N_{\text{seg},d}(k)} v_c \quad (3-4)$$

Finally, the densities and average speeds are averaged over the macroscopic time step using the arithmetic mean.

As stated, it is necessary to count the number of cars within a segment for each microscopic time step. In MATLAB the positions of all the vehicles in one particular time step are stored in one column of the matrix with position data. To count the number of cars in a segment for one microscopic time step, only one column of this matrix needs to be accessed. This makes that the macroscopic data can be computed much faster by this method than by the detector mimicking method. The simulation of the same scenario as used as example for the first method carried out on the same computer, takes 10.6 seconds when using the density averaging method.

### 3-2-3 Average flow

The third method of conversion is inspired by the other two methods. The idea of the first method is to mimic a loop detector by using the crossing of the detector for calculating the flow and the average speed. The idea of the second method is to use
all available data in a segment and time step. The third method also aims at using all available data in a segment and time step, but then by calculating the flow and average speed like a loop detector does. As can be seen from Fig. 3-3(c) this conversion method introduces virtual detectors throughout the segment. Unlike the density averaging method there is no limit to the number of virtual detectors that can be placed because the space is continuous while the time is discretised.

The implementation of this method in MATLAB is simple since it is functioning in the same way as is the detector mimicking method. There only need to be defined more detectors and the new virtual detectors need to be linked with the original detectors. In this thesis project the flows and speeds as calculated by the virtual detectors were averaged to indicate the flow and speed for the original detector.

Since the functionality of this method is an exact copy of the detector mimicking method, also the mathematics can be reused. Therefore, the MATLAB-code used for this method is the same as the code used for the detector mimicking method except in plurality. The computation time thus increases linearly with the number of virtual detectors. For example, when using two detectors per segment, the computation time to simulate the same scenario as used before will be 42 seconds. The density averaging method uses 20 time steps, thus to convert a scenario with that many virtual detectors will take at least 5 minutes. Therefore, this method can certainly not be used in the envisioned traffic management system. Nevertheless, for studying the differences between the conversion methods, this method is still useful.

3-2-4 Discussion

Evaluating the differences between the conversion methods enables to select the most suitable method. Two main criteria are the validity of the method and the computational load.

Checking the validity of a conversion should be done by examining the differences between result of the conversion and the measurement data. However, this poses a problem since it is not guaranteed that the IDM model is calibrated such that the error between the results and the measurement data is negligible. In this project the error in the results of the traffic flow model is of a factor 10 higher than the differences between the conversion methods. Therefore, the methods are compared by looking at the differences between the conversion methods. Since this is not a conclusive evidence, further research should be carried out. It is recommended to evaluate the IDM model for data sets of other freeways and again examine the differences between the conversion methods by using a Root-mean-square measure or Theil’s inequality.

One would expect that the detector mimicking method gives almost the same result as the real world loop detectors if the vehicles on the freeway would drive exactly as the IDM model describes and that the density averaging method already has a disadvantage. The difference between the detector mimicking method and the density averaging method is indeed high for some parts of the scenario as shown in Figures 3-4 and 3-5(a). It can be seen that the main differences are situated around congested parts, or in other
words, during low flows. This is not surprising, because the detector mimicking method cannot compute a flow if less than two vehicles in ten seconds are passing. For these situations a flow of 360 or 0 veh/h/lane is computed. The result of this are spikes in

Figure 3-4: Flow as calculated by (a) the detector mimicking method, (a) the density averaging method, and (c) the flow averaging method
the resulting flow, as depicted in Fig. 3-4(a) between $t = 1.6$ h and $t = 1.8$ h, most clear at $x = 3500$ m. The spikes can cause problems in the calibration. This is the main drawback of the detector mimicking method.

![Comparison of the flow as calculated by the three methods of conversion](image)

**Figure 3-5:** Comparison of the flow as calculated by the three methods of conversion
The spikes in the flow will not occur if using one of the other conversion methods, see Fig. 3-4. Both of these methods use the whole segment to calculate the flow, density, and speed. For the density averaging method the density an average speed of all microscopic time steps is calculated. This can be seen in Fig. 3-3(b), were all data points are marked with a circle to indicate usage in the conversion method. Thus, there is no chance a slow moving vehicle will be missed while it actually is present simply because all position data is used.

By using the flow averaging method, the issue of too few cars is also reduced because the average of multiple virtual detectors is taken. If the segment is not completely empty or the vehicles are moving slowly, there will almost always be a virtual detector that detects a vehicle. Of course, the number of virtual detectors is important in this context. The results presented in this report are simulated with 19 virtual detectors per segment plus the normal detector since the number of microscopic time steps within a macroscopic time step is also 20. The average of all the virtual detectors will show a non-zero flow while the detector mimicking method will show a flow of 0 veh/h/lane for most of the data points and 360 veh/h/lane for some other data points which are seemingly randomly distributed through the jam. This last phenomenon is of importance for the calibration process since it is a big step from zero to 360 veh/h/lane which cannot be reproduced by the IDM model nor any other model. The law of conservation of vehicles disallows this. Furthermore, the measurement data does not show a zero flow either. For readability the figures showing the measurement data are given in Appendix A.

With this in mind it is interesting to investigate the difference between the two conversion methods that use averaging. First of all, the difference between the density averaging method and the flow averaging method, as shown in Fig. 3-5(b), is of much smaller magnitude than the other two combinations of methods which can be seen in Figures 3-5(a) and 3-5(c). This means that both methods capture the same characteristics of uncongested traffic flows.

However, the two conversion methods are not in total agreement about the congested part on the right. The density averaging method calculates a higher density than the flow averaging method does, as is shown in Fig. 3-6. When examining the corresponding calculated flow, density, and speed, it was found that the speed is calculated equally. This is not as expected since the density averaging method calculates the space-mean speed while the flow averaging method calculates the time-mean speed. The density is calculated higher by the density averaging method, however, the density from the density averaging method is more reliable than the density calculated by the flow averaging method since it is most directly calculated by counting the vehicles and dividing by the length of the segment. This in opposite of the flow averaging method where the density is approximated by using Eq. (2-5). It is therefore arguable whether the speed actually is the same. Therefore it might be valuable to investigate in future research whether the space-mean speed of the density averaging method should be converted to time-mean speed. This can presumably compensate for the differences between flow and density, the density of the flow averaging method will become higher and the flow of the density averaging method will become lower.

When comparing the computation times it is immediately clear that the flow averaging
method also has a drawback. Since the conversion method was ideally envisioned to be used in an on-line Traffic Management System (TMS) that needs to calculate a new control measure every minute, it is impossible to use a conversion method that takes up all this time while an on-line Model Predictive Controller (MPC) should be doing so. Therefore, the flow averaging method cannot be selected as answer to the secondary objective of this thesis since the method is not computationally lightweight. The remaining options are the detector mimicking and the density averaging method.

The choice between detector mimicking and density averaging is largely concentrated around the lack of the detector mimicking method during low flows. The aforementioned spikes introduce an unwanted discontinuity which is eliminated by the other methods. Therefore, the density averaging method was selected as the answer to the secondary objective of finding a computationally lightweight method that is also accurate.

![Figure 3-6: Flow, density, and average speed as calculated by the two averaging methods at the downstream boundary of the stretch of freeway](image-url)
3-3 Conclusions

During the literature study little explicit information was found about this topic. The topic is however rather important in order to fulfil the secondary objective of this thesis. Therefore, this chapter introduced and investigated three methods for converting microscopic data to macroscopic data.

In converting traffic data at least two directions exist, from macroscopic to microscopic and vice versa. The conversion of macroscopic to microscopic can be split up in three parts. First, at the start of the simulation, the initial conditions prescribes how to fill a simulated freeway with vehicles. This was done by placing vehicles with a distance according to the measured density. A recommendation for future research is distributing the vehicles more randomly.

During the simulation the boundary conditions have to be evaluated. For the upstream boundary a mechanism was used where a new vehicle is let in into the freeway according to the measured inflow as long as the desired distance is available. This was done to prevent vehicles piling up in the beginning of the simulated part of the freeway.

For the downstream boundary conditions a trivial method was used to start with. However, this method appeared to be invalid. By converting the density to the distance between two cars and using the difference in speed as approach rate, shock waves were not simulated as expected. The solution was to introduce virtual vehicles that behave according to the measurements.

For converting the position data back to macroscopic variables, three methods were researched. The detector mimicking method is based on the functioning of detectors as installed in the road pavements. The density averaging method uses the whole segment to calculate the average density and the average speed and uses these variables to calculate the flow. The flow averaging method calculates the average flow and average speed based on a collection of virtual detectors distributed throughout the segment.

The density averaging method was selected to be used in the rest of the thesis project. Upon investigation it was found that the detector mimicking method is not able to deliver accurate results because during congestion insufficient vehicles cross the detectors. Also, the computation time was high due to the structure of the data. To make advantage of MATLAB the density averaging method was introduced. The computation time of the density averaging method was only 50% of the detector mimicking method. Furthermore, the density averaging method is better than the detector mimicking method in converting position data during congestion. This was found by comparing the three methods using a scenario with a shock wave jam. A recommendation for future research is to investigate whether the results of the detector mimicking method can be improved by including a low pass filter. Unfortunately, this will also increase the computation time.

By comparing the two averaging methods it was found that the result of the density averaging method is comparable to the result of the flow averaging method. Nevertheless, the density averaging method shows an offset in the density and flow which is presumably the result of the incorrect use of arithmetic mean and harmonic mean.
recommendation for future research is to shift the window of the averaging methods and to investigate the use of harmonic mean for the density averaging method.
Chapter 4

Calibration and validation

The primary objective of this thesis project is to calibrate a microscopic and a macroscopic traffic flow model with the use of a macroscopic dataset. In previous chapters, the two models were presented and the methods for the conversion of microscopic data to macroscopic data and vice versa were described. In this chapter the methods used for the calibration and for the validation will be presented. These methods will be used to calibrate the two presented models for which also the conversion methods are used.

