Researching the possibility to calibrate a PARAMICS model with a phase-based algorithm.

With the purpose of generating simulated trajectories which can be used for microscopic traffic emission predictions.
Calibrating a traffic microsimulation model with a phase based algorithm to make the trajectories suitable for traffic emission predictions.

September 9th 2009

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Preface

This report is written within the scope of the master thesis (CT5060) of the Delft University of Technology, faculty of Civil Engineering in the Netherlands. The thesis is mainly performed at the Institute for Sustainable Systems and Technologies – Transport Systems of the University of South Australia. The thesis is a graduation project to obtain a Master’s degree in Civil Engineering at the Delft University of Technology. In this project is tried to calibrate the traffic microsimulation model PARAMICS with a phase-based algorithm and probe vehicle data. The general idea behind this calibration is to generate simulated trajectories which can be used for traffic emission predictions.

During the process of writing this thesis I tried to stick to a quote of Albert Einstein which I found in one of the books I used for my literature research (Klemens, 2009): “Make everything as simple as possible, but not simpler.” Although writing scientific proper, and above all readable report is quite a challenge for me, I hope that I managed to create a report which is worthy of reading by those who are interested in the topic.

During the work on the thesis I received a lot of direct and indirect support from people. This varies from receiving help with respect to the content, to people who said hello while I was running simulations in the middle of the night. All were valuable to me, but I want to extricate some people here in the preface to express my gratitude to them for supporting me.

I would like to start with thanking my graduation committee for all the work they have done over past months. The chair of my committee, Serge Hoogendoorn, for helping me in many ways besides his function as chairman of the committee, from helping me to do my final examinations a bit earlier to bringing me in contact with the ISST-TS people in Adelaide. My daily supervisor from the TUDelft, Hans van Lint, for helping me focus on the key elements of my research, and writing it in clear sentences. This helped me tremendously to converge it all to a proper end result. And last but certainly not least Rocco Zito, my host and daily supervisor at the TSC. He helped me a lot, especially with matters regarding the Drive Cycle Splitter. Besides that he made sure that I enjoyed my time at the Transport Systems group. For all of this and much more I am very grateful towards my supervisors.

I also enjoyed it very much to be part of the Transport Systems team for nearly half a year. I want to thank everybody for the all the scientific input, but even more for the social small talk during coffee breaks or Friday afternoon beers. There are two people who I want to mention in particular: Nikolaos Vogiatzis and Branko Stazic. Nik for helping me with my endless database questions and attempts to automate the data analysis further and further. My roommate Branko for sharing all his PARAMICS knowledge with me, but especially for being a great roommate day after day.

Everybody who knows me a bit knows that writing is, opposite to talking, not my strongest feature. Therefore I would like to thank my former 4.42 roommates Maaikele Köenis and Dirk van der Meer for reading my draft versions and providing me with useful comments about how to improve my thesis. Besides that, they were together with Olga Huibregtse fabulous roommates during the time I was preparing my trip to Australia in Delft.

Finally I want to thank my family and girlfriend. My parents and sister for their unconditional faith and support towards me during my long and not always smooth journey at the TUDelft. Where
others would have walked out on me, they kept being there for me, which is enormously appreciated. And as my dad would say in Dutch, and which turned out to be true: “de aanhouder wint” (“the stickler wins”). The last person I want to thank is my girlfriend Lotte. She has been my biggest support during this whole adventure. Although living apart for over five months is big sacrifice, she always encouraged me to chase my dream and write my thesis partly abroad. Besides that she was always there as critical sounding board for me. Because of all of this, and much more I love her tremendously.

Frank de Groen

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Summary English

The goal of this MSc-thesis is to investigate the possibility of calibrating the microscopic traffic simulation model PARAMICS with a phase-based algorithm. The underlying principle is that once the PARAMICS-model is calibrated and validated, its trajectories can be used for the calculation of microscopic traffic emission predictions. This is studied because the ability to correctly predict traffic emissions on a microscopic scale is a valuable instrument with the ever stricter rules regarding traffic emissions.

Trajectories obtained from microsimulation traffic models, which are calibrated with standard and commonly used methods, are not suitable for the calculation of microscopic traffic emission predictions. These trajectories are correct, from a transport engineering view, since the durations and average speeds correspond with the reality. However these trajectories are not suitable, from a emission engineering point of view, as on a (sub)microscopic scale the distribution of characteristics like speed, acceleration and deceleration do not correspond with the reality.

The main problems with current simulated trajectories for traffic emission predictions on a microscopic scale are invalid durations and magnitudes for the different phases in comparison with recorded trajectories. Invalid trajectories can be explained through the use of fundamentally unsuitable car-following models, incorrect numerical implementations of the car-following models, or an inaccurate estimation of the driver behaviour parameters. The assumption in this research is that the driver behaviour parameters can be estimated properly through a phase-based calibration.

The aim is that this will result in valid simulated trajectories. For the determination of these phases in a trajectory a tool is developed by the Institute for Sustainable Systems and Technologies-Transport Systems (ISST-TS) called ‘Drive Cycle Splitter’. The splitter is used to split the trajectories into the six different phases.

The phase-based calibration is executed on a PARAMICS-model of the ‘Adelaide Central Business District’ to obtain suitable simulated trajectories, from this model. The traffic conditions that are simulated, are as observed during the morning peak hours. To calibrate the driver behaviour of the PARAMICS model, parameters are adjusted. The initial adjustments of the parameters are based on an analysis of the car-following model of PARAMICS. In this analysis it is determined which and how parameters need to be adjusted to get an improved match between the recorded and simulated trajectories by a literature and mathematical study. The result of this analysis is that the driver behaviour parameters headway, reaction factor and ‘acceleration-speed and deceleration-speed profiles’ are adjusted. Unfortunately it is not possible to adjust the aggression and the awareness of the vehicles in version 6.0 of PARAMICS. This is unfortunate since the analysis of the car-following model shows that these parameters have substantial influence on the car-following behaviour.

During this MSc thesis a methodology is developed to analyse if the adjustments to the driving behaviour parameters had the predicted and desired results. For this methodology it is required to make an initial set of runs with adjusted driver behaviour parameters. These adjustments are based on the analysis of the used car-following model. The results can be compared with FCTTDAS-data (microscopic data from a dataset which is collected with ISST-TS’s instrumented vehicle). The comparisons between the series of runs is based on error scores. An error score is calculated on two levels and in two ways. The first order error score is determined by the mean durations and mean...
magnitudes, while the second order error score is determined by the standard deviations of the of durations and magnitudes. The mean and standard deviation of the duration or magnitude are for each phase indexed with the values from the FCTTDAS-data as basis. With the first scoring method the difference between the indexed values of the FCTTDAS-data and the simulation are summed. To get an idea off the error distribution over the durations and magnitudes there is also a summation made of the squared difference. For all adjusted parameters a sensitivity analysis is made to find their local optimal value. After analysing all individual parameters, simulations with logical combinations of parameter adjustments are performed. Out of all these different series of runs the series with the lowest error score is selected, provided that the adjustments made can still be justified. The best performing series of runs scores significantly better than the default runs, but is still far from the desired outcome. It can be concluded that it was not possible to calibrate the PARAMICS-model to satisfaction within the given boundary conditions of this research.

As the conclusion of this thesis is that it is not possible to calibrate the PARAMICS-model to satisfaction, it seems not logical to start a validation. However, the validation is performed to investigate if the errors that occur after the calibration are consistent. If these errors are consistent the approach can be used for relative emission comparisons, even if the absolute emission calculations are not correct due to the fact that trajectories cannot be simulated optimally yet. Secondly, by analysing multiple trajectories of different drivers under further identical conditions, it has been concluded that the influence of the driver of the probe vehicle on the collected data is significant.

Finally this results in a set of recommendations for further research and practice. The recommendations are bipartite. The recommendations are divided in recommendations for similar research under improved conditions, and recommendations for additional research on this topic. A key component in both parts is the presence of a adequate dataset for calibration and validation, as this is necessary for the applied method as well as for an improved and more reliable result.

For further similar research under improved conditions to investigate the capability of traffic microsimulation models to generate trajectories which are suitable for traffic emission predictions, it is recommendable to use models where all driving behaviour parameters can be adjusted. Secondly a qualitative and quantitative good dataset for calibration and validation purposes is recommended for a reliable outcome.

For additional research on this topic, it would be desirable to research which car-following model gives the best results for a phase-based calibration of a traffic microsimulation model, under further similar circumstances. Next to this it is recommendable to derive the true optimal parameter settings of PARAMICS for which the phase-based calibration approach gives the most reliable predictions.
Het doel van dit afstudeerproject is de mogelijkheid onderzoeken of met behulp van een fasegebaseerd algoritme, het microscopisch verkeerssimulatie model PARAMICS gekalibreerd kan worden. De achterliggende gedachte is dat na deze kalibratie de trajectoriën afkomstig uit het PARAMICS model gebruikt kunnen worden voor de berekening van verkeersemisssies op microscopische schaal. Dit is onderzocht, omdat het vermogen tot het correct voorspellen van verkeersemisssies op een microscopische schaal een waardevol instrument is met het oog op de steeds strenger wordende regels ten aanzien van verkeersemisssies.

Trajectoriën die verkregen zijn uit microscopische verkeerssimulatiemodellen, die met beproefde methoden worden gekalibreerd, zijn niet geschikt voor de berekening van microscopische verkeersemisssies. Vanuit een verkeerskundig oogpunt zijn deze trajectoriën juist, aangezien grootheden zoals reistijden en gemiddelde snelheden overeenkomen met de realiteit. Maar vanuit een emissie oogpunt zijn de trajectoriën niet geschikt, omdat op een (sub)microscopische schaal de verdeling van eigenschappen zoals snelheid, acceleratie en vertraging niet overeenstemmen met de realiteit.

Het voornaamste probleem met de huidige gesimuleerde trajectoriën, die gebruikt worden voor het verspellen van microscopische verkeersemisssies, is een ongeldige duur en omvang van de verschillende fasen in vergelijking met de waargenomen trajectoriën. Ongeldige trajectoriën kunnen worden verklaard door het gebruik van fundamenteel ongeschikte auto-volg modellen, onjuiste numerieke implementaties van de auto-volg modellen, of een onjuiste schatting van de parameters die betrekking hebben op het rijgedrag. De veronderstelling in dit onderzoek is dat de parameters die betrekking hebben op het rijgedrag onjuist zijn. Deze zouden door middel van een fase gebaseerde kalibratie wel goed geschat kunnen worden. Het is de bedoeling dat dit zal resulteren in geldige gesimuleerde trajectoriën. Voor de bepaling van de verschillende fasen in een trajectorie is het Institute for Sustainable Systems and Technologies - Transport Systems (ISST-TS) een instrument ontwikkeld genaamd 'Drive Cycle Splitter'. Deze splitter wordt gebruikt voor opdelen van de trajectoriën in de zes verschillende fasen.

De fase gebaseerde kalibratie is uitgevoerd op het PARAMICS-model van het 'Adelaide Central Business District', om gesimuleerde trajectoriën te genereren. De verkeerscondities in de simulatie, zijn zoals waargenomen tijdens de ochtendspits. Voor het kalibreren van het rijgedrag van het PARAMICS model zijn een aantal parameters aangepast. De initiële aanpassingen van de parameters zijn gebaseerd op een analyse van het auto-volg model van PARAMICS. In deze analyse wordt bepaald welke en hoe de parameters moeten worden aangepast om tot een betere afstemming tussen de waargenomen en gesimuleerde trajectoriën te komen doormiddel van een literaire en wiskundige analyse. Het resultaat van deze analyse is dat rijgedragparameters zoals wigafstand, reactiefactor en 'acceleratie-snelheid en deceleratie-snelheid profielen' worden aangepast. Helaas is het niet mogelijk om de parameters agressie en bewustzijn in het auto-volg model in versie 6.0 van PARAMICS aan te passen. Dit is spijtig, omdat de analyse van het auto-volg model aantoont dat deze parameters grote invloed hebben op het auto-volg gedrag.

Tijdens dit afstudeerproject is een methodologie ontwikkeld om te analyseren of de aanpassingen aan de rijgedragparameters de voorspellede en de gewenste resultaten hadden. Voor deze methode is
het nodig om een initiële set met runs te maken met aangepaste rijgedragparameters. Deze initiële aanpassingen zijn gebaseerd op de analyse van het gebruikte auto-volg model. De resultaten kunnen worden vergeleken met de FCTTDAS-data (microscopische data van een dataset die is verzameld met een geïnstrumenteerd voertuig van het ISST-TS). De vergelijkingen tussen de reeksen van runs is gebaseerd op een foutscore. Een foutscore is berekend op twee niveaus en op twee manieren. De eerste fout score wordt bepaald door de gemiddelde duur en de gemiddelde grootte van de betreffende fase. Terwijl de tweede orde foutscore wordt bepaald door de standaarddeviatie van de duur en grootte van de betreffende fase. Het gemiddelde en de standaarddeviatie van de duur of grootte zijn voor elke fase geïndexeerd met de waarden uit de FCTTDAS-data als basis. In de eerste berekening vormen de gesommeerde verschillen tussen de geïndexeerde waarden van de FCTTDAS-data en de simulatie data de foutscore. Om een idee te krijgen van de foutverdeling over de duur en omvang is er ook een tweede foutscore berekend waarin de kwadraten van de geïndexeerde verschillen worden gesommeerd. Voor iedere aangepaste parameter is er ook een gevoeligheidsanalyse gemaakt om hun lokale optimale waarde te verkrijgen. Na een analyse van alle simulaties, waarin steeds een enkele parameter is aangepast, zijn logische combinaaties van parameteraanpassingen opgesteld en uitgevoerd. Uit al deze verschillende reeksen simulaties is de reeks simulaties met de laagste foutscore geselecteerd, op voorwaarde dat de veranderingen aan de parameters nog kunnen worden gerechtvaardigd. De best presterende reeks simulaties met aangepaste parameters scoort aanzienlijk beter dan de reeks simulaties met standaard parameterwaardes, maar benadert nog steeds niet het gewenste resultaat. Er kan dus geconcludeerd worden dat het niet mogelijk is om het PARAMICS model naar tevredenheid te kalibreren binnen de gegeven randvoorwaarden van dit onderzoek.