4-1 Calibration method

The calibration of both traffic flow models can be seen as minimizing the error between a measurement of a real freeway and the simulation of the same freeway with a model by changing parameters of the model. For this, a dataset is needed, an error measure is necessary, it has to be clear which parameters to change, and an optimization technique has to be chosen. These aspects will be the subject of this section.

Calibration data  As stated, a dataset is needed to have a description of the behaviour of the drivers on the freeway. A dataset was made available by the Dutch Governmental Department for Infrastructure and Environment (RWS) which, among other tasks, stores measurements from most of the freeways in the Netherlands. The received dataset contains measurements for most days in the period October to December 2009 for a part of the A12, depicted in Fig. 1-3. The selected stretch of freeway has no on-ramps or off-ramps since the IDM model used in this project does not support this. The freeway has double-loop detectors installed in the road pavement of which the data is used in this project.

The detectors measure a) the flow by counting the vehicles that crossed the detector in one minute and b) the average speed of these vehicles. The resolution of the data...
was increased by RWS from sixty to ten seconds by using a moving average method for a experiment RWS is running. The high resolution data is also used in this thesis project. Furthermore, there is no data available on the distribution of passenger cars and trucks.

Not all data of all days in this period of three months was usable for the calibration process since sometimes a detector measured a flow of zero while other detectors measured normal flows which breaks the law of conservation of vehicles. Another reason was a band of zero flow for all the detectors which can be the cause of a bad data connection. However, there was a sufficient amount of measurement data to select data with none of the mentioned deficiencies for a period of 24 hours.

For the calibration process the data was selected from a day on which a shock wave was encountered. This was done because the models should be able to predict this phenomenon. The dataset used in the validation process was extracted from a day on which a less severe shock wave and a slow driving congestion occurred. This was done to be able to check if the calibration does not lead to a model that always predicts a severe shock wave but only when there actually is a shock wave. Note that not all days contained shock waves or congestion.

**Error measure** To define the performance of the model with a certain parameter set an error measure is needed. In this thesis project the root-mean-square of the normalized error was used. The error was normalized to be able to include both the speed and the flow in one error measure. Furthermore, the root-mean-square was used for multiple reasons. First of all, it uses the distance between the optimal value and the simulated value. It is unnecessary to make separation between the simulation being higher or lower than the optimal value, only the magnitude of the error is necessary. By using the square, the sign of the error is eliminated. Second, by means of the square, errors with larger magnitude are emphasized.

Both the error in speed and flow are used in the error measure. This was done because using only one of the three quantities flow, density, or speed, would not be sufficient for tuning the parameters adequately. A certain flow can be accompanied with different speeds as can be seen in Fig. 2-1. On the other hand, using all three quantities would be overdue because the density can be approximated by dividing the flow over the speed according to Eq. (2-5). And actually, the density is not given in the dataset and would indeed have to be calculated.

The errors are divided by the nominal value to have the same range of errors for both speed and flow. This was done because all errors are summed together to one number representing the overall error. As a consequence, the errors in speed and in flow should be balanced to have the same weight in the overall error. This is necessary to counteract the case of errors in flow being minimized while the errors in speed are still very large. The nominal value for flow is taken to be 2400 veh/h/lane and the nominal value for speed is taken to be 120 km/h which are the values for free-flow traffic.

The evaluation of both models results in three data sequences, which specify for each time step and detector the flow, the density, and the speed. The data sequences for flow
and speed are used in the error measure. The individual elements are only normalized because the optimization algorithm calculates the sum of the squared errors internally. The final error measure $E_{\text{RMS,norm}}$ reads as

$$E_{\text{RMS,norm}} = \sqrt{\frac{1}{N_d \cdot N_k} \sum_{j=1}^{N_d \cdot N_k} \left( \frac{Q_{\text{sim},j} - Q_{\text{dat},j}}{2400} \right)^2 + \frac{1}{N_d \cdot N_k} \sum_{j=1}^{N_d \cdot N_k} \left( \frac{V_{\text{sim},j} - V_{\text{dat},j}}{120} \right)^2}$$ (4-1)

Here, capital Q and V are the data sequences for flow and average speed, the subscript 'sim' indicates data from the simulation and the subscript 'dat' indicates data from the measurements. The number of detectors is given by $N_d$, the number of macroscopic time steps is given by $N_k$, and the product of these two values gives the total number of elements in the data sequence.

Optimization parameters  The parameters that were altered during the calibration process were all the parameters available from the models except the compliance rate $\alpha$ of the MET ANET model. All calibrated parameters are listed in Tables 4-1 and 4-2. Since a lot of dependencies exist between the parameters, using all parameters gives the model more potential to adequately replicate the behaviour of the drivers on the freeway. The compliance rate was copied from Hegyi [13] since the data showed an average speed which is around or below the speed limit instead of above.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Name</th>
<th>Lower Bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_0,\alpha$</td>
<td>Jam distance 1</td>
<td>0.4</td>
<td>100</td>
</tr>
<tr>
<td>$d_1,\alpha$</td>
<td>Jam distance 2</td>
<td>1</td>
<td>20</td>
</tr>
<tr>
<td>$T_{\alpha}$</td>
<td>Safe time headway</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>$l_{\alpha}$</td>
<td>Length of vehicles</td>
<td>0.8</td>
<td>2</td>
</tr>
<tr>
<td>$a_{\alpha}$</td>
<td>Maximum Acceleration</td>
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<td>0.7</td>
</tr>
<tr>
<td>$b_{\alpha}$</td>
<td>Deceleration factor</td>
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<td>8</td>
</tr>
<tr>
<td>$\delta_{\alpha}$</td>
<td>Acceleration Exponent</td>
<td>0</td>
<td>$\infty$</td>
</tr>
<tr>
<td>$v_{\alpha}^{\ast}$</td>
<td>Free flow speed</td>
<td>20</td>
<td>50</td>
</tr>
</tbody>
</table>

Table 4-1: List of IDM parameters that are changed in the calibration

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Name</th>
<th>Lower Bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\kappa$</td>
<td>Density offset</td>
<td>0</td>
<td>200</td>
</tr>
<tr>
<td>$\eta_{\text{high}}$</td>
<td>Anticipation increasing density</td>
<td>0</td>
<td>120</td>
</tr>
<tr>
<td>$\eta_{\text{low}}$</td>
<td>Anticipation decreasing density</td>
<td>0</td>
<td>120</td>
</tr>
<tr>
<td>$\phi_m$</td>
<td>Fundamental diagram parameter</td>
<td>0.1</td>
<td>30</td>
</tr>
<tr>
<td>$v_{l,m}$</td>
<td>Free flow speed</td>
<td>50</td>
<td>150</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Speed changing response time</td>
<td>5</td>
<td>120</td>
</tr>
<tr>
<td>$\rho_{cr,m}$</td>
<td>Critical density</td>
<td>5</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 4-2: List of MET ANET parameters that are changed in the calibration
For the IDM model the scenarios where simulated with only one class of vehicles since no information on the distribution of vehicles was known. The METANET model used in this thesis project is actually also single-class. Furthermore, the same parameters were used for all segments in the stretch of freeway.

**Optimization method**  The calibration of both traffic flow models was carried out using MATLAB. This software package has a number of optimization functions built in which can easily be used for the calibration of models, or in other words fitting a model to data.

The function used for the calibration in MATLAB is `lsqnonlin`. This function implements various least-squares optimization methods for non-linear objective functions, for both traffic flow models are non-linear. The selected optimization method is the large-scale trust-region-reflective method based on the interior-reflective Newton method [8, 9].

Furthermore, to increase the reliability of the results a multi-start approach was used. Both models were calibrated multiple times with random initial parameter sets for each iteration. The number of starts was fifty for both model. This is especially useful for non-linear objective functions because non-linear objective functions can have local minima which should be avoided. For each of the parameters a range was chosen which is based on physically possible values and on good judgement. The bounds are given in Tables 4-1 and 4-2. For example, the value for the desired free flow speed $v_0^*$ of most drivers will not exceed 150 km/h so the range of random values for this parameter does not have to exceed this value either. Note that it is also possible to detect that a range is too small if a parameter converges to either one of the bounds.

As explained in Chapter 1, the two traffic flow models are envisioned to operate together. The calibration of both models will be done separately for both models. The models will not be calibrated towards each other, i.e., a calibration of one model using the result of a simulation of the other model as the input data, will not be conducted. This is not necessary since the models do not depend on each other as in a loop. In the envisioned feedback structure, the IDM model only uses the control measures calculated with the help of the METANET model.