Aangezien het niet mogelijk is om het PARAMICS model naar tevredenheid te kalibreren binnen de gegeven randvoorwaarden van dit onderzoek, lijkt het niet logisch om een validatie uit te voeren. Toch is er een validatie uitgevoerd om te onderzoeken of de fouten die optreden na de kalibratie consistent zijn. Want als blijkt dat fouten die optreden consequent zijn kan de aanpak worden gebruikt voor relatieve emissie vergelijkingen, zelfs als de absolute emissie berekeningen niet juist zijn. Hetgeen te wijten is aan het feit dat gesimuleerde trajectoriën nog niet optimaal zijn. Ten tweede wordt in de validatie vastgesteld dat de invloed van de bestuurder van het meetvoertuig op de verzamelde gegevens significant is. Dit gebeurt doordat de analyse van meerdere trajectoriën van verschillende bestuurders onder verder identieke omstandigheden.

Ten slotte leidt dit tot een reeks aanbevelingen voor verder onderzoek of verdere toepassingen. Deze aanbevelingen zijn tweeledig. De aanbevelingen zijn onderverdeeld in aanbevelingen voor een soortgelijk onderzoek onder gunstiger omstandigheden, en aanbevelingen voor aanvullend onderzoek over dit onderwerp. Een cruciaal component in beide delen is de aanwezigheid van een adequate dataset voor de kalibratie en validatie, aangezien dit noodzakelijk is voor de toegepaste methode, alsmede voor een beter en meer betrouwbaar resultaat.

Voor verder soortgelijk onderzoek onder betere omstandigheden om te onderzoeken of verkeers microsimulatie modellen geschikt zijn voor het genereren van bruikbare trajectoriën voor het voorspellen van verkeersemissies, is het aan te bevelen om modellen te gebruiken waar alle rijgedragparameters kunnen worden aangepast. Ten tweede is een kwalitatieve en kwantitatieve adequate dataset voor kalibratie en validatie doebeleinden aanbevelen om een betrouwbaar resultaat te verkrijgen.
Voor aanvullend onderzoek over dit onderwerp, zou het wenselijk zijn om te onderzoeken welk autovolg model de beste resultaten geeft voor een fase gebaseerde kalibratie van een verkeers microsimulatiemodel onder verder gelijke omstandigheden. Daarnaast is het aan te bevelen om de optimale parameter instellingen van PARAMICS te vinden waarmee met de fase gebaarde kalibratie uiteindelijk de meest betrouwbare voorspellingen zijn af te leiden.
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## Glossary of abbreviations

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<th>Abbreviation</th>
<th>Full Form</th>
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<tr>
<td>API</td>
<td>Application Programming Interface</td>
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<tr>
<td>ADAS</td>
<td>Advanced Driver Assistance Systems</td>
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<td>ANOVA</td>
<td>ANalysis Of VAriance</td>
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<tr>
<td>BER</td>
<td>Base Emission Rate</td>
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<tr>
<td>BPR</td>
<td>Bureau of Public Roads</td>
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<td>CAAA</td>
<td>Clean Air Act Amendments</td>
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<td>CAFÉ</td>
<td>Clean Air For Europe</td>
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<tr>
<td>DOT</td>
<td>Department of Transportations</td>
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<tr>
<td>DTA</td>
<td>Dynamic Traffic Assignment</td>
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<tr>
<td>DVU</td>
<td>Driver Vehicle Unit</td>
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<tr>
<td>EPA</td>
<td>Environmental Protection Agency</td>
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<tr>
<td>EMFAC</td>
<td>Emission Factor</td>
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<tr>
<td>ESC</td>
<td>Emission Specific Characteristics</td>
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<tr>
<td>FCCTDAS</td>
<td>Fuel Cycle and Travel Time Data Acquisition System</td>
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<tr>
<td>GHR model</td>
<td>Gazis-Herman-Rothery model</td>
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<tr>
<td>GPS</td>
<td>Global Positioning Systems</td>
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<tr>
<td>HDM</td>
<td>Human Driver Model</td>
</tr>
<tr>
<td>IDM</td>
<td>Intelligent Driver Model</td>
</tr>
<tr>
<td>ISST-TS</td>
<td>Institute for Sustainable Systems and Technologies – Transport Systems</td>
</tr>
<tr>
<td>MOE</td>
<td>Measures Of Effectiveness</td>
</tr>
<tr>
<td>MOVES</td>
<td>MOter Vehicle Emissions Simulator</td>
</tr>
<tr>
<td>MPO</td>
<td>Metropolitan Planning Organisations</td>
</tr>
<tr>
<td>MOBILE</td>
<td>Mobile Source Emissions Factor</td>
</tr>
<tr>
<td>OCTAM</td>
<td>Orange County Transportation Authority’s Model</td>
</tr>
<tr>
<td>RSS</td>
<td>Root Sum Squared</td>
</tr>
<tr>
<td>TSC</td>
<td>Transport Systems Centre</td>
</tr>
<tr>
<td>UniSA</td>
<td>University of South Australia</td>
</tr>
<tr>
<td>VMT</td>
<td>Vehicle Miles Travelled</td>
</tr>
</tbody>
</table>

For a more extensive glossary the author would like to refer to the third edition of the Glossary of Austroads Terms (Milne, 2008)
Chapter 1: Introduction and research approach

Nature and environment are important subjects in society. In the civil engineering process they have become a major factor as well (Haarsma, 2008). This implies that alternatives within a project are not only evaluated on their technical, esthetical and financial scores, but also on their environmental score. In the Netherlands, for example, the so-called Environmental Effect Report (MER - Milieu Effect Rapportage) is a mandatory component for all large scale civil engineering projects. One of the criteria on which infrastructure projects are evaluated in such a MER, is the expected amount of specific traffic emissions attributed to the project. Figure 1.1 schematically illustrates how these traffic emissions contribute to global and local environmental, and societal problems caused by air pollution. With these predicted emissions project alternatives can be assessed and compared on the basis of for example specific emission thresholds.

Ex ante evaluations, such as the ones in MER studies, require the use of traffic (simulation) models, to deduce emission impacts from traffic operations. Until the nineties of the previous century, the main rationale of such an assessment stated that less vehicle kilometres lead to less emissions. However, the number of vehicle kilometres is not the only influence factor on the amount of emission discharge (Holman, 1998).

The ability to predict emissions correctly is necessary since there is an increasing interest to determine an environmental score for a road networks. Network alternatives can be tested, on their environmental score besides the other already existing ones such as costs and network performance. For existing networks, the ability to model the emission level can be a valuable tool because it has several advantages over real-time monitoring. The advantages or disadvantages depend on the network size and location, but the ability to test it from behind a desk instead of on location and the option to test adjustments in the network digitally before implementation are the two main advantages. Other advantages, like saving time and money, are derivatives of those two.

1.1 Current situation

In the current situation, as shown in figure 1.2, the process of estimating traffic emission using vehicle trajectories consists of two separate simulation steps. The first is simulating vehicle trajectories and the second is estimating emission levels out of these trajectories. From earlier studies it is known that the simulated trajectories are not yet fit to use without further processing, for most emission calculation purposes (Nesamani, 2005, De Groen, 2008).
In this study the focus lies on improving traffic simulation and emission models for urban areas, such that these can result in identifying parts in the network where lower levels of emission discharges can be reached. These lower levels of emission can be achieved in many ways, for example by varying the network layout, improving intersection control or by implementing other ITS (Intelligent Transport Systems) applications. Next to this, traffic microsimulation software can be used to generate time-space, time-speed and/or time-acceleration data for all individual vehicles in the study area. With these data it is possible to determine the emission discharge with a so-called micro vehicle emission model. An emission model can do this for each vehicle, per emission type, per time step. Why microsimulation software cannot be used as input for emission calculations is explained in section 1.2.

1.2 Problem analysis

In the current situation vehicle trajectories, for example obtained with a default parameter setting run of PARAMICS (a typical traffic microsimulation model) are not similar to vehicle trajectories measured in practice. As a result, the emission models fed with these incorrect trajectories produce incorrect emission values (De Groen, 2008). The simulated trajectories differ from the real trajectories in a number of ways, which becomes clear by comparing the time-distance and time-speed diagrams, depicted by figure 1.3 and figure 1.4 and described below.

The primary cause of the differences in the trajectories is a incorrect simulation of the acceleration and speed. On average the accelerations and speeds are correct as can be seen in figure 1.3, but figure 1.4 shows that duration and magnitude of the acceleration and speed are not. A secondary cause of the differences is that vehicles in microsimulation software (PARAMICS in this example) operate predominantly reactive instead of predictive, which can lead to strong jolting behaviour in the time-acceleration diagram (figure 1.4, visible between second 35 and 75). Since emission models
use these (wrong) speeds and accelerations as an input, their predictions (of the resulting emissions) will be invalid.

To improve traffic simulation and emission models for urban areas two major problems should be overcome. Below these two are described, together with possible solution directions.

Traffic microsimulation models typically do not produce valid vehicle trajectories. The reason for this, is that in most cases these microsimulation models are calibrated with macroscopic data (e.g. vehicle counts, average speeds or travel times). This means that they may produce valid macroscopic results, even if the underlying microscopic drive behaviour is incorrect. There are a number of approaches to validate these vehicle trajectories for use in emission models. First, one could improve the underlying mathematical models (e.g. car-following, lane changing models). Secondly, one could calibrate these models with microscopic data (Ossen, 2008). Alternatively, one could post-process the vehicle trajectories such that they represent actual vehicle trajectories better, for example by filtering.

If one wants to use data generated by microsimulation models on a microscopic level for predicting traffic emissions, it should be kept in mind that the data most probably contains errors on a (sub)microscopic level. Since generating flawless microscopic vehicle data is not yet possible as explained in the previous section, additional steps should be incorporated between the traffic and the emission models. These additional steps are necessary to overcome the impurities in the data, otherwise no accurate emission predictions can be made. There are chiefly two solution directions. The first one tries to make the data realistic by filtering out the errors, while the second one makes the emission models more robust so that the microscopic flaws have less influence on the emission predictions. Based on this second direction a method has been developed by the Transport System Centre to determine vehicle emissions (Zito, 2003). This approach is phase based, i.e. the trip of a vehicle is split into different phases like acceleration, deceleration, idle and cruise. For each phase, the emission discharge is calculated on the basis of its specific characteristics. The main advantage of this method is that microscopic errors in the vehicle data have less influence, because for the emission calculation is phase based, with the premise that the phase determination is correct (Zito, 2003).
1.3 Problem definition

In theory, linking transport simulation models and emission models is a promising idea with a lot of potential as mentioned in the introduction. Linking these models has been performed by Nesamani, with the same intention to be able to predict emissions of road traffic on specific link or a specific area. Nesamani concludes that microsimulation models may not accurately model acceleration or deceleration when compared to actual on-road vehicle activities (Nesamani, 2005). The poor performance of the microsimulation model regarding to the simulation of the human driving behaviour has three possible causes:

1. Car-following models are unsuitable for the generation of valid trajectories.
2. The numerical implementation of the otherwise correct car-following models is not properly done and causes the invalid trajectories.
3. Inaccurate estimation of the driver behaviour parameter which results in a poor performance of an otherwise correctly functioning car-following model.

The phase-based calibration developed by the ISST-TS is based on the assumption that main cause of the invalid trajectories is the incorrect estimation of the driver behaviour parameters. The problem lies in the fact that the traffic microsimulation models are generally calibrated with macroscopic data such as travel time and intensities. This results in an incorrect estimation of the driving behaviour on a microscopic level, because these parameters can only be estimated correctly with microscopic data. This incorrect estimation of the driving behaviour parameters results in an incorrect duration and magnitude of the phases. The incorrect durations and magnitudes results in invalid emission predictions.

Recapitulating this leads to the following problem definition:

“Linking traffic simulation models to emission models has a big potential, but without additional corrective measures, false and inaccurate emission predictions will occur as a result of the inferior performance of the traffic microsimulation model regarding to the aspect of generating output on a microscopic level.”

1.4 Research goal

After analysis of the problem definition, the goal of this thesis is formulated as:

“Acquiring insight into the behaviour of simulated trajectories and their errors, and determine if a PARAMICS model can be calibrated with a phase-based algorithm, so that the trajectories are suitable for reliable traffic emission predictions.”
1.5 Research questions

In order to solve the problem formulated in section 0 and to achieve the research goal of section 1.4, research questions have to be answered.

Research questions:

- How well do microsimulation traffic models, and in particular longitudinal driving behaviour and car following modules, perform with respect to generating trajectories which are suitable for traffic emission predictions?
- If unnatural behaviour occurs in the trajectories, what are the causes of these errors?
- What are the optimal parameter settings of PARAMICS for which the phase-based calibration approach gives the most reliable predictions?
- How well is the fit of the statistical distributions of the phases found in the simulated data in comparison with the distributions of the real life data?
- Is it possible to predict traffic emissions in urban areas, within the determined error margin, with the phase-based method?
- Are the errors in the emission predictions consistent? I.e. can the predictions still be used for relative performance comparisons even if the absolute prediction is not correct?