### 4-2 Validation method

For the purpose of drawing conclusions it is necessary to have a method which can measure how good a calibration result is. Since the result of a calibration are parameter values, one can examine the values and see if they are of reasonable order. With the help of the parameter values a simulation can be carried out to see whether the simulation of flow, density, and speed compares to the desired evaluation for flow, density, and speed. Plots of the flow, density, and speed can be helpful in quickly examining the quality of parameter values, however, in this project conclusions are only being drawn by using error measures.
Parameter validation  For both traffic flow models alternative parameter values were taken from literature. The values are used as a guide for the discussion on the calculated values and are presented in Tables 4-3 and 4-4. Although the alternative values for the IDM model seem to be picked by hand since the values are rounded, the information is still valuable because it gives an idea of the proper order. The first alternative set of parameter values was copied from Hegyi [13]. The second alternative set for the METANET model was adopted from RWS which also uses the METANET model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Literature [15]</th>
<th>Unit</th>
</tr>
</thead>
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<tr>
<td>$d_0,\alpha$</td>
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<td></td>
<td>m</td>
</tr>
<tr>
<td>$d_1,\alpha$</td>
<td>10.00</td>
<td></td>
<td>m</td>
</tr>
<tr>
<td>$l,\alpha$</td>
<td>5.00</td>
<td></td>
<td>m</td>
</tr>
<tr>
<td>$T,\alpha$</td>
<td>1.20</td>
<td></td>
<td>s</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.80</td>
<td></td>
<td>m s$^{-2}$</td>
</tr>
<tr>
<td>$b,\alpha$</td>
<td>1.25</td>
<td></td>
<td>m s$^2$</td>
</tr>
<tr>
<td>$v^*,\alpha$</td>
<td>33.33</td>
<td></td>
<td>m/s</td>
</tr>
<tr>
<td>$\delta,\alpha$</td>
<td>4.00</td>
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</tbody>
</table>

Table 4-3: An alternative set of parameter values for the IDM model

<table>
<thead>
<tr>
<th>Value</th>
<th>Parameter</th>
<th>Literature [13]</th>
<th>RWS</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\kappa$</td>
<td>40.00</td>
<td>32.90</td>
<td>veh/km/lane</td>
<td></td>
</tr>
<tr>
<td>$\eta_{low}$</td>
<td>26.00</td>
<td>64.20</td>
<td>km$^2$/h</td>
<td></td>
</tr>
<tr>
<td>$\eta_{high}$</td>
<td>65.00</td>
<td>26.27</td>
<td>km$^2$/h</td>
<td></td>
</tr>
<tr>
<td>$\tau$</td>
<td>14.76</td>
<td>14.76</td>
<td>s</td>
<td></td>
</tr>
<tr>
<td>$v_{f,m}$</td>
<td>120.00</td>
<td>117.69</td>
<td>km/h</td>
<td></td>
</tr>
<tr>
<td>$\phi_m$</td>
<td>1.80</td>
<td>2.83</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>$\rho_{cr,m}$</td>
<td>32.00</td>
<td>24.18</td>
<td>veh/km/lane</td>
<td></td>
</tr>
</tbody>
</table>

Table 4-4: An alternative set of parameter values for the METANET model

Visual validation  Before calculating the quality of a calibration result, the plots of the flow, speed and densities of the simulation were compared with the measurements. By this it is possible to check the ability of both models to predict a shock wave based on a peak in the density on the downstream end of the selected part of the freeway.

For each simulation the flow, density, and average speed per segment and time step was plotted in three-dimensional plots as shown in Appendix A. These plots show the measurement data for the selected part of the freeway. The figures show the measurement data used for the calibration, in which a shock wave is present.

Methodological validation  In this thesis project Theil’s inequality and the Variance-Accounted-For (VAF) were used to calculate the quality of a parameter set [4, 17, 30, 33, 37]. Theil’s inequality is widely used in econometrics to find the quality of a model which forecasts earnings. The traffic flow models in this project can also be seen as forecasting models, but then for traffic conditions. Theil’s inequality gives a number between zero and one were zero represents a perfect fit. This was a major reason to prefer Theil’s inequality over the measure used during the calibration: the result of Theil’ inequality does not depend on the size of the data set nor the values in the data set. Theil’s inequality reads as
Calibration and validation

\[
U = \frac{\sqrt{\frac{1}{N_d \cdot N_k} \sum_{j=1}^{N_d \cdot N_k} (X_{\text{sim},j} - X_{\text{dat},j})^2}}{\sqrt{\frac{1}{N_d \cdot N_k} \sum_{j=1}^{N_d \cdot N_k} (X_{\text{sim},j})^2} + \sqrt{\frac{1}{N_d \cdot N_k} \sum_{j=1}^{N_d \cdot N_k} (X_{\text{dat},j})^2}}
\] (4-2)

The numerator gives the Root-Mean-Square (RMS) of the error between the data of the simulation, \(X_{\text{sim}}\), and the data of the measurements, \(X_{\text{dat}}\). If the simulation and the measurement data is exactly the same, the value of \(U\) will naturally also become zero. The denominator calculates the root mean square of both the simulation data and the measurement data to give the magnitude of the data. In case the data in \(X_{\text{sim},j}\) and \(X_{\text{dat},j}\) have the same sign\(^1\), the value of the denominator is exactly the highest possible value of the numerator, therefore the value of \(U\) is maximally one. Since all terms in the numerator and the denominator are squared, a negative value of \(U\) is impossible.

The \(X_{\text{sim}}\) and \(X_{\text{dat}}\) are substituted with the data for which variable Theil’s inequality should be calculated which is flow or speed. For calculating the inequality for the flow the substitution is \(X_{\text{sim},j} = Q_{\text{sim},j}\) and \(X_{\text{dat},j} = Q_{\text{dat},j}\) and for the speed it becomes \(X_{\text{sim},j} = V_{\text{sim},j}\) and \(X_{\text{dat},j} = V_{\text{dat},j}\). In this thesis project the inequality was not calculated for the density because this quantity is not used in the calibration either.

Theil’s inequality also can be composed in three components that can be examined to find the main source of error. This is usually omitted if \(U\) is low. These components can calculate the proportion of systematic error or bias, the proportion of difference in variability, and the proportion of covariance or unsystematic error. The proportion of systematic error or bias is given by \(U_{\text{bias}}\):

\[
U_{\text{bias}} = \frac{(\bar{X}_{\text{sim}} - \bar{X}_{\text{dat}})^2}{\sqrt{\frac{1}{N_d \cdot N_k} \sum_{j=1}^{N_d \cdot N_k} (X_{\text{sim},j} - X_{\text{dat},j})^2}}
\] (4-3)

The difference between the mean value of the simulation data, \(\bar{X}_{\text{sim}}\), and the mean value of the measurement data, \(\bar{X}_{\text{dat}}\), gives the bias. The bias is squared and divided by the RMS of the difference to normalize the value to the range [0, 1].

The proportion of error in variability of the simulation and the data is given by \(U_{\text{var}}\), which uses the standard deviation for the simulation data, \(\sigma_{\text{sim}}\), and for the measurement data, \(\sigma_{\text{dat}}\):

---

\(^1\)This is exactly the case for the data considered in this project.
Validation method

\[ \sigma_{\text{sim}} = \sqrt{\frac{1}{N_d \cdot N_k} \sum_{j=1}^{N_d \cdot N_k} (X_{\text{sim},j} - \bar{X}_{\text{sim}})^2} \quad (4-4) \]

\[ \sigma_{\text{dat}} = \sqrt{\frac{1}{N_d \cdot N_k} \sum_{j=1}^{N_d \cdot N_k} (X_{\text{dat},j} - \bar{X}_{\text{dat}})^2} \quad (4-5) \]

\[ U_{\text{var}} = \frac{(\sigma_{\text{sim}} - \sigma_{\text{dat}})^2}{N_d \cdot N_k \sum_{j=1}^{N_d \cdot N_k} (X_{\text{sim},j} - X_{\text{dat},j})^2} \quad (4-6) \]

Pearson’s correlation coefficient, \( \rho \), gives the degree of linear correlation between the simulation data and the measurement data:

\[ \rho = \frac{1}{N_d \cdot N_k} \sum_{j=1}^{N_d \cdot N_k} (X_{\text{sim},j} - \bar{X}_{\text{sim}}) \cdot (X_{\text{dat},j} - \bar{X}_{\text{dat}})}{\sigma_{\text{sim}} \cdot \sigma_{\text{dat}}} \quad (4-8) \]

The value of \( \rho \) lies between 1 and -1 where 1 denotes maximal linear correlation. This correlation coefficient is used in the calculation of the unsystematic error, given by \( U_{\text{cov}} \):

\[ U_{\text{cov}} = \frac{2 \cdot (1 - \rho) \cdot \sigma_{\text{sim}} \cdot \sigma_{\text{dat}}}{N_d \cdot N_k \sum_{j=1}^{N_d \cdot N_k} (X_{\text{sim},j} - X_{\text{dat},j})^2} \quad (4-9) \]

By subtracting the correlation coefficient from one, the value of the numerator of \( U_{\text{cov}} \) is maintained positive.

All three components are in the range of \([0, 1]\) and always add up to one. It is wanted to minimize the contribution of systematic error and the contribution of difference in variability and only be left with a remaining error. If \( U \) is higher than appreciated, one can examine the components to see the main source of error. If \( U_{\text{bias}} \) and \( U_{\text{var}} \) are both low, the error is most likely due to measurement errors.

With the measures defined above, it is possible to set a threshold below which the parameter values can be defined as valid. The threshold for \( U \) for both flow and speed of the validation scenario is set to 0.2. Hourdakis et al. [17] use a value of 0.3 as threshold. However, in this thesis project it was found this bound is not strict enough since this can mean there is a bias of 750 veh/h/lane with respect the measurement data for the validation scenario. The selected threshold of 0.2 can mean a bias of 750 veh/h/lane or 30 km/h. However, this value will become smaller if also a variance or unsystematic error is detected.

The second measure that is used in this thesis project is the Variance-Accounted-For (VAF) [4]. The measure calculates the variance of the measurement data and the variance of the error between the measurement data and the simulation data. These
two values are then divided and normalized to show how much of the variation from the measurement is simulated by the model. Or in other words, as the name of the measure suggests, how much of the variation from the measurement data is accounted for in the model. VAF reads as

\[
\text{VAF} = \left(1 - \frac{\sum_{j=1}^{N_d \cdot N_k} (X_{\text{dat},j} - X_{\text{sim},j})^2}{\sum_{j=1}^{N_d \cdot N_k} X_{\text{dat},j}^2}\right) \cdot 100\% \tag{4-10}
\]

4-3 Summary

This chapter has described the methods for calibrating and validating the traffic flow models which were presented in Chapter 2. Calibrating a model consists of optimizing the parameter values such that the simulation of the model is as close as possible to measurements of a real freeway according to an error measure. For this, a data set was made available by RWS with flow and average speed data measured by loop detectors installed in the road pavements of the A12. The used loop detectors are marked in Fig. 1-3. To define how close the simulation is to the measurement, an error measure was defined. In this project, the root-mean-square of the normalized error was used during the calibration. The error in flow and in speed were normalized and combined in one error measure. The root-mean-square was used because it is independent of the sign of the error and it adds more weight to errors of great magnitude.

The validation can be split up in three consecutive steps. First, the parameters are given an inspection by comparing them with an alternative parameter set. Second, the result of a simulation with the validation data set is visually inspected. If both checks are passed, Theil’s inequality is calculated. This inequality gives a measure between one and zero, indicating the quality of the simulation result compared with the measurement. The threshold for validating a set of parameter values using Theil’s inequality was set to 0.2.
Chapter 5

Results and discussion

This chapter presents the results of the calibration and validation of the traffic flow models developed in this thesis project using graphs of the evaluation of the models and a table with the parameter values. An extensive list of figures is given in Appendices B and C for the interested reader. These figure show the flow, density and average speed of evaluations of the traffic flow models.

5-1 Calibration and validation of the IDM model

The calibration of the IDM model has resulted in parameter values for which the simulation has the lowest error possible as described by the error measure in Chapter 4. The parameter values are shown in Table 5-1. When comparing these values with the values given by the authors of the IDM model [15], especially the values for $d_{0, \alpha}$, $l_{\alpha}$, $T_{\alpha}$, and $b_{\alpha}$ stand out. Although the values of [15] are for another country with different norms, it is necessary to analyse the major differences. Another reason for analysis is that the error between the measurements and the results when simulating the validation scenario is too large to pass the validation. This section will discuss the results of the calibration of the IDM model using the methods described in Chapter 4 starting with the parameter validation, followed by Theil’s inequality and the Variance-Accounted-For (VAF). The visual inspection is left to the reader.

5-1-1 Calibration

The calibration was carried out using a multi-start approach with random parameter values for each start. All calibrations ended with a warning from MATLAB that a possible local minimum was found since the first-order optimality is above zero [27]. Note that none of the calibrations was limited in iterations. The best parameter values were
reused as starting point in a new calibration. This resulted in the same parameter values and first-order optimality, reducing the chance of having found a local minimum. However, it is still possible that the measurement data does not have enough information for adequately calibrating the IDM model since the validation was not carried out satisfactory. Therefore future research should investigate whether enlarging the scenarios leads to better results.

5-1-2 Parameter validation

As stated above, the parameters $d_0, l, T, a$ obtained by calibrating the IDM model for a part of the A12 as shown in Fig. 1-3 have high values if compared with parameter values obtained in [15]. As will become clear in this section, the results of the IDM model for the validation scenario show high errors compared to the measurement data. It seems as if the parameters are too sensitive in some cases which occur in the validation scenario. Therefore, the differences between the calibration parameter values and values given in [15] are analysed.

The first parameter, $d_0$, is important during low speeds. The comparison with the parameter value in [15] suggests that the calibrated value for this parameter is quite high. First of all, it should be noted that parameter $l$ is used in the calculation of the actual distance with the opposite sign, this can be seen in Eq. (2-14) and (2-17). The value for $l$ is actually quite low. To see the net effect, the front-to-front distance between vehicles on the freeway is calculated below.

In the scenario used for the calibration, a shock wave is measured which is also simulated using the calibrated parameter values as can be seen in Fig. 5-1. The measured maximum density is 73 veh/km/lane which means that the front-to-front distance is 13.7 meters. At this moment the measured speed is 1.7 m/s or 6 km/h. If the measured speed is substituted in Eq. (2-14) with the calibrated parameter values, the desired front-to-rear distance becomes 14.75 m ($8.53 + 11.31 \cdot \sqrt{1.07} + 1.07 \cdot 1.7$). This is significantly more than 13.7 m since the front-to-front distance will become 17.4 m. When using the parameter values from [15], the desired distance becomes 6.88 m ($1 + 10 \cdot \sqrt{1.2} + 1.2 \cdot 1.7$) and the front-to-front distance becomes 9.5 m, which is significantly less than in the

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Calibration</th>
<th>Literature [15]</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_0$</td>
<td>8.53</td>
<td>1.00</td>
<td>m</td>
</tr>
<tr>
<td>$d_1$</td>
<td>11.31</td>
<td>10.00</td>
<td>m</td>
</tr>
<tr>
<td>$l$</td>
<td>2.60</td>
<td>5.00</td>
<td>m</td>
</tr>
<tr>
<td>$T$</td>
<td>1.07</td>
<td>1.20</td>
<td>s</td>
</tr>
<tr>
<td>$a$</td>
<td>0.67</td>
<td>0.80</td>
<td>m/s²</td>
</tr>
<tr>
<td>$b$</td>
<td>0.21</td>
<td>1.25</td>
<td>m/s²</td>
</tr>
<tr>
<td>$v_{\alpha}$</td>
<td>32.51</td>
<td>33.33</td>
<td>m/s</td>
</tr>
<tr>
<td>$\delta_{\alpha}$</td>
<td>12.23</td>
<td>4.00</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 5-1: Calibrated parameter set and an alternative sets for the IDM model

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5-1 Calibration and validation of the IDM model

Figure 5-1: Simulated flow for the first two hour of the calibration scenario with the calibrated parameter values using the IDM model

measurements. It is however more intuitive that most drivers keep a low distance to the predecessor if the speed is very low, since otherwise other drivers will fill up the space and effectively make profit. The above desired distances are calculated by assuming the approach rate to be zero since the vehicles are moving at low speed and high density and will thus, on average, have an invariable distance.

Negating the difference between the measured 13.7 m and the simulated 17.4 m can be done by decreasing only $d_0$. The other terms alone cannot result in a difference of 4 m since the value for $d_1$ or $T_\alpha$ would become negative; the influence of the anticipation term is too low. In Fig. 5-2 the calibration and validation scenarios are simulated with different values for $d_0$. By comparing the two lower figures with $d_0 = 4.53$ m it can be seen that a difference of 4 m results in a better simulation. The simulation is better since the two upper right figures show a large error after $t = 1.6$ h, which is not seen in the lower right figure.

The shape of the equilibrium speed trajectory in the fundamental diagram is also different. This can be seen by comparing the two diagrams in Fig. 5-3, the peak of the equilibrium speed trajectory is of a different sharpness and the maximum density is at a different density. Furthermore, the shape of the equilibrium speed trajectory for both sets of parameter values neither follow the shape of the measurement data. From Fig. 5-4 can be seen that the highest flow of the measurement is higher than the highest flow of the simulation. The equilibrium trajectory of the IDM model in combination with the calibrated parameter values is even lower.

The result of this smoother peak for the parameter values from [15] and the lower peak for both sets of parameter values can be that congestion is predicted at a lower flow. In the calibration scenario and the validation scenario the start of a rush hour is captured. Over time, the density and the flow become higher as more vehicles enter the freeway. Below the critical density the measurement and the simulation will show a similar behaviour. However, if the density comes above the critical density of the IDM model with the calibrated parameter values, the IDM model will predict a traffic breakdown since the highest flow is reached. According to the measurements the density and flow
Results and discussion

Calibration, $d_{0,\alpha} = 8.53$

Validation, $d_{0,\alpha} = 8.53$

Calibration, $d_{0,\alpha} = 6.53$

Validation, $d_{0,\alpha} = 6.53$

Calibration, $d_{0,\alpha} = 4.53$

Validation, $d_{0,\alpha} = 4.53$

Figure 5-2: Comparison between different values of $d_{0,\alpha}$ for the calibration scenario (left) and the validation scenario (right). The plots show the error between the measurement data and the simulation data.

can increase further before a traffic breakdown should occur. Fig. 5-5 confirms this by showing a shock wave congestion which starts at $t = 1\ h$ since the flow coming in to the stretch of freeway is too high according to the parameter values from [15]. In the measurement data the shock wave starts at $t = 1.4\ h$.

This overdone reaction is of course not wanted, however the calibrated parameter values lead to even worse results when using the validation scenario. The sensitivity of...
Calibration and validation of the IDM model

Literature parameter values

Calibrated parameter values

Flow (veh/h/lane)

Density (veh/km/lane)

Measurement data

Simulation data

Equilibrium speed

Figure 5-3: Fundamental diagrams for the calibration parameter values and the parameter values from [15]

Measurement data

Simulation data

Equilibrium speed

Figure 5-4: Fundamental diagram for the measurement data and the simulation data and equilibrium trajectory for the calibrated parameter values and the calibration scenario
the parameter values becomes clear when looking at the simulation of the validation scenario of which the flow is depicted in Fig. 5-6. It can be seen that the parameter values in [15] lead to slightly better results, however, both sets of parameter values result in a much too sensitive model. Therefore, it can be said that a balance should be found between the parameter values of the calibration and from literature [15]. Also, as will become clear in the next section, the METANET model is less sensitive while being calibrated with the same scenario.