1.6 Research approach

For the research approach a second look is given to the current situation. Figure 1.5 shows the chronological steps with respect to traffic emissions until the current situation. It starts with the knowledge that traffic in a certain network produces a number of emissions. The second step is determining the amount of emissions with measure equipment. With properly calibrated equipment, a correct measurement of the emission levels is possible (hence the arrows are black and the measurement box is filled green). The third, and also the last step that can be accomplished correctly, shows the possibility to determine emission levels from recorded trajectories. Of course this is under the presumption that there were no significant measurement or recording errors during the data collection.

\[\text{Traffic in a network} \rightarrow \text{Emission produced}\]
\[\text{Traffic in a network} \rightarrow \text{Measure equipment} \rightarrow \text{Emission measurement}\]
\[\text{Traffic in a network} \rightarrow \text{Recorded trajectories} \rightarrow \text{Emission model} \rightarrow \text{Emission calculation}\]
\[\text{Simulated traffic} \rightarrow \text{Simulated trajectories} \rightarrow \text{Emission model} \rightarrow \text{Emission prediction}\]

\[\text{Figure 1.5: Chronological steps with respect to traffic emission until the current situation.}\]

The goal in this research is to acquire vehicle data from simulated traffic and use this as an input for the emission model. However if the same traffic situation, as the one recorded is simulated in a traffic microsimulation model and the corresponding trajectories are used for emission calculations, the emission predictions are incorrect. If the deviation of the mean duration and magnitude over the phase is incorrect, overestimation as well as underestimation of the traffic emissions can occur. The
second order effect of unnatural jolting behaviour in the second derivative of the trajectories always leads to an overestimation of the traffic emissions (De Groen, 2008).

In the case of the jolting behaviour, the problem can be reduced by decreasing the time step size. However with decreasing the time interval, the running time of a simulation will increase significantly. Besides that it is also not a real solution for two reasons. Mainly because of the distribution of the mean duration and magnitudes does not change significantly if the time interval decreases. And the incorrect deviation of the mean duration and magnitude is the main cause of the inaccurate predictions. Secondly because nothing changes to the (car following) model itself, only the numerical implementation changes. So although decreasing the time step seems to be a good opportunity, it is not improving the problem significantly. Besides that, one should bear in mind that decreasing the times step results in a longer computational time of the simulation. This makes it economically less feasible to simulate. So although decreasing the time step seems to be a good first step, in practice it is not.

Now it is clear that producing valid trajectories with traffic microsimulation models without additional measures is not possible yet, the solution should be found in these additional measures. These can be divided into two groups. The first is based on smoothing the trajectories into the correct shape. The second option is using an emission calculation approach with is less sensitive to unnatural behaviour in the trajectories. This second solution direction is based on the TSC's phase-based approach.

**Phase-based approach**

Input to the phase based approach, as shown in figure 1.6, are individual speed-time profiles. These are subdivided into periods, which belong to any of the following six phases:

1. Idle
2. acceleration from idle
3. deceleration to idle
4. intermediate acceleration
5. intermediate deceleration
6. cruise

Besides these six phases, there is also a null phase. The null phase is called error/indeterminate and contains the phases that did not match to the criteria of one of the other six phases. Once the trajectories are split up into the six types of phases, they are automatically filled in the accompanying emission functions. These functions, which exists for each phase type, are derived from an experimental set of emission data. This data is gathered through a substantial amount of tests with a dynamometer and real data collection (Zito, 2001). After the emission calculations of the individual phases are finished, they are combined again to determine the total amount of emissions of the selected trajectories (Zito, 2001).
1. Traffic simulation model runs.
2. Plugin selects acquired data.
3. Drivecyclesplitter splits trajectories up into the six different phases.
4. Phases duration and magnitude do not approach the reality within the set error margin.
5. Phases duration and magnitude do approach the reality within the set error margin.

Figure 1.6: TSC approach (based on Zito, 2001)

The results of the particular simulation are now compared with the results of real data. If the results match within a certain error margin the process ends and the calibration process of the traffic microsimulation model is completed. However if the results do not match, the process is started again with different parameters in the traffic simulation model. This iterative loop continues until the parameters are found which give a result within the error margin. It could however also be the case that none of the simulation runs will provide a match within the error range. In that case further research is necessary why the simulation runs did not converge to the desired outcome. The advantage of this method is the use of phases which makes it less sensible to minor deviations in the trajectories.

More detailed information about the algorithm and its use can be found in section 2.5 (splitting part) and 2.2.2 (emission part) of the literature study chapter.

1.7 Research outline

Several steps have to be taken to answer the research questions formulated section 1.5. The research project is divided in the following three steps once the research approach is determined:

1. Literature study
   - Overview of traffic microsimulation models with a special focus on car-following modules.
   - Overview of traffic emission models.
   - Overview of calibration methods of traffic simulation models with a focus on calibrating traffic microsimulation models on their longitudinal driving behaviour. Within this a special focus is made on the phase-based calibration.
   - Overview of the TSC splitting algorithm and emission functions.
   - Overview of probe vehicles.

2. Calibration & Validation
   - Assembling selection criteria for calibration.
   - Assembling selection criteria for validation, with special focus on the correct distributions of the phases.
   - Design/Select one or multiple test cases, for calibration and validation.
- Generating simulated datasets with different parameter settings and compare them mutually and with the actual FCTTDAS dataset.
- Evaluation of the results.

3. Evaluation of the project and results
   - Summarizing all results.
   - Conclusions.
   - Recommendations.

The relationship between the individual parts is shown by figure 1.7. The analysis methodology of the series of runs is already shown here, although the design of the methodology is dealt with in chapter 3.
Chapter 2: Literature study

Through performing a thorough literature study, existing theoretical knowledge is found about this topic. This is used as a theoretical basis for this thesis. This chapter starts with a section about traffic microsimulation models. The most important part of this section is the part where the different car-following modules are explained. This is because car-following models have, in urban areas, the biggest influence on the trajectories and their derivatives. And related to that also the biggest influence on their errors. Section 2.2 introduces the different types of traffic emissions and the programmes to calculate emissions. Section 2.3 introduces some available methods for calibrating traffic microsimulation models. The TSC approach uses probe vehicles to gather data. The concept of working with probe vehicles, their advantages and disadvantages will be explained in section 2.4. Although briefly earlier introduced in section 1.6, section 2.5 explains the phase detection and splitting algorithm in detail.

2.1 Microscopic traffic simulation models

In this section different car-following models are examined which are used in microsimulation models. Discussed are the relationships between their parameters, assumptions made and the errors in the resulting vehicle trajectories. Different microscopic traffic simulation models execute in essence the same job, but through relatively small differences, results acquired from different models can be quite dissimilar. Even with the same input, diverse outcomes can be found based on differences in theoretical concepts regarding the underlying modules, or difference in parameter settings. Due to that aspect it is important to understand what the different models do. Although PARAMICS is used in this thesis, which arises out of the fact that a great part of the thesis is done at the ISST-TS, it is important to know which other models are available and what kind of car-following models they use. The focus in this study lies on the car-following modules because this is believed to be the primary source of the irregular acceleration behaviour in congested urban areas. Although lane changing modules may also influences the trajectories, it is not believed that they contribute significantly to the inaccurate trajectories in urban areas. Therefore they are left out of the research scope of this thesis.

2.1.1 Traffic flow simulation models

Traffic flow simulation models are models which simulate traffic flows under user determined settings. These models are often used for assessing designs of new or adjusted road networks. Dynamic traffic management, flow optimizing and the training traffic managers are some applications of these models. This can often also be achieved by field research and field experiments of real-life traffic flows. However, apart from the scientific problem of reproducing such experiments, costs and safety are dominant aspects as well. The ability to perform an “unlimited” number of equal runs in a safe environment against relative low costs makes these models a very convenient tool. There is nevertheless a big possible pitfall; a correct calibration and validation of the model. If the model does not resembles the correct situation, the expected optimal solution could turn out to be a debacle once it is implemented. Traffic flow models can be categorised according to various criteria: level of detail, operationalisation and representation of the processes (Hoogendoorn, 2003). The categorisation into the three different levels of scale is however the most commonly used method:
Similar levels of scale can be found within the traffic emission models which will discussed in section 2.2. Since this study only uses microscopic models, only these are elaborated below.

**Microscopic models**

Microscopic is a term to describe the smallest parts in a model. In this research these parts are the individual vehicles. Microscopic models model the propagation of vehicles individually on the whole network, accounting for their variability and heterogeneity. Out of this propagation, information like travel times can be derived. Microscopic models have been developed with the main aim of simulating the movement of vehicles on the roads at the individual level. Each vehicle movement is determined through the simulated network infrastructure at fractions of a second. Interactions with other vehicles are simulated on the basis of driving modules (e.g. car-following, overtaking etc.) and modelled through mathematical relationships. Each vehicle is characterized by a preferred speed profile that depends on its own characteristics, on the traffic rules in the network (which are shaped by the behaviour models) and the characteristics of the vehicles interacting with it. However, not all aspects of these models are completely realistic. Different driving behaviour and vehicle types are aggregated into a limited number of classes. The simulated vehicles enter the system according to controlled probability distributions, which often do not resemble the real ones. The movements and interactions are determined via analytical relationships, which do not always catch the real human behaviour. This is not an exact resemblance of the reality but that was already in the word model which means a simplified description of the reality and not a pure resemblance of the reality itself.

The behaviour of a vehicle passing a signalized intersection, which often occurs in urban areas, is a particularly difficult modelling subject, since it strongly varies depending on the traffic control signal met and the encountered traffic conditions. Drivers in general increase their attention level in these areas, they are taught to moderate their speed when green, they stop when the light is red, and may stop, keep their speed or even accelerate when the signal is amber. This choice depends on their risk perception and driving skills. This particular behaviour is difficult to model with the existing behaviour models. The driver of vehicle 1 in figure 2.1 for example has to decide before he reaches...
point D if he is going to decelerate like in the picture or accelerate for the amber traffic light. When this is simulated wrong, it has quite a big impact on the output because the difference between acceleration and deceleration phases are quite substantial. Moreover, when in queue, they sometimes make micro-movements (creeping, which is the behaviour distinguished by short-acceleration and decelerations in proportion to the time spent in other operating modes, shown in (viti, 2008) figure 2.2) to advance gradually until they are served, or they can change lane to gain positions. In terms of emissions these movements are quite important, since accelerations can be strong and frequent. The calibration and validation processes in a microscopic model are in this sense of crucial importance, since the effect of modelling errors made at the microscopic level can grow considerably when looking at the macroscopic output parameters.

### 2.1.2 Commercial traffic flow models

There are many different commercial traffic flow models. Figure 2.3 gives an overview of the most commonly used traffic flow models. The available models are arranged by their detail level and study area. In this thesis a microscopic model is needed to simulate the emissions of individual cars. The possible models which can be used are in the blue area. They are fit for the task because they all can simulate in high detail in a small network. The traffic microsimulation model which is used in this thesis is PARAMICS. The reason for choosing PARAMICS instead of one of the other programs in the highlighted area is not based on technical reasons but on practical reasons. The most important reason is the presence of a full operational network of Adelaide CBD in PARAMICS at the ISST-TS. Rebuilding this in one of the other programs costs a lot of time, which is not available in this thesis. One thing to keep in mind with all these programs is that they all look like a kind of panacea. There are possibly close to it, but a good traffic modeller can create a good traffic model out of most modelling systems, and a bad traffic modeller will most of the time create an unsatisfactory traffic model out of the best system available (Viti, 2008). But without fear of contradiction can be stated that microsimulation can be very effectively deployed for traffic flow modelling if used well.
2.1.3 Car-following models

A traffic simulation model always consist of multiple modules as is partly shown in figure 2.4. Each of these modules handles one specific task in the simulation. These modules include, among others, car following behaviour, which can be seen as the core of the microsimulation model (Rhaka, 2009). Based on the origin of the errors this module is most likely the main cause of incorrect emission predictions till so far, when combining traffic microsimulation models and emission models. The module controls the interactions with the preceding vehicle in the same lane. In other words it calculates the acceleration and deceleration behaviour of the driver. The three factors that influence the driving behaviour the most are the individual differences between drivers, situational factors and other traffic (Miska, 2005).

A car-following model controls driver’s behaviour with respect to the preceding vehicle in the lane. Within car-following models there are often different sub models for different driving regimes. A vehicle is classified as ‘following’ when it is constrained by a preceding vehicle, and driving at the desired speed will lead to a collision. When a vehicle is not constrained by another vehicle it is considered free and its speed is largely determined by its desired speed (Ossen, 2008). Some models also include an approaching regime which handles the transition between the free driving and following regimes. The follower’s actions are commonly specified through the followers accelerations, although some models specify the follower’s actions by the followers speed, as explained further in this section.

Some car-following models only describe drivers’ behaviour when actually following another vehicle, whereas other models are more complete and determine the behaviour in all common situations. In the end, a car-following model should deduce both in which regime or state a vehicle is and what actions it applies in each state. Most car-following models use several regimes to describe the follower’s behaviour. A common setup is to use three regimes: one for free driving, one for normal following and one for emergency deceleration. Vehicles in the free regime are unconstrained and try to achieve their desired speed, whereas vehicles in the following regime adjust their speed with respect to the vehicle in front. Vehicles in the emergency deceleration regime decelerate at full power to avoid a collision. Although this is the most common regime division, it can vary between two and five in the different models. Generally all the models use the same following notation as stated below, but some models may use some different unities as shown in figure 2.5. This occurs for example with some models which are developed in a non metrical system.
The different car-following models can be split up into different classes. The difficulty lies in the fact that different information sources use a different number of classes. Some use three classes (Olstam, 2004), while others use five different ones (Brackstone, 2000) and some even six (Wang, 2006). For this thesis it is important to understand the effects of each different class on the trajectories. In an ideal situation this would be performed through running exactly the same simulations for each different car-following model. The problem is that none of the available commercial models in section 2.1.2 offers the option to change the class of used car-following module. Because it not possible to test if different models overlap each other in behaviour, all the following eight well-known different car-following classes are described. This is done because they each can have different effects on the shape of the time-acceleration profiles of vehicles and correspondingly on the emission predictions.

1. Gazis-Herman-Rothery models (GHR)
2. Safety distance or collision avoidance models (CA)
3. Linear (Helly) models
4. Psychophysical or action point models (AP)
5. Fuzzy logic-based models
6. Car-following model based on neural network
7. Car-following model based on desired headway
8. Human driver model
Gazis-Herman-Rothery models (GHR)

The GHR model is the most well-known model and dates from the late fifties and early sixties. These kind of models state that the following vehicle's acceleration is proportional to the speed of the follower, the speed difference between follower and leader and the space headway. It formulation is:

\[ a_n(t) = c v_n^m(t) \frac{\Delta v(t-T)}{\Delta x(t-T)} \]  

- \( a_n(t) \): acceleration of vehicle \( n \) implemented at time \( t \) [\( \text{ft/s}^2 \)]
- \( v_n(t) \): speed of the \( n \)th vehicle [\( \text{mph} \)]
- \( \Delta x \): the relative spacing between the \( n \)th and \( n-1 \)th vehicle [\( \text{m} \)]
- \( \Delta v \): the relative speed between the \( n \)th and \( n-1 \)th vehicle [\( \text{mph} \)]
- \( t \): time when the acceleration is implemented [\( \text{s} \)]
- \( T \): driver reaction time [\( \text{s} \)]
- \( c, m, l \): to be determined model constants [\( \text{ft/s}, \text{-}, \text{-} \)]

The dominant primary model properties are (Wang, 2006):

- Local stability and asymptotic stability can be achieved.
- Indifferent of using test vehicle or film, there are errors in collection of experiment data, the model parameters and the optimal model constants \( m \) and \( l \) cannot be calibrated accurately.
- The model has no limit on the acceleration and deceleration which, in reality, is dictated by the dynamic performance of the vehicle. Considering the fact that in real world unstable conditions do not last long, but tend to settle quickly, limiting values of acceleration and deceleration should be incorporated.
- It is a deterministic stimulus-response model. It assumes that the stimulus as well as the distance headway can be perceived precisely and that the driver can tune the response precisely. Due to the deterministic properties of the model, the inherent uncertainty in car-following process and the approximate essences of car-following behaviour both are neglected. The stimulus-reaction properties are so simple that the complexity of psychophysics behaviour, such as stimulation, perception, reaction, and so on, can hardly be reflected.
- The response of the driver is based on only one stimulus, namely, the relative speed. Once the relative speed is zero the following vehicle neither accelerates nor decelerates irrespective of the distance headway between the vehicles. Owing to the single stimulus nature of the model, it fails to explain behaviour such as closing-in and shying-away.

Safety distance or collision avoidance models (CA)

Another approach of car following models is the safety distance or collision avoidance model. The original formulation of this approach originates from Kometani and Sasaki (1959). The base relationship does not describe a stimulus-response type function as proposed by the GHR model, but seeks to specify a safe following distance, within which a collision would be unavoidable if the driver of the vehicle in front were to act unpredictably. The next major development of this model was made by Gipps (1981), in which he considered several mitigating factors the earlier formulation neglected. These neglected factors were that drivers will allow an additional 'safety' reaction time. Since the developments by Gipps, the collision avoidance model continues to see widespread use in simulation models. Part of the attractiveness of this model is that it may be calibrated using common sense assumptions about driver behaviour, needing chiefly only the maximal braking rates that a
Chapter 2: Literature study

driver will wish to use, and predicts other drivers will use, to allow it to fully function. Its formulation is:
\[ \Delta x(t - T) = \alpha v_{n-1}^2(t - T) + \beta_1 v_n^2(t) + \beta v_n(t) + b_0 \] (2)

- \( \Delta x \): the relative spacing between the \( n \)-th and \( n-1 \)-th vehicle [m]
- \( v_n(t) \): speed of the \( n \)-th vehicle [km/h]
- \( t \): time when the relative spacing is determined [s]
- \( T \): driver reaction time [s]
- \( \alpha, \beta_1, \beta, b_0 \): to be determined model constants [-, -, -, -]

The dominant primary model properties are (Wang, 2006):

- Drivers' “perception threshold” is not considered.
- Length of the simulation clock steps cannot be decreased easily in most cases, and the brake reaction time of drivers are restricted by it.
- The model is appropriate for computer simulation. However, it cannot be used on intelligent vehicle to control vehicle’s operation in reality, because the discrete simulation clock step is adopted in the model, and the model updates the vehicles sequentially in the simulation, which conflicted with synchronous operation of vehicles in real world.
- The hypothesis used to avoid collision is reasonable. To a certain extent, it can simulate car-following behaviour in congestion state; however, there are certain differences from the real vehicle operation. In reality, the “retaining wall” brake is rarely used by the leading vehicle, because driver can make good use of the multi-resource information and react to the changes of the leading vehicle in time. In fact, drivers do not keep the safety distance in most cases. Therefore, if the traffic capacity analysis based on the safety distance car-following model is used, it will be very difficult to make it consistent with real maximum traffic volumes.

**Linear (Helly) models**

The class of linear models is generally attributed to Helly (1959). He proposed a model that includes additional terms for the adaptation of the acceleration according to whether the vehicle in front (and the vehicle two in front) is braking. The next major calibration of this model is performed by Hanken and Rockwell (1967) and Rockwell, Ernst and Hanken (1968), who conducted experiments on both 'free roads' and on a congested urban freeway. The Helly model is used again when Bekey, Burnham and Seo (1977) attempt to derive a car-following model using traditional methods from the design of optimal control systems. Aron (1988) investigated the model further along with the GHR model, and split his data into phases of acceleration and deceleration. The formula of the model is:

\[ a_n(t) = C_1 \Delta v(t - T) + C_2 (\Delta x(t - T) - D_n(t)) \] (3)

\[ D_n(t) = \alpha + \beta v(t - T) + \gamma a_n(t - T) \] (4)

- \( a_n(t) \): acceleration of vehicle \( n \) implemented at time \( t \) [m/s²]
- \( D_n \): desired following distance, [m]
- \( t \): time when the acceleration is implemented [s]
- \( T \): driver reaction time [s]
- \( C_1, C_2 \): to be determined model constants [-, -]
Psychophysical or action point models (AP)

In 1963, some underlying psychophysics driving factors were analyzed, and the action point model was brought forward by Michaels. The model assumes that drivers would initially be able to tell they were approaching a vehicle in front, primarily due to changes in the apparent size of the vehicle, by perceiving relative velocity through changes on the visual angle subtended by the vehicle ahead. The next point in the development of these models came through a series of perception-based experiments conducted in the early seventies, by researchers such as Evans and Rothery (1973), aimed at quantifying the thresholds that Michaels suggested. A review of the many investigations conducted in these areas at that time can be found in Evans and Rothery (1977), where is shown that the wide body of research conducted on this topic during the seventies is all consistent from a statistical point of view. The individual properties were first combined into a fully working simulation model by staff at IfV Karlsruhe in Germany and has been in progress continually since (Leutzbach & Wiedemann, 1986). The formula of the model is:

\[
\frac{d\theta}{dt} = \frac{-w\Delta v}{R^2}
\]

- \(\theta\): visual angle, [radians]
- \(w\): width of the observed vehicle, [m]
- \(R\): distance between observer and target, [m]
- \(\Delta v\): relative speed between observer and target, [km/h]
- \(t\): time when the \(d\theta/dt\) is determined, [s]

The dominant primary model properties are (Wang, 2006):

- The “dead zone”, which is caused by the subtended change threshold of angle vision and angle velocity, must be considered in traffic flow model including human vision characteristic. However, it is not considered in this model.
• The non-linear relationship between the perception relative speed and the real one is not considered.
• If the subtended angle speed is under the threshold, drivers will fail to perceive the speed of imminent vehicle. As a result of this the opportunity for overtaking will be lost or accident will happen because of the blindfolded overtaking manoeuvre.
• It is difficult to calibrate and validate the model.

Wiedemann

Wiedemann (1974) developed the first psycho-spacing model. He distinguished constrained and unconstrained driving by considering perception thresholds. Moreover, lane-changing and overtaking are incorporated in his modelling approach. There is also a Wiedemann 1999 model, which is suggested for modelling freeway conditions. The Wiedemann 1974 model, which is also used in VISSIM, is graphically shown in figure 2.7 and the corresponding thresholds are formulated afterwards.

\[
AX = L_{n-1} + AX_{add} + RND_{1n}.AX_{mult}
\]

\[
AX_{add}
\]

\[
RND_{1n}
\]

\[
AX_{mult}
\]

\[
ABX = AX + BX
\]

\[
BX = (BX_{add} + BX_{mult}.RND_{1n}).\sqrt{v}
\]
BX model parameter, [m]
AXadd calibration parameter, [m]
AXmult calibration parameter, [-]

\[ v = \begin{cases} 
    v_{n-1} & \text{if } v_n > v_{n-1} \\
    v_n & \text{if } v_n \leq v_{n-1} 
\end{cases} \]

\[ SDX = AX + EX.BX \] (9)

SDX maximum following distance, varies between 1.5 and 2.5 times ABX, [m]

\[ EX = EXadd + EXmult. (NRND - RND2_n) \] (10)

EXadd calibration parameter, [m]
EXmult calibration parameter, [-]
RND2n normally distributed driver dependent parameter, [m]
NRND normally distributed random number, [m]

\[ SDV = \left( \frac{Ax-L_{n-1}-AX}{CX} \right)^2 \] (11)

SDV approaching point, driver notices he is approaching a slower vehicle, [m]

\[ CX = CXconst. (CXadd + EXmult. (RND1_n - RND2_n)) \] (12)

CX model parameter, [m]
CXconst calibration parameter, [-]
CXadd calibration parameter, [m]
CXmult calibration parameter, [-]

\[ CLDV = \left( \frac{Ax-L_{n-1}-AX}{CX} \right)^2 \] (13)

CLDV decreasing speed difference, to model the perception of small speed differences at short decreasing distances (ignored in VISSIM because assumed equal to SDV), [m]

\[ OPDV = CLDV. (-OPDVadd - OPDVmult NRND) \] (14)

OPDV increasing speed difference, point where the driver observes that he is travelling slower than the leader, [m]

OPDVadd calibration parameter, [m]
OPDVmult calibration parameter, [-]

The threshold stated above give shape to the following car-following regimes:

- Following
  The thresholds SDV, SDX, OPDV and ABX constitute the following regime. In order to account for inexact handle of the throttle, vehicles acceleration rate is assumed at all times to be unequal to zero. When a vehicle passes into the following regime, passing either the SDV or the ABX threshold it is assigned the acceleration rate \(-b_{\text{null}}\) and when passing the thresholds OPDV or SDX it is assigned to the acceleration \(b_{\text{null}}\).

\[ b_{\text{null}} = BNULLmult. (RND4_n + NRND) \] (15)

\( b_{\text{null}} \) acceleration or deceleration rate, [m/s²]
Chapter 2: Literature study

- Free driving

The vehicle is located above all thresholds in the phase diagram (figure 2.7) and travels uninfluenced by the surrounding traffic. The vehicle uses its maximum acceleration to reach its desired speed. When the desired speed is reached, inexact handling of the throttle is modelled by assigning an acceleration of \(-b_{null}\) or \(b_{null}\) to the vehicle. The maximum acceleration, \(b_{max}\), for passenger vehicles can be defined as:

\[
b_{max} = BMAX\text{mult}. (v_{\text{max}} - v.FaktorV)
\]  

(16)

\[
FaktorV = \frac{v_{\text{max}}}{v_{\text{des}} + FAKTORV \text{ mult}.(v_{\text{max}} - v_{\text{des}})}
\]  

(17)

- Closing in

When passing the SDV threshold, the driver notices that he is approaching a slower vehicle. The driver decelerates in order to avoid collisions. \(b_n\) will be used as deceleration rate and is defined as:

\[
b_n = \frac{1}{2} \cdot \frac{(\Delta v)^2}{ABX - (\Delta x - l_{n-1})} + b_{n-1}
\]  

(18)

- Emergency regime

When the front to rear distance is smaller than \(ABX\) the follower will adopt, if necessary, the following deceleration to avoid collision with the vehicle in front:

\[
b_n = \frac{1}{2} \cdot \frac{(\Delta v)^2}{ABX - (\Delta x - l_{n-1})} + b_{n-1} + b_{\text{min}} \cdot \frac{ABX - (\Delta x - l_{n-1})}{8X}
\]  

(19)

\[
b_{\text{min}} = -BIMIN\text{add} - BMIN\text{mult} \cdot BMIN\text{mult} \cdot v_n
\]  

(20)

| \(BNULL\text{mult}\) | calibration parameter, [-] |
| \(RND4_n\) | normally distributed driver dependent parameter, [m] |

- Fritzsche

Another model which is based on the psycho-physical model is the Fritzsche model. A Fritzsche kind of model is also used in PARAMICS although the differences between the published Fritzsche model and the implemented one in PARAMICS are not publicly known (Brockfield, 2003). The Fritzsche model accounts for human perception in the definitions of the regimes, although they have to be of a certain magnitude to be perceived by the driver. The Fritzsche model is graphically shown in figure 2.8 and the corresponding thresholds are formulated afterwards.
Figure 2.8: The different regimes and thresholds in the Fritzsche car-following model (Olstam, 2004)

\[
\text{PTN} = -k_{\text{PTN}} (\Delta x - s_{n-1})^2 - f_x
\]

\[
\text{PTP} = -k_{\text{PTP}} (\Delta x - s_{n-1})^2 + f_x
\]

PTN: perception of negative speed differences, [km/h]
PTP: perception of positive speed differences, [km/h]
\(s_{n-1}\): target separation vehicle n-1 and n, [m]
k_{\text{PTN}}: model parameter, [-]
k_{\text{PTP}}: model parameter, [-]
f_x: model parameter, [-]

\[
\text{AD} = s_{n-1} + T_D \cdot v_n
\]

\[
\text{AR} = s_{n-1} + T_r \cdot v_{n-1}
\]

\[
\text{AS} = s_{n-1} + T_s \cdot v_n
\]

\[
\text{AB} = \text{AR} + \frac{\Delta v^2}{\Delta b_m}
\]

\[
\Delta b_m = |b_{\text{min}}| + a_{n-1}
\]

\[
T_D > T_s > T_r
\]

AD: desired distance, [m]
T_D: desired time gap, [s]
AR: risky distance, driver have to decelerate heavily to avoid collisions, [m]
T_r: risky time gap, [s]
AS: safe distance, the smallest headway where positive acceleration is accepted if the distance between follower and leader is increasing, [m]
T_s: model parameter, [s]
**Chapter 2: Literature study**

<table>
<thead>
<tr>
<th>AB</th>
<th>breaking distance, distance needed to avoid collisions in the case of an initial large positive speed difference when leader and follower break at maximum deceleration, [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_{\text{min}}$</td>
<td>model parameters controlling maximum deceleration, [-]</td>
</tr>
<tr>
<td>$a_{n-1}$</td>
<td>model parameters controlling maximum deceleration, [-]</td>
</tr>
</tbody>
</table>

Similar to the Wiedemann model, the given thresholds above describe the vehicle behaviour in different regimes.