As can be seen from Fig. 2-5 the safe headway time parameter $T_\alpha$ has an important role in Eq. (2-14). By changing this parameter, the relation between speed and desired distance can be influenced strongly. Setting a lower value will allow the vehicles to drive closer to each other, which can help eliminate the false predictions of congestion as shown in Fig. 5-6. The IDM model is simulated by using the calibrated parameter values with different values for $T_\alpha$ and both the calibration and validation scenario. A higher $T_\alpha$ means a slightly lower flow and thus a slight increase in error between the simulation and the measurements for the calibration scenario. However, a decreased $T_\alpha$ can help in reducing the incorrect prediction of shock waves in the validation scenario.

Nevertheless, the value in the parameter set from the authors of the model [15] is higher than the calibrated value as well as in parameter sets from informal sources. Furthermore, governments generally advise that the safe time headway be 2 or 3 seconds. But, some reasons can be thought of when drivers temporarily come closer to their predecessor and thus effectively have a low safe time headway [36]. Also, Chandler et al. state that the safe distance time to the predecessor should not be too high in order to keep traffic flow stable [7]. This can possibly be introduced in the IDM model by varying the value of $T_\alpha$ locally to overcome little perturbations that are not leading to congestion in the measurement data. Unfortunately, time did not allow to research the possible extensions and therefore it remains an open issue that can be researched in future work.

The $b_\alpha$ parameter indicates the desired deceleration of the average driver and has a low
value. A low value for $b_\alpha$ helps to enlarge the effect of the anticipation term or, in other words, the reaction to the speed ahead. This is similar to the behaviour found for the METANET model with the calibrated parameters: a high amount of anticipation. It is well possible that the value for this parameter can differ among countries or even on a single freeway, thus also between the calibrated parameter value and the value from [15].

5-1-3 Methodological validation

For the methodological validation, the results of the simulation and the measurements were subjected to Theil’s inequality, the VAF was calculated, and the values of the error measure are presented as described in Section 4-2.

The results of Theil’s inequality are listed in Table 5-2. The high values for $U$ for the validation scenario confirm that the IDM model cannot be labelled as valid. The false predictions of congestion result in a large mismatch between the measurement data and the simulation data. The value for $U_{\text{bias}}$ is therefore quite high since the mean of the
Results and discussion

Calibration, $T_\alpha = 1.27$

Validation, $T_\alpha = 1.27$

Calibration, $T_\alpha = 1.07$

Validation, $T_\alpha = 1.07$

Calibration, $T_\alpha = 0.87$

Validation, $T_\alpha = 0.87$

Figure 5-7: Comparison between different values of $T_\alpha$ for the calibration scenario (left) and the validation scenario (right). The plots show the error between the measurement data and the simulation data.

simulation data is very low with respect to the mean of the measurement data. Also the value for $U_{\text{var}}$ is high because the simulation shows a flat surface after $t = 1.6 \text{ h}$ while in the measurement data the flow varies in time.

The values for the VAF are presented in Table 5-3. The value for the calibration scenario is reasonably high while all other values are zero. This means that the variance of the measurement data in comparison with the variance of the error between the
5-1 Calibration and validation of the IDM model

## Table 5-2: Values of Theil’s inequality for the calibration scenarios and the validation scenario simulated by the IDM model.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Quantity</th>
<th>$U$</th>
<th>$U_{bias}$</th>
<th>$U_{var}$</th>
<th>$U_{cov}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>Flow</td>
<td>0.0591</td>
<td>0.0462</td>
<td>0.867</td>
<td>0.0866</td>
</tr>
<tr>
<td></td>
<td>Speed</td>
<td>0.0814</td>
<td>0.0662</td>
<td>0.877</td>
<td>0.0569</td>
</tr>
<tr>
<td>Validation</td>
<td>Flow</td>
<td>0.295</td>
<td>0.463</td>
<td>0.354</td>
<td>0.183</td>
</tr>
<tr>
<td></td>
<td>Speed</td>
<td>0.39</td>
<td>0.394</td>
<td>0.436</td>
<td>0.17</td>
</tr>
</tbody>
</table>

## Table 5-3: Values of the VAF for the calibration scenarios and the validation scenario simulated by the IDM model.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Quantity</th>
<th>Calibrated Values</th>
<th>Literature [15]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>Flow</td>
<td>95.98</td>
<td>5.79</td>
</tr>
<tr>
<td></td>
<td>Speed</td>
<td>98.63</td>
<td>1.36</td>
</tr>
<tr>
<td>Validation</td>
<td>Flow</td>
<td>8.36</td>
<td>8.36</td>
</tr>
<tr>
<td></td>
<td>Speed</td>
<td>1.74</td>
<td>1.74</td>
</tr>
</tbody>
</table>

## Table 5-4: Values of the error measure for the calibration scenarios and the validation scenario simulated by the IDM model.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Calibrated Values</th>
<th>Literature [15]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>0.03281</td>
<td>0.94946</td>
</tr>
<tr>
<td>Validation</td>
<td>1.16987</td>
<td>1.16987</td>
</tr>
</tbody>
</table>

The values of the error measure that is used in the calibration process are presented in Table 5-4. Note that the values for the calibration scenario and for the validation scenario should not be compared since the size and content of both scenarios differ. However, it is clear that the parameter values from [15] cannot be used for the freeway considered in this thesis project since the value of the error measure is roughly 30 times higher. The error measure for the validation scenario is even higher, confirming the disapproval of the calibrated parameter values.

### 5-1-4 Discussion

The calibration of the IDM model was carried out satisfactory. Although all repetitions ended with a warning of MATLAB that a local minimum was possibly found, a new calibration with the best parameter values resulted in the same parameter values and first-order optimality. This increases the reliability of the found parameter values. However, since the validation was not satisfactory, further research is necessary. The first option for improving the quality of the parameter values is using bigger scenarios, ideally including on-ramps and off-ramps. This will allow for a broader view on the measurement data and the simulation data is negligible. Or in other words, the error simply is too large.
different aspects of the behaviour of drivers. For example, it is quite good possible that on the day of the calibration scenario, the weather was bad and all the drivers where very cautious. Including more days can negate this kind of problems.

The results of the validation state that the IDM model with the calibrated parameters is not able to adequately predict the behaviour of the drivers on the selected stretch of the A12 for every situation. The measured flow on the selected stretch of freeway in the calibration scenario leads to a capacity flow that is not sufficiently high to adequately simulate the validation scenario. This can be seen in the fundamental diagram in Fig. 5-4 where the measurements are plotted in the same axes as the equilibrium speed trajectory. The result of the validation is that the values for Theil’s inequality become higher than the proposed threshold. Also, the VAF is very low for the validation scenario, meaning the variance of the measurement data is not reflected by the IDM model.

In this section it was already pointed out that some parameter values have a large difference with respect to values from Helbing et al. [15]. By examining the differences and the results of the IDM model when using each of the sets of parameter values and also varying parameter values, it was seen that the error of the validation scenario can be reduced if the value for $d_{0,\alpha}$ and/or $T_{\alpha}$ is lowered. Lowering the value for $d_{0,\alpha}$ is in accordance with the parameter value from [15], however, a lower value for $T_{\alpha}$ is contradicting to [15]. Therefore, it is stated in this section that the value of $T_{\alpha}$ should be linked to one of the variables in Eq. (2-14) such that in stable traffic flow the value is higher and gives the IDM model a higher capacity flow, however, in marginally stable traffic flow preserves the sensitivity to shock waves. This is still an open issue that should be researched in future work.

Another parameter that shows large differences between the calibrated value and the value from [15] is $b_{\alpha}$, the parameter for the desired deceleration. The higher calibrated value increases the effect of the anticipation term in the equation for the desired distance. This is however in accordance with the findings in the next section: a high amount of anticipation.

### 5-2 Calibration and validation of the METANET model

The METANET model has been calibrated in the same way as the IDM model, resulting in a parameter set with optimal performance according to the error measure. The parameters are given in Table 5-5. When comparing these values with the values of alternative parameter values, there are only a few parameters that are similar. Although the starting point is not the same since the alternative parameter sets were found using a freeway with on-ramps and off-ramps, the magnitude of the calibrated parameter values varies widely. Therefore, the differences between the parameter values will be discussed and analysed in the next section. Furthermore, the plots of the simulation are interpreted in Section 5-2-3 followed by the results of the various measures that can be used in deciding whether the parameter values are valid in Section 5-2-4.
5-2 Calibration and validation of the MET ANET model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Calibration</th>
<th>Literature [13]</th>
<th>RWS</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\kappa$</td>
<td>5.55</td>
<td>40.00</td>
<td>32.90</td>
<td>veh/km/lane</td>
</tr>
<tr>
<td>$\eta_{\text{low}}$</td>
<td>35.18</td>
<td>26.00</td>
<td>64.20</td>
<td>km$^2$/h</td>
</tr>
<tr>
<td>$\eta_{\text{high}}$</td>
<td>119.99</td>
<td>65.00</td>
<td>26.27</td>
<td>km$^2$/h</td>
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<tr>
<td>$\tau$</td>
<td>66.57</td>
<td>14.76</td>
<td>14.76</td>
<td>s</td>
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<tr>
<td>$v_{f,m}$</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_m$</td>
<td>3.58</td>
<td>1.80</td>
<td>2.83</td>
<td>-</td>
</tr>
<tr>
<td>$\rho_{cr,m}$</td>
<td>26.07</td>
<td>32.00</td>
<td>24.18</td>
<td>veh/km/lane</td>
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</table>

Table 5-5: Calibrated parameter set and two alternative sets for the METANET model

5-2-1 Calibration

The calibration of the METANET model was carried out using a multi-start approach with random parameter values for each start. Likewise as was the case with the IDM model, all calibrations ended with a warning from MATLAB that a possible local minimum was found since the first-order optimality was above zero [27]. None of the calibrations was ended because of a limit in iteration. To test the reliability of the results, the best parameter values were reused as starting point in a new calibration. This resulted in the same parameter values and first-order optimality, reducing the chance of having found a local minimum. However, it is still possible that the measurement data does not have enough information for adequately calibrating the IDM model since the validation was not carried out satisfactory. Therefore future research should investigate whether enlarging the scenarios leads to better results.