- **Danger**
  
The distance to the leading vehicle is smaller than the risky distance $AR$. The follower uses its maximum deceleration, $b_{\text{min}}$, to extend the headway.

- **Closing in**
  
The speed difference is larger than $PTN$ and the space headway is between $AB$ or $AD$ and $AR$. The follower decelerates in order to obtain the speed of the vehicle in front. The decelerations rate is taken such that the speed of the leader will be obtained when the space headway equals the risk distance $AR$. Saldana and Tabares (2000) determined an expression for the acceleration of vehicle $n$.

\[
a_n = \frac{(v_{n-1}^2 - v_n^2)}{2d_c} \tag{29}
\]

\[
d_c = x_{n-1} - x_n - AR + v_{n-1} \Delta t \tag{30}
\]

$\Delta t$ simulation time step, [s]

- **Following I**
  
Following I occurs when the speed difference is between $PTN$ and $PTP$ and space headway is between $AR$ and $AD$ or the space difference is larger than $PTP$ and a space headway is between $AS$ and $AR$. The follower takes no conscious action. A parameter $b_{\text{null}}$ (similar as in the Wiedemann model) is used to model the driver's inability to maintain constant speed. When a vehicle passes into the following regime is assigned the acceleration rate $-b_{\text{null}}$ if it passes the $PTN$ threshold and when passing the $PTP$ threshold or $AD$ it is assigned the acceleration $b_{\text{null}}$.

- **Following II**
  
Following II occurs when the speed difference is larger than the $PTN$. The space headway is larger than $AB$ or $AD$. In this regime the driver has noticed that he is closing in on the vehicle in front, but the space headway is still too large for any action to be necessary.

- **Free driving**
  
Free driving occurs when the speed difference is smaller than $PTN$ and the space headway is larger than $AD$ or the positive speed difference is larger than the $PTP$ and the space headway is larger than the $AS$. The follower accelerates with a normal acceleration rate, $a_{\text{f}}$, in order to achieve the desired speed. When driving at the desired speed, the parameter $b_{\text{null}}$ is again used to model the driver’s inability to maintain constant speed.
**Fuzzy logic-based models**
The use of fuzzy logic within car-following models is mentioned by some researchers as the latest distinct stage in their development, as it represents the next logical step in attempting to accurately describe driver behaviour more accurately. In reality, the stimulus-response is not a deterministic one-to-one relationship, but a series of driving rules based on the drivers experience. So, these driving rules are not rigorous. Different rules might be applied for different drivers, even for the same driver under different circumstances. To deal with this problem, a fuzzy inference logic-based model is established. There are two methods to reflect the drivers' rules, one is to fuzzify parameters in deterministic models, and the other makes use of fuzzy logic reasoning system, which consists of direct-natural languages based on the driving rules. The latter has become the point of focus, because it reflects the car-following decision procedure better. The use of the first method was introduced by attempting to fuzzify the traditional GHR model (Kikuchi & Chakroborty, 1992). The second approach, which has a bigger impact, because it calibrates the membership sets, was introduced by investigating road subjectivity tests (Brackstone, 1997).

**Car-following model based on neural network**
Based on the research returns for processing human information obtained by modern neurobiology and cognitive science, ANN is developed. ANN is a complicated non-linear dynamic system, in which simple nerve cells are widely connected with certain topological structure. Based on the studies of biology neural organization structure and behaviour characteristics, ANN is proposed. Furthermore, it focuses on the simulation of certain special functions of the human brain as well as the synergetic effect among numerous nerve cells. In recent years, neural networks are widely used in both traffic forecast and control.

The dominant primary model properties are (Wang, 2006):

- Calibration of the model is relatively complex, and a number of training data and higher data equilibrium are required.
- Because of higher self-learning ability, real time threat and fault-tolerant, the model is appropriate for simulating uncertainty of drivers' perception and decision process.
- The model does not need pre-programming. It could calculate at real-time concurrently, and find the internal relationships among data that are difficult to be expressed accurately by mathematical functions. However, because of the repeated call among modules, it will waste a significant part of machine-time, and the execution will be inefficient. Furthermore, there will be 'over-study' and 'under-study' phenomena in the data training process.

**Car-following model based on desired headway**
Parker brought forward the car-following model based on desired headway, when he did research on the different following behaviours on a throughway construction road. The model assumes that when the following vehicle \( n \) is following/approaching the leading vehicle \( m \) at time \( t \), it will adjust its acceleration to get the desired headway after \( T \) seconds. The formula of the model is:

\[
x_{n-1}(t + T) - x_{n}(t + T) = D_n(t + T) \tag{31}
\]

\[
D_n(t + T) = \alpha \cdot v_n(t + T) + \beta
\]

\( x_i \) position of vehicle i at time t, [m]
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$D_i$: desired headway of vehicle i at time t, [m]
$v_i$: speed of vehicle i at time t, [km/h]
i, $\alpha, \beta$: model constants, [-, -, -]

The dominant primary model properties are (Wang, 2006):

- Drivers with different driving behaviours and same speed have different expectation distances.
- More full and accurate field data are needed to discuss the driving characteristics, as well as issue the model in public and study the model in different traffic environment.

**Human Driver Model (HDM)**

The Human Driver Model is an extension for basic physics orientated models. It incorporates four additional elements into the physical orientated model (Treiber, 2006):

i. Finite reaction times
ii. Estimation errors
iii. Spatial anticipation (for several vehicles ahead)
iv. Temporal anticipation

For matters of illustration Treiber et al. use an Intelligent Driver Model as point of departure. However this could also have been any other basic model characterized by a continuous acceleration function based on the, velocity, gap and relative velocity. The general form of the HDM model is:

$$\frac{dv_a}{dt} = a_{mic}(s_a,v_a,\Delta v_a)$$

$a_{mic}$: acceleration, [m/s$^2$]
$s_a$: net distance, [m]
$v_a$: own velocity, [m/s]
$\Delta v_a$: velocity difference, [m/s$^2$]

The model has two deterministic parameters, namely the reaction time $T'$ and the number $n_a$ of anticipated vehicles. The only stochastic parameters used in the model are $V_r$ (relative distance error) and $r_c$ (inverse time-to-collision error), they are used for modelling for finite estimation capabilities. Summarizing can the HDM be used to extend a wide class of car-following models, where the acceleration depends only on the positions, velocities and accelerations of the own and the preceding vehicle. By applying the HDM extensions to the existing model, quantitative details of the balance conditions and the remaining differences in the dynamics are provided.

### 2.1.4 Review of the driving behaviour models.

By accurately describing the limitations of humans and individual preferences in a model, the model aims to seek the essence of the variability between individual drivers. However, they always ignore one or more of the following seven issues that characterize to observed driver behaviour (Boer, 1999). This

1. Car-following is only one of many tasks that drivers perform simultaneously and receives therefore only intermittent attention and control (task scheduling/attention management).
2. In each driving task, drivers use a set of highly informative perceptual variables, rather than only Newtonian inputs, to guide decision making and control.

3. The variables that drivers could perceive are limited. They fail to estimate the longitudinal distance, absolute velocities and accelerations of other vehicles in visual field. Furthermore, the running state satisfied by the drivers is confined by the perception and control limitation.

4. Driving behaviour cannot be described and predicted accurately by continuously using a single control rule. The model can be operated well in a special traffic condition, but not be applied in a wide range. In reality, vehicles with different driving behaviour control rules under different traffic status will be called in different operating patterns.

5. In reality, drivers evaluate performance based on acceptability, rather than optimality. Because drivers need to call all resources in order to achieve the optimal level.

6. The study of driving behaviour simulation model should be synthetically considered by traffic engineering, traffic psychology and human machine efficiency.

7. The model should represent drivers skilled control stage in car-following process. Furthermore, when car-following modules are called by higher level attention management strategy, the switching of operation patterns needs clear transition period.

From the provided information in the previous section and the researched papers concerning this topic a couple of conclusion can be drawn regarding to the different car-following models:

- All the car-following models have their limitations, although some work better than others. These limitations can be grouped in two ways. Limitations based on a certain weakness. A good example of this are the GHR models who lack the influence of human perception. The other way of grouping their limitations is determining in which traffic state they underperform. An example for this is the relative poor performance of safety distance models in heavily congested traffic. These classifications are related which each other. This relation can roughly be seen as a cause result relation, where the first group is the cause and the second group the result.

- The level of complexity, and related to this the number of needed parameters, varies between the different models. While some only focus only on vehicle characteristics others also include aspects of the human psyche. This makes the models more complex trough the model gets more variables.

- The car-following models which are mainly used at by the commercial microsimulation models are based on psychophysical or so called action point models. From the three most used microsimulation models PARAMICS (Fritzsche) as well as VISSIM (Wiedeman) uses models based on this principle. AIMSUN is however based on a Gipps model which is a safety distance or collision avoidance model. In this thesis an existing PARAMICS model is used, therefore we have to use the Fritzsche model.

From the stated above can concluded that car-following models that do not model human perception are not suitable for generating trajectories that can be used for traffic emission predictions. Action point models have a weakness with their thresholds. For the average driver in the average city these thresholds could be calibrated properly, but these thresholds cannot be adjusted for specific situations. This makes them not ideal in for generating trajectories for that can be used for traffic emission predictions. The car-following model which has the most potential to generate suitable trajectories for microscopic traffic emission predictions are models based on fuzzy logic. The
stimulus-response process is not a deterministic one-to-one relationship, but a series of driving rules based on the drivers experience and mental and physical condition of the moment. For this reason driver behaviour rules should not be predetermined. Different rules might be applied for different drivers, even for the same driver under different circumstances.

2.2 Emission models

Although the focus in this thesis does not lie on the actual prediction of traffic emissions or a comparison between the available models, it is still important to have some knowledge of emission models, because the goal of the thesis is to create more reliable input for them. This is applicable to the different types of emission, source based and chemically, as well to the different types of available models.

2.2.1 Overview of types of emissions

With exception of a relatively small number of electricly powered vehicles, all vehicles are equipped with a combustion engine for propulsion. In the combustion process chemical energy from fuels, like petrol, diesel and LPG, is transformed into mechanical energy. During this process there is also a release of emissions. Besides the combustion emission there are also emissions from the evaporation of fuel and cooling liquids, the wear out of tyres, brakes and road pavement and the leakage and usage of motor oil. All those emission producing processes can be divided in groups of origin (based on Klein, 2007).

**Combustion emissions (via the exhaust)**

- Carbon monoxide (CO), volatile organic substances (hydrocarbons), nitrogen oxides (NOx), dinitrogen oxide (N2O), ammonia (NH3) and fine particles (PM10). The emissions are mainly dependent on the type of fuel and the used exhaust gasses post-processing technologies.
- Sulphur dioxide, carbon dioxide and heavy metals. These emissions are primarily dependent on the fuel consumption and the type of fuel.
- Hydrocarbon-components. Hydrocarbons are a large group of diverse substances. Hydrocarbons in exhaust gasses can be divided into alkynes, alkenes (for instance benzene), aromatics, polycyclic aromatic hydrocarbons and chlorinate hydrocarbons. The total amount of those hydrocarbons is measured and then divided into the sub groups standard hydrocarbon profiles.

**Evaporation emissions (out of the fuel system of petrol vehicles)**

- Hydrocarbons in total and hydrocarbon components. The rate of emissions depends mostly on the annual mileage and the production year of the vehicle.

**Emissions trough wear out processes**

- PM10-emission caused by wear out of tyres, brakes and pavement. The calculations mainly depends on the type of vehicle, number of tyres and the annual mileage.
- Heavy metals and polycyclic aromatic hydrocarbons due to wear out of tyres, brakes and the pavement. The emission is measured as a total and then divided, like the hydrocarbon-components, with standard profiles into subgroups.
Remaining emissions

- Heavy metals and polycyclic aromatic hydrocarbons due to leakage of motor oil. The calculation takes place through combining the annual leakage through the gaskets per vehicle per year and the percentage of heavy metals and polycyclic aromatic hydrocarbons in lubricants.
- Heavy metals due to use (combustion) of motor oil. Calculation is based on the combination of the total oil use (=leakage from the piston springs to the combustion chamber) per vehicle per year and the percentage of heavy metals and polycyclic aromatic hydrocarbons.

2.2.2 Commercial traffic emission models

The number of commercial traffic emission models has increased rapidly the last few years. This is probably due to the still increasing demand of emission predictions and forecasts. In contrast with the traffic microsimulation models the approach of emission calculation of these models differs a lot. For example TREMOVE and COPERT are standalone black box tools which give good predictions but need a vast amount of input parameters. VT-Micro on the other hand is much more simplistic. It is not a standalone program, but an algorithm with some tables with constants for the different types of emission or fuels and for the different types of vehicles.

In this thesis the focus lies on calibrating traffic microsimulation models such that their trajectories can be used for accurate emission predictions. Therefore, an emission model is chosen to be used which uses trajectories as input and is easy to implement in Excel or Matlab. Models like BASE, CARII, EMFAC, MOBILE, MOVES, VERSIT+, TRRL or TREMOVE fall outside the scope of this research. VT-Micro and the TSC’s emission model are the only two options, therefore only these two models are reviewed.