5-2-2 Parameter validation

In this section the values for $\tau$, $\kappa$, $\eta_{\text{low}}$, and $\eta_{\text{high}}$ are first discussed. These four parameters are of importance for the reproduction of traffic jams, because they are used in the anticipation term in Eq. (2-2). The value of $\phi_m$ was expected to be lower than calibrated and will be discussed secondly.

The value for $\kappa$ should be sufficiently low to have the correct sensitivity for increasing densities and thus be able to predict incoming shock waves at the moment described in the measurements and not minutes after. A high value for $\kappa$ makes the anticipation term less curved, which can be seen in Fig. 5-8(b). The mathematical explanation is that the point where the denominator is zero and the anticipation term would be infinite, is shifted to even more negative values of the densities. The hyperbolic curve of the anticipation term is shifted to the left and the relevant part, which consists only of positive densities, is less curved. From the data it was found that the density can change from 20 veh/h/lane in a certain segment to 73 veh/h/lane in the adjacent segment at the beginning of a shock wave. This means that the anticipation term should be able to predict a negative change in the average speed sufficiently high to accomplish this increase in density. However, since the anticipation term is dependent on other parameters as well, these will be discussed first.
The values for $\eta_{\text{low}}$ and $\eta_{\text{high}}$ indicate how large the change in average speed per time step should be as a result of anticipation. The change in average speed is linearly dependent on $\eta_{m,i}(k)$ as can be seen from Eq. (2-2). For the calibrated parameter values the reaction at the entrance of a jam is almost four times higher as compared to the reaction when leaving a jam. This mainly comes from the fact that an average vehicle cannot accelerate as much as it can decelerate by breaking. But the slow-to-start rule as described by Barlovic et al. [3] can also play a role as stated by Hegyi [13].

The high value of the calibrated $\tau$ in comparison with the alternative parameter values reduces the anticipation term with a factor of roughly four. The differences in $\eta_{\text{low}}$, $\eta_{\text{high}}$, and $\tau$ thus more or less cancel out against each other. Fig. 5-8 depicts the net effect of the different parameter values. In this figure the change in average speed as a result of the anticipation term with respect to the current density is depicted for the calibrated parameter values and the parameter values from [13]. It can be seen that for densities above the critical density, $\rho_{\text{cr},m} = 26.07 \text{ veh/km/lane}$, the values are comparable, although the parameter values from [13] prescribe a slightly smaller magnitude. However, for lower densities the magnitude of the change in average speed is prescribed higher by the calibrated parameter values. If the current segment is occupied with a density below 20 veh/km/lane the calibrated parameter values thus prescribe a higher amount of anticipation than the parameter values from [13].

Another effect of the high value of $\tau$ is that the effect of the relaxation term is being reduced in comparison with the two alternative parameter values. This means that the drivers take a longer time to accelerate to the desired velocity. It is difficult to say if this originates from a high amount of heavy duty trucks since no information is given in the data about the vehicle types distribution. The value for the free-flow speed, $v_{f,m}$, is also a little bit lower than the static speed limit on the freeway which can be another sign of possibly a high amount of heavy duty trucks.
5-2 Calibration and validation of the METANET model

When evaluating the calibration scenario with all the three sets of parameter values given in the previous section, it was found that the simulations with the two alternative sets of parameter values do not result in an adequate prediction of the measured shock wave. This is depicted in Fig. 5-9 for the parameter values of the Dutch Governmental Department for Infrastructure and Environment (RWS). The flow that enters the stretch of freeway drives with an almost constant speed until the end of the stretch is reached. If the flow at the upstream end of the freeway is lower in the measurement data because the shock wave arrives at that point, less vehicles are let in. The vehicles that are still let in can accelerate because the density is low. The effect is that a region of low density and low flow travels down the stretch of freeway. In the figure, the region of low flow therefore has the same direction as the little variations in the rest of the

Figure 5-9: Simulated flow and average speed for the first two hours of the calibration scenario with parameter values from RWS using the METANET model. The region of low flow starting at $t = 1.6$ h in (a) has the same direction as the small variation in the rest of the scenario in contradiction to Fig. 5-10(a). This shows that the METANET model is unable to predict shock waves when using the parameter values from RWS.

5-2-3 Visual inspection
Results and discussion

Time (h)  Distance (m)  (veh/h/lane)

0 0.2 0.4 0.6 0.8 1 1.2 1.4 1.6 1.8 0

(a) Flow

(b) Speed

Figure 5-10: Simulated flow and average speed for the first two hours of the calibration scenario with the calibrated parameter values using the METANET model. In this figure, the shock wave is correctly simulated, starting at $t = 1.5\, \text{h}$ at the downstream end of the freeway.

As can be seen from the Fig. 5-10 the shock wave is actually predictable by using the calibrated parameter values. This means that the shock wave can be simulated when triggered by certain traffic conditions at the downstream end of the stretch of freeway. This can be seen by the fact that the region of low flow has another direction than the rest of the scenario: the shock wave is travelling in opposite direction of the traffic. In other words, a high density is first observed at the downstream end of the stretch of freeway and causes the traffic flow to stagnate until the upstream end of the stretch of freeway is affected. Being able to predict a shock wave in advance is especially important in on-line settings where it is wanted to suppress the shock wave.

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5-2 Calibration and validation of the METANET model

<table>
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<tr>
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<th>$U_{bias}$</th>
<th>$U_{var}$</th>
<th>$U_{cov}$</th>
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<td>Speed</td>
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Table 5-6: Values of Theil’s inequality for two evaluations of the METANET model

<table>
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<tr>
<th>Scenario</th>
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<th>VAF %</th>
<th>Calibration</th>
<th>Literature [13]</th>
<th>RWS</th>
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<tr>
<td>Validation</td>
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Table 5-7: Values of the VAF for the calibration scenarios and the validation scenario simulated by the METANET model.

<table>
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<tr>
<th>Scenario</th>
<th>Error measure</th>
<th>Calibration</th>
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Table 5-8: Values of the error measure for the calibration scenarios and the validation scenario simulated by the METANET model.

5-2-4 Methodological validation

The methodological validation of the METANET model is carried out using Theil’s inequality and the VAF. The value for $U$ should be below 0.2 for the model to pass the validation. As can be seen from Table 5-6 the METANET model with the calibrated parameter values gives much lower values for $U$. Therefore it can be concluded that the calibrated parameter values are valid to be used in the METANET model to simulate the A12. Since the value for $U$ is very low, it is unnecessary to examine the three components of the inequality.

Table 5-7 confirms the conclusions that can be drawn by examining Theil’s inequality. The VAF for the calibration scenario and the parameter values resulting from the calibration is almost 100%. Also, the VAF for the validation scenario gives values of almost 100%, except for the flow as predicted by the parameter values of RWS. The value of 84.5% is however still very good.

The values of the error measure that is used in the calibration process are presented in Table 5-8. Since the shock wave is only a small portion of the whole scenario, the difference between the values of the error measure is quite small.

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5-2-5 Discussion

The results in this section state that the calibration and the validation of the METANET model have been successful. Most of the differences between the calibrated parameter values and the parameter values from [13] and RWS could be led back to the fact that the amount of anticipation on the A12 is higher than found by Hegyi [13] or RWS.

The visual inspection exposed the fact that the METANET model is able to correctly predict shock waves. Theil’s inequality shows that the match between the measurement data and the simulation data is equal for the calibration scenario and the validation scenario. The values for the VAF, however, show that the variance of the error between the measurement data and the simulation is somewhat higher for the validation scenario. This is however normal since the content of the scenarios differ.

5-3 Conclusions

In this chapter the results of the calibration and the validation of the IDM model and the METANET model were presented. The simulation of the IDM model with the calibrated parameter values and the validation scenario resulted in a large error with respect to the measurement data. Improving the quality of the calibration can be done in multiple ways. Further research should first focus on increasing the size of the scenario to multiple days. It is possible that the day of the calibration had unusual weather or was busier than other days.

Also, four of the eight parameters had a large difference with respect to the alternative set of parameter values. By analysing the differences and the effect of different values it was found that the error between the measurement data and the simulation data can be reduced by setting the values for $d_0$, $\alpha$, and/or $T$ lower. However, since the calibrated value for $T$ is already very low, it was suggested to research the effect of changing the value of $T$ depending on one of the variables in the equation for the desired speed. This can presumably give the IDM model a higher capacity flow while at the same time preserving the sensitivity to shock waves.

An important point that was found in the calibration and validation of both the IDM model and the METANET model was a high amount of anticipation. For the IDM model this was observed in the high value for $b_\alpha$ and for the METANET model this was observed in the low value for $\kappa$.

The simulation of the METANET model with the calibrated parameter values and the validation scenario resulted in a small error between the simulation data and the measurement data. The good result is confirmed by the low value for Theil’s inequality and the high percentages of VAF. In the comparison of the parameter values with alternative sets of parameter values it was found that the major differences can be led back to the aforementioned higher anticipation. The METANET model with the calibration scenario with the calibrated parameter values is able to correctly predict the shock wave seen in the measurement data.
In this chapter the conclusions of this thesis project and some recommendations for future research will be discussed. The conclusions will be referring to the problem statement as given in Chapter 1 but also pointing towards the greater goal of improving the quality of Traffic Management Systems (TMSs).