VT-Micro

The full name of this model is: Virginia Tech microscopic energy and emission model. The model was developed from experimentation with numerous polynomial combinations of speed and acceleration levels. Linear, quadratic, cubic and quartic terms of speed and acceleration were tested using chassis dynamometer data collected at the Oak Ridge National Laboratory in the USA. The final regression model includes a combination of linear, quadratic and cubic speed and acceleration terms because it provides the least number of terms with a relatively good fit to the original data.

\[
\log(MOE_e) = \sum_{i=0}^{3} \sum_{j=0}^{3} k_{i,j}^e \cdot s^i \cdot a^j
\]  

MOE Measures Of Effectiveness [mg/s for emissions and l/s for fuel consumption]

\(k_{i,j}^e\) Regression coefficient for MOE\(e\) at speed power \(i\) and acceleration power \(j\) [-]

There are 2 sets of 16 coefficients, one for \(a \geq 0\) and a set used for \(a < 0\)

\(s^i\) Speed at power \(i\) [km/h]

\(a^j\) Acceleration at power \(j\) [km/h/s]

This model has however one big disadvantage. It works very good with flawless vehicle trajectories and in theory can work with an endless number of different vehicle types as long as their corresponding \(k_{i,j}^e\) tables are available. However if trajectories with errors or impurities are used, the quality and reliability of the predictions decreases rapidly due to the polynomial function. Since traffic simulation models produce less than perfect trajectories it is not recommendable to use VT-Micro without any additional measures.
**TSC experimental based estimated emission functions**

The process of estimating the emission functions starts with making engine maps through using a dynamometer. An engine map is a three-dimensional plot with on the manifold pressure on the x axis, the engine speed in RPM on the y axis and the emission level of a certain emission on the z axis. This has been done for the common emissions and the fuel use. This method has proven to be an effective method for determining vehicle emissions under real traffic situations (Taylor, 1996). The collected engine data is than split up into the six phases (idle, acceleration from idle, deceleration to idle, acceleration, deceleration and cruise which are further explained in the section about the TSC’s splitting algorithm). Once all the data points are known for a certain phase they are plotted against their magnitude (acceleration in this case) in a graph of which figure 2.9 is an example. Afterwards a second order polynomial function is fitted through the data. The formula of this polynomial function indicates the amount of emission per second at certain magnitude (corresponding to the selected phase) in the corresponding phase.

![Mean Fuel v's Mean Acceleration (Type 2)]

\[ y = 0.035472897x^2 + 0.451175255x + 1.259395262 \]

\[ R^2 = 0.331873712 \]

Figure 2.9: Example of the fuel function estimation (Zito, 2001)

The advantage of this model is that is that it is robust (Zito 2003), because of its phase based nature. It is less sensitive to minor flaws in trajectories then for example VT-Micro. The problem however with this model is that a detailed engine map is needed for all major vehicle types. This is a costly procedure and needs to be repeated quite frequently due to the continuous introduction of new vehicle models with new engine techniques.

A problem of both emission models is how well their vehicle types represent the mean of a vehicle class in the reality. Due to the existence of enormous number of different vehicle types and influence factors such as age and mileage, it is difficult to maintain representing emission levels. However, since producing actual predictions lies beyond of the scope of thesis, this is not further researched.
2.3 Methods for calibrating car-following models of traffic microsimulation models

Calibration is necessary to ensure that the representation of the current situation by the microsimulation is indeed correct. In an abstract sense, calibration is a comparison between measurements. One measurement of known magnitude or correctness made or set with one device and another measurement made in a similar way as possible with a second device. In this case, real life data can be used to define the parameters of the driving behaviour, or more specific the car-following behaviour. Normally the car-following model is only one of many components in a traffic microsimulation model that needs to be calibrated. Because this thesis uses an existing PARAMICS network that has already been calibrated for ‘normal’ applications, it most likely only needs a recalibration or fine tuning of the driver behaviour parameters. In this chapter is discussed how car-following models can be calibrated. The chosen approach chosen for fine tuning the existing PARAMICS Adelaide CBD model is described in section 3.1 of the next chapter.

Calibrating car-following models

In this thesis PARAMICS is used as traffic simulation model, hence the focus lies on the calibration of a Fritzsche (psychophysical) car-following because PARMICS uses a variant of this car-following model. PARAMICS does not provide any specific tool for calibration, but the build-in analyser can provide the necessary information. Finding an optimal parameter set for a car-following model with a nonlinear acceleration function (linear over 17 intervals) corresponds to a nonlinear optimization problem which has to be solved numerically. Although there exist quite a lot of methods for the calibration of traffic microsimulation models, there are less option for the calibrating only the car-following model. Especially when is taken in to consideration that probe vehicle data is used for the calibration.

A commonly used algorithm for calibrating car-following models is the genetic algorithm (Ozbay, 2005). The genetic algorithm, which uses the error in the spacing gap and to solve the errors in the mean speed as well (this does not work in the reverse order), proceeds as follows (Kesting, 2007):

1. An ‘individual’ represents a parameter set of a car-following model and a population consists of N such sets.
2. In each generation, the fitness of each individual in the population is determined via one of the objective functions (34, 36 or 37):

\[
F_{rel} \left[ s^{\text{sim}} \right] = \sqrt{\left( \frac{s^{\text{sim}} - s^{\text{data}}}{s^{\text{data}}} \right)^2} \tag{34}
\]

\[
F_{rel} \left[ s^{\text{data}}, s^{\text{sim}} \right] \quad \text{relative error, [-]}
\]

\[
\langle z \rangle = \frac{1}{\Delta T} \int_{0}^{\Delta T} z(t) \, dt \tag{35}
\]

\[
\langle . \rangle \quad \text{temporal average of a times series of duration } \Delta T
\]

\[
F_{abs} \left[ s^{\text{sim}} \right] = \sqrt{\left( \frac{s^{\text{sim}} - s^{\text{data}}}{s^{\text{data}}} \right)^2} \tag{36}
\]
As the absolute error systematically overestimates errors for large gaps (at high velocities), while the relative error systematically overestimates deviations of the observed headway in the low velocity range, there also exist a combination of both error measures.

\[ F_{\text{mix}}[s_{\text{sim}}] = \sqrt{\frac{1}{(s_{\text{data}})^2} (s_{\text{sim}} - s_{\text{data}})^2} \]  

3. Pairs of two individuals are stochastically selected from the current population based on their fitness score and recombined to generate a new individual. Except for the best individual, which is kept without any modification to the next generation, the ‘genes’ of all individuals, i.e., their model parameters, are varied randomly corresponding to a mutation that is controlled by a given probability. The resulting new generation is then used in the next iteration.

4. The termination criterion is implemented as a two-step process: Initially, a fixed number of generations is evaluated. Then, the evolution terminates after convergence which is specified by a constant best-of-generation score for at least a given number of generations.

The construction of such objective functions and determination of the optimum values, although very attractive, is a very time-consuming task, especially for complex and very large networks. Also, this process based on the use of the simulation as the objective function does not have a closed form solution, and it can be infeasible given the numerous and highly randomized parameters that PARAMICS uses. So a trial-and-error approach that attempts to modify various important input variables to achieve an acceptable level of accuracy, which is far less sophisticated, is also an option.

The car-following model can be calibrated with many parameters. The most important in PARAMICS are (Quadstone, 2006):  

- **Aggression, [-]**  
  A high level of aggression causes a vehicle to drive more aggressively than a vehicle with an average aggression level. This results in higher speeds and accelerations, but also in smaller headways and gap acceptances.

- **Awareness, [-]**  
  A higher level of awareness causes a vehicle to adopt sooner changes in the surrounding than a vehicle with a lower with an average level of awareness. This results in selecting target lanes earlier and responding earlier to signposts along the road. Besides this it also results in longer headways.

- **Mean reaction time (also called reaction factor), [s]**  
  This is a global parameter, that is used to set the mean reaction time of drivers. The default value for this parameter is set under the behaviour sliders.
parameter is 1.0 second.

- **Mean target headway, [m]**
  This is a global parameter, which is used to set the mean headway that vehicles aim to maintain during the simulation. The default value for this parameter is 1.0 second.

- **Minimum gap, [m]**
  This parameter is used to set the minimum gap between the vehicles when they are in a queue.

The aggression and awareness parameters cannot be set manually in PARAMICS version six, in contradiction with earlier versions. The aggression and awareness parameters are set for each vehicle when the vehicle is released onto the network with the levels sampled from a normal distribution. In previous versions of PARAMICS the distributions of the aggression and awareness could manually be altered with sliders as shown in figure 2.10. Hereby the magnitudes and the deviations could be adapted if the user thought they were not consistent with the monitored network (standard calibration was based on UK loop detectors). However, PARAMICS strongly recommends that the normal distribution is used as it has been validated to this behaviour distribution. Users wishing to change the distribution from normal should do so with caution and should be able to substantiate their changes.

The speed memory is also often raised as an important setting. The speed memory is the number of time steps that each vehicle 'remembers' its current speed. The speed memory must be increased or decreased in conjunction with the number of time steps of the simulation and the mean reaction time, so that higher or lower reaction times can be modelled accurately for the same number of time steps per second (Quadstone, 2006). This is however not considered to be a true calibration parameter since a higher number of steps will always give an equal or better simulation result. The trade-off in this parameter is that when the speed memory increases the simulation time also increases. So the deliberation should be made where the threshold lies between more accurate results and additional running time of the simulation.
2.4 Data collection with probe vehicles

This section describes the advantages and disadvantages of the use of probe vehicles (or floating cars) compared to other data collection methods for transportation research such as loop detectors. This comparison with other methods is done because the calibration and validation data used for this research is gathered with a probe vehicle. Therefore knowing its strong, but especially its weak points is essential.

With the development of wireless location and communication technology, significant attention has been paid to the probe vehicle. The use of probe vehicles is one possible approach to obtain traffic information from running vehicles on the road as probes. The key idea of using probe vehicles is to collect traffic information that is reasonable representative of the behaviour of the traffic it is driving between. The probe vehicles can report data on their positions, speeds, space between vehicles and so on. Compared to the conventional stationary detectors installed on the road, probe vehicles may provide benefits such as an easier implementation, more precise information and lowered costs for constructing and maintaining the information system. For probe vehicles to be the basis of a real-time traffic information system, it is necessary that the traffic situations sampled by them are reliable and adequate. Hence, a key problem of using probe vehicles as a source of data is to determine the probe sample size. Over the past decades, numerous studies discussing probe sample size have been carried out mainly based on two theories, quality-control theory and large sampling theory (Hong, 2007). Most research work focuses on estimating the sample size on a certain space during some period. The difficulty in using probe vehicles lies in determining a big enough sample size, without losing the flexibility and relatively low cost of the probe vehicle technology through using a large number of probe vehicles.
2.5 Phase-based splitting algorithm

The phase splitting algorithm is an algorithm which is used to separate a trajectory into parts with specific characteristics. Parts with the same characteristics get an identical phase assigned. After a trajectory is split, each phase (group) has its own characteristics consisting of a duration and a magnitude. If it is known how these characteristics should look like, for example by analysing a series of recorded trajectories, traffic microsimulation models can be calibrated to generate simulated trajectories with phases that have identical characteristics.

The phase splitting algorithm (Biggs, 1985) was designed for testing the polynomial function and the elemental model. To do this properly is was necessary to identify the idle, acceleration, deceleration and cruise sections in the time-speed data. The start and end points of each mode is, to some extent, subjective and the choice of these points affects the profile related parameters and default estimation equations. The subjective part lies in the fact that you can adjust the list of phase criteria.

Idle
Idle or stopped periods were identified as those with speeds smaller than 1,0 km/h.

Accelerations from a stop
Speeds smaller than 1,0 km/h were identified and the minimum speed prior to acceleration was taken to be the initial speed \(v_i\). The end of the acceleration was identified as when speed stopped increasing and did not increase greatly during the next five seconds. If a maximum speed following \(v_i\) occurred at time \(t_f\), this was taken to be the end of the acceleration if:

\[
\begin{align*}
    v(t_f) &> v(t_f + 1) \\
    v(t_f) &> v(t_f + 2) - 0.5 \\
    v(t_f) &> v(t_f + 3) - 1.0 \\
    v(t_f) &> v(t_f + 4) - 1.5 \\
    v(t_f) &> v(t_f + 5) - 2.0
\end{align*}
\]

Otherwise the next maximum speed after \(t_f\) was identified and tested similarly. The procedure allows small breaks in the acceleration due to, for example, changing gear and minor speed fluctuations of other vehicles. Accelerations from stop can be limited to a threshold speed (default speed is 20 km/h). Once the speed becomes higher than this speed, the phase after that point is no longer been seen as an acceleration from stop.

Deceleration to a stop
The procedure deceleration to a stop is similar to accelerations from a stop. Speeds of less than 1,0 km/h were identified and the time of the minimum speed after this was taken to be the end of the deceleration. The maximum speed prior to this, say at time \(t_i\), was taken to be the start of the deceleration provided that:

\[
\begin{align*}
    v(t_i) &> v(t_i - 1) \\
    v(t_i) &> v(t_i - 1) - 0.5 \\
    v(t_i) &> v(t_i - 1) - 1.0 \\
    v(t_i) &> v(t_i - 1) - 1.5 \\
    v(t_i) &> v(t_i - 1) - 2.0
\end{align*}
\]
Otherwise the next maximum prior to \( t_j \) was identified and tested in a similar way. The decelerations to a stop phase has a maximum threshold speed as well. If the deceleration would start above the threshold then the part till the threshold speed will be assumed a regular deceleration. The default threshold speed for this is also \( 20 \) km/h.