Each of the following sections is started with an enumeration of the conclusions or recommendations after which each item is elaborated.

6-1 Conclusions

In this section the conclusions of the thesis will be discussed. The first part of this thesis project focused on a method for converting microscopic data to macroscopic data and vice versa. The conclusions of this part will be discussed in Section 6-1-1. The second part focused on the calibration and validation of the IDM model and the METANET model. The conclusions of this part will be discussed in Section 6-1-2

6-1-1 Traffic data conversion

The method for converting microscopic data to macroscopic data should be computationally lightweight such that it can be used in an on-line application and also give accurate results. The density averaging method was selected since it gives accurate results and is the most computationally lightweight of the three researched methods.

- The first reason for selecting the density averaging method is that it is as accurate as the flow averaging method and more accurate than the detector mimicking method. The accuracy was researched by comparing the results of the detector mimicking method and the flow averaging method. The density averaging method
and the flow averaging method show a higher accuracy than the detector mimicking method, especially during low flow. Furthermore, the difference between the density averaging method and the flow averaging method is very low compared to the differences between the density averaging method and the detector mimicking method. Based on the methodologically significant difference between the two averaging methods, a not negligible difference in the result was expected. The density averaging method first calculates the density in a way that is cumbersome if not impossible to implement in the real-world and also approximates the flow. The flow averaging method converts the position data in a similar way as is done by real-world loop detectors. Since, however, the difference between the flow averaging method and the density averaging method is low, it can be concluded that the density averaging method can be used in the envisioned feedback structure or a TMS.

- The second reason for selecting the density averaging method is that the computation time of the density averaging method is the lowest of all three researched conversion methods. The method can easily be used in the off-line version of the envisioned structure where the IDM model is used as a surrogate of the real-world. However, traffic data conversion cannot yet directly be used in on-line applications where the IDM model is used in a Model Predictive Controller (MPC). This is of interest since it would increase the accuracy of predicting emissions since information about individual vehicles is known. The simulation of the IDM model and the conversion of the data for 2 hours and 6 detectors consumes 10.6 seconds. This computation time can also be assumed for situation where a TMS is used since normally a shorter time span but more detectors are used. An MPC thus needs around 10 seconds for each iteration that is necessary in the optimization of the control measure. The number of iterations can easily become higher than 6 and the time for computing a control measure more than a minute. Since it is desired to compute a new control measure every minute, the usage of microscopic models is not yet possible for a TMS that uses a MPC and a computer similar to the one used for this thesis project. Of course, the current state of art for parallel computing can help, however, taking costs into account, using microscopic traffic flow models is not yet within reach. Nevertheless, current TMSs that do not use on-line optimization techniques can actually use the conversion methods discussed in this thesis, so that the calculation of emissions can be improved.

6-1-2 Calibration and validation

The second main part in this thesis project deals with the calibration of the IDM model and the METANET model. As stated in the problem statement the calibration should result in a set of parameter values which yields the lowest possible value for the error measure. It can be concluded that the IDM model is calibrated properly but not validated satisfactory and the METANET model is calibrated and validated properly.

- The validation of the IDM model showed that the model in combination with
parameter values found in the calibration is not able to handle different kinds of scenarios. The reason for the low performance in the validation can be that the capacity flow in the calibration scenario is different from the capacity flow in the validation scenario. It is thus possible that the sensitivity of the IDM model is calibrated too high. Directions on how to handle this issue are given in the next section.

- The calibration as well as the validation of the METANET model were both successful. Although differences were found between the calibrated parameter values and the benchmark parameter values, the overall behaviour was similar because some of the differences were neutralised by other differences in parameter values. The value for $\kappa$ is very low in comparison with the benchmark parameter values. The parameter $\kappa$ is used in the anticipation term as well as the parameter $\tau$; the value for $\tau$ is higher than the benchmark parameter values. The effect is that the overall result of the anticipation term is similar to the result with the benchmark parameter values except for low densities where a higher amount of anticipation is found. However, this is no reason to reject the parameter values since for the IDM model also a higher amount of anticipation was found. The parameter values found in this project can be used in the METANET model to simulate the A12 in a TMS or other studies. The parameter values can also be used in conjunction with a on-line TMS in the envision feedback structure.

6-2 Recommendations for future research

During the thesis project several issues were found which should be investigated in future work. The recommendations are: narrow the view of the averaging methods, investigate suitability of using an harmonic mean for the density averaging method, investigate the validity of the conversion methods, extend the IDM model for capacity drop and for a deceleration limit and for on-ramps and off-ramps, use multi-lane and multi-class features for both the IDM and the METANET model, and increase the size of the scenarios both in time and in space. Also more in general some recommendations for TMSs are discussed at the end of this section.

- The density averaging and flow averaging method use the whole segment after the loop detector to calculate the density, flow, and average speed for the segment. In the detector mimicking method, only vehicles that pass the loop detector are used in the calculation of density, flow, and average speed. In other words, the view of the averaging methods is much wider than the view of the detector mimicking method. Future research should be carried out on the question whether the density averaging method can be improved in accuracy if the view is, so to say, narrowed down to a region around the detector. In the density averaging method this means that the selection criteria for finding the vehicles in a segment is changed. For example the downstream bound is shifted to halfway the current detector and the next downstream detector and the upstream bound is shifted similar but in the
Conclusions and future research

upstream direction. Another example is to have the bounds a certain distance away from the detector to maintain symmetry, which is presumably better.

An even more sophisticated option is to use a weighted average. The aforementioned selection criteria can be used, however vehicles that are further away from the detector are weighted less in the calculation of the density and average speed. This can possibly be accomplished by using convolution or other filtering techniques.

- The substantial difference between the flow averaging method and the density averaging method touches the fact that the density averaging method uses the arithmetic mean to calculate the average speed. Since the samples used for calculating this average are all on the same time step, a space-mean is calculated. To be able to compare the space-mean speed with the time-mean speed data from the measurements an harmonic mean should be used.

- The validity of the conversion methods should be researched by simulating several scenarios other than the calibration and validation scenario. In this project, it was inconclusive to compare the results of the conversion methods with the measurement data since the error between the simulation and the measurement data was a factor 10 higher than the differences between the conversion methods. By examining different scenarios of possibly other freeways and using a Root-Mean-Square error measure or Theil’s inequality, the validity of the conversion methods can be confirmed. Also, the selection of proper scenarios is important in this topic. Future research should consider using multiple scenarios altogether; varying in the number of shock waves and varying in the average flow, density, and speed. Especially a scenario with a low flow is of interest since the detector mimicking method has a low performance for low flows. Calibrating such a scenario can increase the quality of the parameter values which makes comparing the result of the conversion methods with the measurement data more conclusive.

- Extending the IDM model was put forward in the discussion on the calibration and validation of the IDM. The idea behind this is the mismatch between capacity flow of the calibration scenario and the validation scenario. The discussion concentrated around the parameter for safe headway time, $T_\alpha$, since this parameter has a large influence on the desired distance. The value of this parameter can be altered based on the approach rate, the sign of the approach rate, or the speed of the vehicle. Future research should be carried out to find out whether one of these extensions to the IDM model can increase the flexibility of the IDM model such that it can adequately simulate both the calibration scenario which includes a shock wave and the validation scenario which has a higher capacity flow.

- A nice feature of the IDM model is the limit on acceleration since it is very realistic. However, the deceleration does not have a limit. Future research should answer the question if the IDM model can be improved by including a tangent or sigmoid function in the equation for the acceleration. By doing so, the acceleration is bounded below and above in a smooth fashion. The smoothness reflects the fact that is less convenient to accelerate or decelerate at extremes.
Note that the limit for acceleration is of smaller magnitude than the limit for deceleration. Also note that for the METANET model a limit for acceleration or deceleration is not relevant since the model uses the average speed of a whole segment, the acceleration of a single vehicle can thus differ from the change in average speed of the whole segment.

- The IDM model used in this thesis project is not capable of handling on ramps and off-ramps. Helbing et al. [15] use a micro-macro link for this purpose. However, future research should answer the question whether it is possible to extend the IDM model so that it is able to simulate on ramps and off ramps without converting to macroscopic data.

- The IDM model used in this project does not account for multi-lane freeways. Making the IDM capable of simulating multiple lanes involves introducing a model for overtaking [19]. In this light it is also meaningful to include other types of vehicles, for example heavy duty trucks. The METANET model is already capable of simulating multi-lane freeways and was extended for multi-class vehicles by Deo et al. [11], however, this was not used in this project. To keep both models as close as possible to each other and to the real-world, both models should be used with the multi-lane and multi-class features.

- The scenarios for the calibration and validation did not include on-ramps or off-ramps. Although the IDM model and the METANET model are both able to properly simulate shock waves without the on ramps, more reliable results can be acquired if including on-ramps and off-ramps since these are a typical source of shock waves [13].

Some more general recommendations for improving the quality of TMSs can be to use on-line calibration and to investigate the including of acceleration for macroscopic traffic flow models. By using on-line calibration is might be possible to overcome the risk of calibrating a traffic flow model towards a specific day with for example strong wind or heavy rain. Using on-line calibration, the parameter values can be updated on a regular basis making TMSs more adaptive. The frequency of parameter values update should of course not be too high in order to neglect the influence of accidents and the like.