**Acceleration and decelerations without stopping restrictions**

The accelerations and decelerations which do not start or stop in the idle phase (or threshold speed if used for acceleration from stop and deceleration from stop) will be part of these two phases. For accelerations from, and deceleration to, the threshold the following stepwise procedure is used which is clarified by Figure 2.11.

![Speed-time trace showing the way acceleration and decelerations were identified (Biggs, 1985)](image)

**Step 1**

Start at \( t_j \).

*For example, \( v(t_j) = 30 \)*

**Step 2**

Determine when speed has changed significantly. Find the next time \( t_k \) where:

\[
v(t_k) \geq v_{xa} \text{ or, if } v(t_j) > 15 \text{ where } v(t_k) \leq v_{xd}
\]

Where:

\[
v_{xa} = \begin{cases} 1.5v(t_j) + 5.0 \\ 15 \end{cases} \quad \text{whichever is greatest}
\]

\[
v_{xd} = \frac{v(t_j) - 5.0}{1.5}
\]

*For example, \( v_{xa} = 50, v_{xd} = 17 \text{ and } t_k \text{ is the time at which the speed equals 50.})*

**Step 3**
Determine the start and end points of the acceleration/deceleration which includes \( t_k \).

a) If \( v(t_j) < v(t_k) \), then find the start and end of the acceleration:

i) Move backwards from \( t_k \) to find the time of the next minimum \( (t_j) \) such that:

\[
\begin{align*}
v(t_j) &< v(t_j - 1) \\
v(t_j) &< v(t_j - 2) + 0.5 \\
v(t_j) &< v(t_j - 3) + 1.0 \\
v(t_j) &< v(t_j - 4) + 1.5 \\
v(t_j) &< v(t_j - 5) + 2.0
\end{align*}
\]

The acceleration starts at time \( t_j \) with the initial speed \( v_i = v(t_j) \).

ii) Move forwards from \( t_k \) to find the time of the next maximum speed \( (t_f) \) which satisfies equation 38. The acceleration ends at time \( t_f \) with the final speed \( v_f = v(t_f) \).

b) If \( v(t_j) > v(t_k) \), then find the start and end of the deceleration:

i) Move backwards from \( t_k \) to find the time of the next maximum speed \( (t_i) \) which satisfies equation 39. The deceleration starts at this time with initial speed \( v_i = v(t_i) \).

ii) Move forwards from \( t_k \) to find the time of the next minimum speed \( (t_f) \) such that:

\[
\begin{align*}
v(t_f) &< v(t_f + 1) \\
v(t_f) &< v(t_f + 2) + 0.5 \\
v(t_f) &< v(t_f + 3) + 1.0 \\
v(t_f) &< v(t_f + 4) + 1.5 \\
v(t_f) &< v(t_f + 5) + 2.0
\end{align*}
\]

The deceleration ends at time \( t_f \) with the final speed \( v_f = v(t_f) \).

c) If the change in speed during acceleration/deceleration is greater than 10 km/h (i.e. \( |v_i - v_f| > 10 \)) include acceleration/deceleration in set for calibration of fuel consumption functions.

For example, \( v(t_j = 30 < v_{xa} = 50) \), then using equations 38 and 42 and the initial and final speeds of acceleration were found to be 28 and 54, respectively.

**Step 4**
Set \( t_j \) equal to the time of the end of the acceleration or deceleration \( t_f \) and start again at step 1.

**Cruise**
The classification was chosen so that the cruise fuel consumption function would suit traffic models which can identify stops and slowdowns to low speeds, but cannot identify speed fluctuations at higher speeds. The cruise phases are identified as stated below and are clarified by figure 2.12.
Figure 2.12: Speed-time trace showing the way cruise sections were identified (Biggs, 1985)

a Major accelerations and decelerations were identified as those where speed increased above or dropped below 20 km/h.

b The end time and final speed \( v_f \) of an acceleration above 20 km/h and the start time and the initial speed \( v_i \) of the next deceleration to below 20 km/h were found for each major acceleration or deceleration.

c So that the speed at the start and end of each cruise section are equal, the start and end points were chosen as follows:

i If \( v_f \geq v_i \), the point during acceleration when speed equals \( v_i \) is the start of cruise phase and the end of deceleration is end of the cruise phase.

ii The point during decelerations when speed equals \( v_f \) is end of the cruise phase and the start of the acceleration is start of the cruise phase.

Idle-Acceleration-Cruise Deceleration (IACD) cycles

IACD cycles are identified in the on-road data so that the elemental and running speed models could be tested over sections between successive stops or major slowdowns. The procedure used was similar to the one used to indentify cruise phases and is shown in figure 2.13. Starting at the end of one cycle, the next acceleration above 15 km/h and following deceleration below 15 km/h are identified. Then, using the procedure explained in the cruise subsection, the cruise section between the acceleration and deceleration is identified and the mean cruise speed calculated. The minimum speed between the deceleration below 15 km/h and the next acceleration above 15 km/h is taken to be the end of the cycle. If this speed was larger than zero, no idle period occurs during the cycle. The mean cruise speed is used as final acceleration and initial deceleration speeds.
Idle
Acceleration
to above
15 km/h
Cruise with initial and
final speeds equal
Deceleration
to below
15 km/h
No Idle
in next
cycle

Figure 2.13: Speed-time trace showing the way idle-acceleration-cruise-deceleration cycles were identified (Biggs, 1985)

**Error**

All phases that have a duration of less than four seconds for PARAMICS data and less or equal then three seconds for FCTTDAS or GPS data, are changed into phase type 0 (error / indeterminate phase). Emission calculations for these phases are based on formulae that would have been used before being converted from their original phase type to phase type 0. The relative amount of error phase time gives an approximation of the quality of the phase cutting process. A relative low amount of error time provides the knowledge that the emission predictions are accurate, while a relatively high amount of error time shows that there exists a certain uncertainty in the prediction.
Chapter 3: Calibration of the PARAMICS model

In this chapter the calibration procedure is performed. This will lead to calibrated parameter values which will be validated in chapter four. The road section used for calibrating the PARAMICS model is the King William street, the central street of the Adelaide CBD. The used data for the calibration is gathered with the TSC’s Holden Commodore in 2005. This chapter follows roughly the theoretical steps as described in the first section. After explaining the calibration method the chapter continues with a look into the calibration data and how it is splitted into the different phases. A important part of this chapter is section 3.4 where the setup of the simulation is determined. Sections 3.5 and 3.6 treat the simulation data and how this is put through the Drive Cycle Splitter. In the penultimate section all the different settings are compared and the optimal settings are selected. Finally is in the last section a feedback given over the calibration process.

3.1 Calibration method

The thesis uses an existing PARAMICS model of the Adelaide CBD that is already calibrated for the standard usage. The model only needs driver behaviour calibration, since that seemed to be cause of the incorrect trajectories. This section describes the calibration of the driving behaviour. This is a process of six steps, as displayed in figure 3.1, with an iterative loop between the last step and third step.

Step 1: Creating a known dataset

In this step a known dataset is created. This known dataset should contain recorded speed time profiles from individual vehicles in the area of interest and serves a starting point for the calibration. The data collection method is for the process not of importance. However if probe vehicles data is used, engine statistics can be acquired as well through reading out the vehicles engine map.

Step 2: Phase splitting the known dataset

The known dataset is transformed with the ISST-TC’s splitter into two files. The first file is called PS (per second) and is similar to the entered dataset but added with the phase type for each time step. The second file is called Stats and provides information per phase. This information can be split into three different groups of columns. The first five columns give information like phase type and duration about the phase itself. The next twelve columns show information of the speed and acceleration in the particular phase. This information is shown in the minimum, maximum and mean value in the particular phase and is completed with a standard deviation. The last group, which consist of forty-three columns, gives similar statics as shown in the second group, only about consumed fuel and produced emissions.

Figure 3.1: Calibration steps
Step 3: Simulating a dataset similar to the known dataset
In this step the area of study is simulated in a traffic simulation package and the same routes are recorded as the one collected in step 1.

Step 4: Phase splitting the simulated dataset
This step is similar to second step, with the exception that the last group only consist 14 columns of emission data instead of 43. The emission values are calculated per phase with the TSC experimental based estimated emission functions. Because the emissions are calculated per phase, it only shows the total amount within that phase and the mean.

Step 5: Statistical comparison of both datasets
The phase splitting results of the known and simulated dataset are statistically compared in this step. This is done for each type of phase except for the error phase. Table 3.1 shows that the calibration criteria are split up into two different sections. The first section looks at the duration of the phases and how they are distributed. The second sections looks at the magnitude of the of the phase. In contradiction to the time section most phases have a different parameter on which they are compared.

Table 3.1: Calibration criteria

<table>
<thead>
<tr>
<th>Phase</th>
<th>Time</th>
<th>Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nr</td>
<td>ID</td>
<td>Average</td>
</tr>
<tr>
<td>0</td>
<td>Error / indeterminate</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Idle</td>
<td>$t_{phase,n}$</td>
</tr>
<tr>
<td>2</td>
<td>Acceleration from idle</td>
<td>$t_{phase,n}$</td>
</tr>
<tr>
<td>3</td>
<td>Deceleration to idle</td>
<td>$t_{phase,n}$</td>
</tr>
<tr>
<td>4</td>
<td>Acceleration</td>
<td>$t_{phase,n}$</td>
</tr>
<tr>
<td>5</td>
<td>Deceleration</td>
<td>$t_{phase,n}$</td>
</tr>
<tr>
<td>6</td>
<td>Cruise</td>
<td>$t_{phase,n}$</td>
</tr>
</tbody>
</table>

The idle phase is not compared in the magnitude section, because the thresholds of the phase idle do not leave room for significant deviations. In theory idle even has no magnitude, but the algorithm indicates very low speeds (< 0.5 km/h) to be idle as well. Phases three to six are compared with common parameters, and the acceleration for phases three and five will be presented as a deceleration. Phase two, ‘acceleration from idle’, however is compared with a parameter called $\beta$. $\beta$ is derived out of the acceleration, but where the acceleration provides the speed change per second gives $\beta$ the speed change per square root second. The advantage of this that the equation of $\beta$ in this phase has a linear form ($y = Bx+c$) where the equation of the acceleration is parabolic. Using beta instead of the acceleration gives better approximations for the acceleration profiles. The advantage of calibrating on the duration and magnitude of the phase types over calibrating on travel times, is that once the model is calibrated it is also sure that behaviour between start and the end is correct. While by calibrating on travel times, it is only known that duration is correct, but there is now conformation that the behaviour between the start and the end is correct.

For comparing the distribution between two sets, two different tests can be used. The Kolmogorov-Smirnov test is used when the known dataset and the simulated size are of the same magnitude. If however the known dataset is significantly smaller then the simulated one, the t-test is a better option. For a more accurate result of these tests it is recommended to normalize the distributions first if they are not initially normal distributed. When the initial distribution is not normally
Chapter 3: Calibration of the PARAMICS model

- Inverse
- Power transformation including all the above and cube root

These transformation techniques have however a left side positive skewed distribution as a starting point. For this reason right skewed and/or negative distributions should first be made left skewed and/or positive. All the steps that are taken to make a distribution normal, should be performed on both datasets. If there are many outliers in the dataset, these outliers should be removed.

**Kolmogorov-Smirnov test**
This test quantifies the difference between two datasets. It computes the maximum difference between the distribution functions of the datasets. In formula it can described as (Dekking, 2005):

\[ t_{ks} = \sup_{a \in \mathbb{R}} |F_n(a) - F_X(a)| \]  

\[ t_{ks} \]  

Kolmogorov-Smirnov distance between \( F_n \) and \( F_X \)
\( F_n \) estimation of the distribution function of the known dataset
\( F_X \) estimation of the distribution function of the simulated dataset

**T-test**
The t-test determines if a data sample from a data set is a representative part of that set. The test works with a hypothesis. At the start should be stated that the sample set is, or is not, a subset of a normal distribution (in our case it is actually inverse, we know that the sample is correct and we try to find out with a certain possibility whether the sample could be drawn out of the distribution). In formula the t-test looks as follows (Dekking, 2005):

\[ T = \frac{\bar{X}_n - \mu_0}{S_n / \sqrt{n}} \]  

\( \bar{X}_n \) mean value of the data sample
\( n \) sample size
\( \mu_0 \) mean value of the normal distribution
\( S_n \) sample variance of a random sample

If the calculated T value is between the T values acquired out of a table of t-distributions (a positive and negative one) the hypothesis is accepted with an indefinite certainty. If the T value is over the threshold, then the hypothesis is rejected. The well-known threshold is 1.96 for a 95 percent confidence interval.

**Step 6: Within the defined confidence interval?**
If the values are within the predefined confidence interval the calibration process is finished. If however the values are not within the confidence interval, the driving behaviour parameters should be adjusted. After the values are adjusted the calibration process continues at step 3 again.
3.2 Calibration data

The calibration data is the data which is used for calibrating the PARAMICS model. The data set used for this thesis was gathered for another TSC research project (Chang, 2006) from June till November 2005. Data were collected on Wednesdays during school terms as it is believed that traffic volume is lower during school holidays. The car used for collecting this data is the TSC's research vehicle, a 1997 General Motors Holden Commodore sedan. The vehicle is instrumented to enable recording in real time of the variables shown in table 3.2. The vehicle is also fitted with a global positioning system (GPS) receiver which provides real-time position information in the form of latitude, longitude, altitude and heading. The GPS receiver is equipped with a GPS differentiation correction device, to minimize the measurement errors. The manifold pressure, which can be read out of the onboard computer of the car. Coupling the manifold pressure to the engine speed and the engine maps of the different emissions provides CO, CO₂, HC and NOₓ emissions on a second-by-second basis.