Since it was concluded that it is not yet within reach to use a microscopic traffic flow model in an MPC it might be interesting to investigate the including of acceleration for macroscopic traffic flow models. Lebacque and Lesort [25] pose an interesting question on this topic: whether the acceleration of vehicles can be assumed to be within certain bounds. If it is possible to include a notion of the average acceleration, the quality of macroscopic emission models can be increased since the acceleration has a large influence on the emissions.
Appendix A

Measurement data

A-1 Calibration Scenario

Figure A-1: Flow from the measurements
Figure A-2: Density from the measurements

Figure A-3: Speed from the measurements

Figure A-4: Flow from the measurements, zoomed in to the shock wave
Figure A-5: Density from the measurements, zoomed in to the shock wave

Figure A-6: Speed from the measurements, zoomed in to the shock wave
### A-2 Validation Scenario

**Figure A-7:** Flow from the measurements

**Figure A-8:** Density from the measurements
Figure A-9: Speed from the measurements
Appendix B

Simulation results of the IDM model

B-1 Calibration Scenario

![Diagram showing simulation results of the IDM model](image)

**Figure B-1:** Flow as a result of time and space for an evaluation of IDM model
Simulation results of the IDM model

Figure B-2: Density as a result of time and space for an evaluation of IDM model

Figure B-3: Speed as a result of time and space for an evaluation of IDM model

Figure B-4: Error in flow between the data and an evaluation of IDM model
Figure B-5: Error in density between the data and an evaluation of IDM model

Figure B-6: Error in speed between the data and an evaluation of IDM model
B-2 Validation Scenario

**Figure B-7**: Flow as a result of time and space for an evaluation of IDM model

**Figure B-8**: Density as a result of time and space for an evaluation of IDM model
Figure B-9: Speed as a result of time and space for an evaluation of IDM model

Figure B-10: Error in flow between the data and an evaluation of IDM model

Figure B-11: Error in density between the data and an evaluation of IDM model
Simulation results of the IDM model

Figure B-12: Error in speed between the data and an evaluation of IDM model
Appendix C

Simulation results of the METANET model

C-1 Calibration Scenario

Figure C-1: Flow as a result of time and space for an evaluation of METANET model
Simulation results of the METANET model

**Figure C-2:** Density as a result of time and space for an evaluation of METANET model

**Figure C-3:** Speed as a result of time and space for an evaluation of METANET model

**Figure C-4:** Error in flow between the data and an evaluation of METANET model
Figure C-5: Error in density between the data and an evaluation of METANET model

Figure C-6: Error in speed between the data and an evaluation of METANET model
C-2 Validation Scenario

Figure C-7: Flow as a result of time and space for an evaluation of METANET model

Figure C-8: Density as a result of time and space for an evaluation of METANET model
Figure C-9: Speed as a result of time and space for an evaluation of METANET model

Figure C-10: Error in flow between the data and an evaluation of METANET model

Figure C-11: Error in density between the data and an evaluation of METANET model
Simulation results of the METANET model

Figure C-12: Error in speed between the data and an evaluation of METANET model


**List of Acronyms**

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<th>Definition</th>
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<td>IDM</td>
<td>Intelligent Driver Model</td>
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<tr>
<td>METANET</td>
<td>Modèle d’Ecoulement du Trafic Autoroutier: Network</td>
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<td>MPC</td>
<td>Model Predictive Controller</td>
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<td>RMS</td>
<td>Root-Mean-Square</td>
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<td>Traffic Management System</td>
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<td>VAF</td>
<td>Variance-Accounted-For</td>
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<td>RWS</td>
<td>the Dutch Governmental Department for Infrastructure and Environment</td>
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### List of Symbols

- $k$: Time step (-)
- $L_{m,i}$: Length of segment (km)
- $T$: Length of time step (h)
- $v_{f,m}$: Free-flow speed of link (km/h)
- $\phi_m$: Parameter for fundamental diagram (-)
- $\lambda_m$: The number of lanes in a link (-)
- $\kappa$: Offset density in anticipation term (veh/km/lane)
- $\eta_{m,i}(k)$: Acceleration factor in anticipation term (km$^2$/h)
- $\eta_{flow}$: Acceleration factor for a negative spatial density gradient (km$^2$/h)
- $\eta_{high}$: Acceleration factor for a positive spatial density gradient (km$^2$/h)
- $\tau$: Time constant for changing speed (h)
- $\alpha$: Compliance to speed limit (-)
- $O_n$: Outgoing links for node (-)
- $I_n$: Incoming links for node (-)
- $N_m$: Number of segments (-)
- $\rho_{m,i}(k)$: Density for segment and time step (veh/km/lane)
- $q_{m,i}(k)$: Flow for segment and time step (veh/h/lane)
- $v_{m,i}(k)$: Space-mean speed in segment for time step (km/h)
- $v_{lim,m,i}(k)$: Speed limit (km/h)
- $d_o(k)$: Demand flow for origin (veh/h/lane)
- $q_o(k)$: Flow from origin (veh/h/lane)
- $Q_{max,o}$: Maximum flow from origin (veh/h/lane)
- $q_{max,o}(k)$: Maximum flow from origin after calculation (veh/h/lane)
- $\rho_{max,m}$: Maximum density at origin (veh/km/lane)
- $w_o(k)$: Length of waitint queue at on-ramp (-)
- $r_o(k)$: Ramp-metering rate at on-ramp (-)
- $V(\rho_{m,i}(k))$: Desired velocity for given density (km/h)
- $Q_u(k)$: Flow through node (veh/h/lane)
- $\beta_{n,m}(k)$: Splitting rate at node to link (-)
- $\rho_{cr,m}$: Critical density (veh/km/lane)
- $s_\alpha$: Distance to predecessor (m)
- $\Delta v_\alpha$: Approach rate to predecessor (m/s)
- $v_\alpha$: Speed of vehicle (m/s)
- $s^*_\alpha(v_\alpha, \Delta v_\alpha)$: Desired distance to predecessor (m)
- $d_{0,\alpha}$: Parameter for distance during jams (m)
- $d_{1,\alpha}$: Parameter for distance during jams (m)
- $a_\alpha$: Maximum acceleration (m/s$^2$)
- $b_\alpha$: Desired deceleration (m/s$^2$)
- $T_\alpha$: Parameter for safe time headway (s)
- $v^*_\alpha$: Parameter for desired free flow velocity (m/s)
- $x_\alpha$: Position of vehicle (m)
- $\dot{v}_\alpha$: Acceleration of vehicle (m/s$^2$)
- $l_\alpha$: Length of vehicle (m)
\( \delta_{a} \) : Acceleration exponent (-)

\( t \) : Length of a timestep in the IDM model (s)

\( k \) : Microscopic time step (-)

\( N_{\text{cross},d} \) : Number of vehicles crossing a detector in the last macroscopic time step (-)

\( N_{\text{seg},d}(k) \) : Number of vehicles present in the segment after a detector during a microscopic time step (-)

\( L_{d} \) : Length of the segment after a detector (km)

\( \hat{h}_{c} \) : Time head way for a given vehicle (s)

\( \bar{q}_{d} \) : Flow through a segment after conversion (veh/h)

\( \bar{v}_{d} \) : Average speed in a segment after conversion (km/h)

\( v_{d}(k) \) : Average speed in a segment at one time step (km/h)

\( \rho_{d}(k) \) : Density in a segment after conversion (veh/km)

\( N_{k} \) : Number of timesteps in a simulation (-)

\( N_{d} \) : Number of detectors in a simulation (-)

\( E_{\text{RMS}, \text{norm}} \) : Error of a simulation (-)

\( Q_{\text{sim},j} \) : Flow from a simulation (veh/h/lane)

\( Q_{\text{dat},j} \) : Desired flow for a simulation (veh/h/lane)

\( V_{\text{sim},j} \) : Speed from a simulation (km/h)

\( V_{\text{dat},j} \) : Desired speed for a simulation (km/h)

\( \sigma_{\text{sim}} \) : Standard deviation in simulation data (veh/h/lane or km/h)

\( \sigma_{\text{dat}} \) : Standard deviation in measurement data (veh/h/lane or km/h)

\( \bar{X}_{\text{sim}} \) : Values from simulation data (veh/h/lane or km/h)

\( \bar{X}_{\text{dat}} \) : Values from measurement data (veh/h/lane or km/h)

\( \overline{\bar{X}}_{\text{sim}} \) : Mean value of simulation data (veh/h/lane or km/h)

\( \overline{\bar{X}}_{\text{dat}} \) : Mean value of measurement data (veh/h/lane or km/h)

\( X_{\text{sim},j} \) : Element from simulation data (veh/h/lane or km/h)

\( X_{\text{dat},j} \) : Element from measurement data (veh/h/lane or km/h)

\( \rho \) : Correlation coefficient (-)

\( U \) : Theil’s inequality (-)

\( U_{\text{bias}} \) : Theil’s inequality decomposed for bias (-)

\( U_{\text{var}} \) : Theil’s inequality decomposed for variance (-)

\( U_{\text{cov}} \) : Theil’s inequality decomposed for covariance (-)

\( \text{VAF} \) : Variance-Accounted-For (-)

**List of Subscripts**

\( m \) : Link index (-)

\( \mu \) : Secondary link index (-)

\( i \) : Segment index (-)

\( n \) : Node index (-)

\( o \) : Origin index (-)

\( i - 1 \) : Upstream segment (vehicles already past it) (-)

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- \( i + 1 \) Downstream segment (vehicles did not yet enter it) (-)
- \( N_m + 1 \) Virtual segment after link (-)
- \( 0 \) Virtual segment before link (-)
- \( \alpha \) Current vehicle (-)
- \( \alpha - 1 \) Leading vehicle (-)
- \( d \) Detector index (-)
- \( c \) Car index (-)
- \( j \) Index for simulation results (-)