For the calibration process the King William Street, limited by North and South Terrace, was chosen because of its homogeneous profile and the absence of crossings with priority (public transport) traffic. The street divides the Adelaide CBD, which was originally designed as a square of one by one mile, in two almost identical rectangles. The period of day which was calibrated on was the morning peak from 7:45 to 9:00. The reason for choosing the morning peak was that this is the most traffic intensive period of the day. The evening peak has a greater dispersal. The time interval between 7:45 and 9:00 is a bit shorter than some other definitions of the Adelaide CBD morning peak, but by narrowing the interval the traffic intensity becomes more constant over the interval. Strikingly northbound and southbound runs have, despite their similar track layout, significant different travel times as is shown in figure 3.2. The results in the availability of only two complete runs in each direction instead of four for the whole road. Choosing another road for calibration would not have solved the dilemma because travel times on all of the roads in the Adelaide CBD are asymmetric. Also the number of recorded trips per road per peak period has a maximum of four. The low number of recorded runs has however an effect on the statistical validity of the mean, but especially the standard deviation of the duration and magnitude of the different phases.

The original recordings made in 2005 had a different begin and end point then needed for this thesis. Because documentation about at what time the Commodore was at which intersection was contradictory, there is chosen to plot the whole data set in Mapinfo. By loading the Adelaide CBD map in Mapinfo as well, the start and end times could be determined exactly. This resulted into four
runs, graphically plotted in Mapinfo shown in figure 3.3. The two northbound runs are displayed with the light and dark blue triangles and the two southbound runs by the orange and red triangles. Because the north and southbound traffic streams are not similar in travel time and intensity, there is chosen to calibrate the model only on the north bound runs. There is no specific reason for choosing the northbound runs over the southbound runs, it is a random choice without any further consideration.

Figure 3.3: Commodore data north and southbound on King William Street plotted with Mapinfo

A remark to keep in mind during the calibration process is the accuracy of the calibration data. Because in addition to the low number of runs, there was also the fact that the driver during the recording of these runs was a foreign woman who was not used to driving in Adelaide. This is not in essence a bad thing, especially as she tried to drive with the mentality to go with the flow. However it is very probable she did not drive with a mean level of awareness, aggression, familiarity and speed as an average Adelaide driver. Besides this, the fact remains the representativeness of the used Commodore Holden can be questioned regarding to the distribution of the simulated passenger vehicles. Recordings are done in a peak period, which weakens the influence of the used driver and vehicle. However with the used vehicle and driver it is very unlikely that the acquired data is very accurate.

3.3 Splitting calibration data

Splitting the Commodore data with the Drive Cycle Splitter, the phase splitter software’s official name, is an easy process since one of the three input possibilities was specially designed for the Commodore data (figure 3.4). When using the splitter three different datasets can be splitted:
1. Fuel Consumption and Travel Time Data Acquisition System (FCCTDAS) Emission Data (the abbreviation FCCTDAS in the software is incorrect).
2. Data obtained from a random vehicle equipped with a GPS receiver.

Figure 3.4: Screenshot of the Drive Cycle Splitter
3. Simulated PARAMICS data.
The difference between option one and option two is that the FCTTDAS Emission Data contains also emission data. This is calculated by combining the vehicle’s onboard computer data and detailed engine maps of the used car.

3.4 Set up of the simulation runs

Before starting with the simulation the setup of the runs must be determined. An important aspect in this is to determine the minimal needed number of identical runs with different random seeds. For this two things need to be known. This first is the initial difference between the FCTTDAS-data and the defaults simulations. Because the magnitude of this difference determines the magnitude of the acceptable level of deviation caused by the random seeds in a series of runs. The second aspect is to determine the maximum level of influence a random seed can have on the results. In other words, how big is the deviation of a series of runs. A final aspect is practical boundary condition that number of different seeds still needs to be workable. I.e. a substantial part of the analysis of the run is not automated. Hence a large number of different seeds would take more time than is available for this research. Under this last condition the maximum number of identical runs with different random seeds is ten. At the end of section 3.4.1 is determined if this number is sufficient. This is done by comparing three identical sets of ten runs with different random seeds.

In section 3.4.2 is determined which driver behaviour should be adjusted and how they should be adjusted. This based on the a study of the used car-following model combined with knowledge out of the literature research.

3.4.1 Determining an acceptable deviation between identical series of runs

![Graph](image)

Figure 3.5: Difference in the mean duration and magnitudes for the trajectory phases of the FCTTDAS-data and the default simulation series
Chapter 3: Calibration of the PARAMICS model

To determine a level of deviation caused by the random seeds which is acceptable, is first looked into how large the gap is at the beginning of the calibration process. This gap is the difference between the durations and magnitudes derived from the FCCTDAS data and the runs made with the default parameter values of PARAMICS. Further information about the actual parameter setting of the different runs is provided in section 3.5. Figure 3.5 shows with the blue bars the durations and magnitudes derived out of the FCCTDAS-data. The red and green bar represented the average durations and magnitudes of the series of runs with the two default settings. The differences between the bars are presented in figure 3.5. There can be seen that duration are on average over the phases roughly 30% too short, while the magnitudes are almost on average 100% too large. However, these figures are relative numbers and the biggest relative differences are caused by phases which have a short duration or a low magnitude in the FCCTDAS-data. This causes relatively small absolute differences to been blown up. For this reason the absolute differences cannot be ignored.

**Determining the range of outliers in a series of runs**

As mentioned earlier a different random seed in a otherwise identical simulation run can cause a different result. To estimate how big this spread is, ten identical runs are performed with different random seeds. In figure 3.6 a bar chart is shown where the mean duration and magnitudes of the phases from each run are plotted. Each duration or phase starts with a blue bar with represents the average over the ten runs, followed by the ten individual durations and magnitudes. The chart clearly shows that each run with an unique seed results in different durations and magnitudes. Although the level of deviation of duration or magnitude depends on the phase, it is visible for all phases. For example the deviations in the duration in the idle phase are stronger than the deviations in the acceleration phase. The deviations caused by the random seeds on the standard deviations are not shown here, but a similar effect can be seen with them as well. The effect of a different random seed is here even slightly stronger, if looked the relative deviations.

### Table 3.3: Absolute and relative difference between the mean durations and magnitudes of the phases between the FCCTDAS-data and the two defaults simulation runs.

<table>
<thead>
<tr>
<th>Phase</th>
<th>Duration</th>
<th>Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DS 0</td>
<td>DS 1</td>
</tr>
<tr>
<td>0 Error / indeterminate</td>
<td>0.10</td>
<td>0.08</td>
</tr>
<tr>
<td>1 Idle</td>
<td>-4.29</td>
<td>-3.79</td>
</tr>
<tr>
<td>2 Acceleration from idle</td>
<td>-3.16</td>
<td>-3.38</td>
</tr>
<tr>
<td>3 Deceleration to idle</td>
<td>-2.20</td>
<td>-2.59</td>
</tr>
<tr>
<td>4 Acceleration</td>
<td>-2.39</td>
<td>-2.69</td>
</tr>
<tr>
<td>5 Deceleration</td>
<td>-6.12</td>
<td>-6.45</td>
</tr>
<tr>
<td>6 Cruise</td>
<td>-8.08</td>
<td>-8.45</td>
</tr>
<tr>
<td>Average difference</td>
<td>-0.29</td>
<td>-0.49</td>
</tr>
</tbody>
</table>

Average difference: -27% 91% 103%
Determining the deviations between multiple series of identical runs with different random seeds.

To determine if the practical limit of ten runs is indeed high enough to rely on the results three series of ten identical runs were performed. All thirty runs have a random random-seed between 0 and 99,999. In figure 3.7 can be seen that the series are not fully identical. Nevertheless if compared with the deviations seen figure 3.6 the deviations are significantly smaller. For example, if looked at the duration of the idle phase which showed in figure 3.6, the largest deviations between the runs with...
the different seeds. Although in figure 3.6 ten runs are plotted and in figure 3.7 only three series, the biggest difference went down from 5.2 seconds to 0.6 seconds. This 0.6 seconds means that a 0.3 second under or overestimation could occur compared to the mean of an indefinite number of runs. Considering that figure 3.5 shows a 4.3 seconds and 3.8 seconds difference at the start of the calibration a deviation of 0.3 seconds is less than ten percent of the original difference. Based on that is concluded that the average over ten runs might not be optimal, but is satisfactory for calibration purposes. Especially when is taken in consideration that the used FCTTDAS-data set is due to the small sample size also not very accurate.

3.4.2 Theoretical adjustments of the driver behaviour parameters

In figure 3.5 and table 3.3 can be seen that at the start of the calibration some durations and magnitudes of the simulated data already approach the values of the FCTTDAS-data while others differ still significantly. As a starting point for the calibration can be concluded that the duration of the phases cruise, acceleration and deceleration is too short, while their magnitudes are too large. For emission calculations the differences in phases cruise and acceleration are more important than the differences in deceleration because in the first two phases much more emission is generated per second than the during a second in a deceleration phase. Errors in those phases have a bigger influence on total emission discharge than errors in the deceleration phase. However the guarantee that model still resembles the observed situation the decelerations cannot be neglected.

Now that it is clear what the result of the adjustments should be, there is looked into the car-following model of PARAMICS to determine which parameters need to be adjusted to get the desired result. From the literature study in chapter 2 we already know that PARAMICS uses a car-following that is based on the Fritzsche model. Figure 3.8 is a pictorial representation of the car-following model which is used in PARAMICS. There are five discrete areas A, B, C, D and E in the headway/velocity-difference phase space, as shown in figure 3.8.

Region A. The following vehicle has overshot the target point (the headway is less than the target value), and an attempt is made to achieve the target speed as quickly as possible, i.e. as fast as the physical constraints of the vehicle allow.
Region B. The leading vehicle is pulling away from the following vehicle.
Region C. The vehicles are at a constant separation or coming together.
Region D. The vehicle ahead is perceived to be braking (its deceleration is greater than a certain threshold), its perceived speed is decreased by an amount dependent on its maximum deceleration rate (which models a driver’s expectation that if the vehicle ahead is braking, its speed in the next time step will be considerably less than at the current time-step). The method of application of speed difference and current separation to acceleration ensures that a vehicle will over-compensate if the vehicle ahead is braking, and that this over-compensation will increase as the distance between the vehicles decreases.
Region E. The vehicle ahead is perceived to be accelerating at a high rate, and is more than the following vehicle’s safe stopping distance away.

Each of these regions has a separate expression for acceleration, expressed as \( a_A \) to \( a_E \). Of these five, areas A, B and C correspond to conditions where the vehicle is following a leader. In figure 3.9 the leader\( (V_1) \)-follower\( (V_2) \) relationship is shown.

![Diagram](image)

Figure 3.9: Diagrammatic representation of target point for car-following algorithm (Quadstone, 2004)

The reason for a target separation \( s \) and an adjusted target separation \( t \) is that the current perceived speed is the actual speed at some time in the past, due to the influence of the reaction time modelling. In order to pull vehicles together at a faster rate than would be the case with linear acceleration alone, the adjusted target point position is calculated.

\[
t = \frac{s^2}{g}
\]

\[
s = h \cdot \Delta V
\]

\[
\Delta V = V_1 - V_2
\]

In addition to the adjusted target separation \( t \) Quadstone also implemented bunching acceleration \( c \) to bring the vehicles rapidly closer together. This bunching acceleration term decreases to zero as vehicles close in toward the minimum separation distance.

\[
a_A = k_2 \cdot \Delta V + k_3 \cdot \frac{g-t}{g}
\]

\[
a_B = k_2 \cdot \Delta V + k_1 \cdot \frac{g-t}{g}
\]
Chapter 3: Calibration of the PARAMICS model

\[a_C = c - k_3 \frac{(\Delta V)^2}{g - t}\]  

(51)

\[a_D = k_4\]  

(52)

\[a_E = a_{MAX}\]  

(53)

\[a_n \]

acceleration of a vehicle in area n \([m/s^2]\)

\[c \]

bunching acceleration of a vehicle (exists only in area C) \([m/s^2]\)

\[\Delta V \]

speed difference between leader and follower \([m/s]\)

\[k_1 \]

model parameter, default value 1.0 \([m/s^2]\)

\[k_2 \]

model parameter, default value 1.0 \([s^2]\)

\[k_3 \]

model parameter, default value 0.005 \([m/s^2]\)

\[k_4 \]

model parameter, default value 1.0 \([m/s^2]\)

The acceleration formulas \(a_A - a_E\) show that there are two main parameters (groups) that determine the acceleration of a vehicle at a certain time. The first are the target headways/separations and the actual headway/separation. The second group of parameters are the model parameters \(k_1, k_2\) and \(k_3\). The speed difference and the maximum acceleration have significant influence on the acceleration as well but they have given values and cannot be tweaked and are not useful for calibration purposes.

**Headways/Separations**

The target headway and the current headway, or more specific the difference between those two plays a significant role in the determination of the vehicles acceleration. The current headway is in each simulation a given distance and cannot be adjusted. The target headway, and in relation to that the adjusted target headway (40), is influenced by several vehicle parameters as is shown in table 3.4.

*Table 3.4: Influence of vehicle parameters on the mean target headway (Quadstone, 2004).*

<table>
<thead>
<tr>
<th>Condition / Parameter Variation</th>
<th>Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle type: e.g. Heavy goods vehicles</td>
<td>1.6</td>
</tr>
<tr>
<td>Presence of single-lane highway (no lane changing possible, as in road-works),</td>
<td>1.5</td>
</tr>
<tr>
<td>Close to motorway merge (accept smaller headway for limited time)</td>
<td>0.5</td>
</tr>
<tr>
<td>Close to traffic signals: straight ahead</td>
<td>0.5</td>
</tr>
<tr>
<td>Close to traffic signals: turning left</td>
<td>1.1</td>
</tr>
<tr>
<td>Aggressiveness (everywhere)</td>
<td>[\frac{36-Ag}{15}]</td>
</tr>
<tr>
<td>(Ag \leq 4)</td>
<td>[\frac{12-Ag}{8}]</td>
</tr>
<tr>
<td>(Ag \geq 4)</td>
<td>(Aw + 4)</td>
</tr>
<tr>
<td>Awareness (Near Lane-Drop)</td>
<td>(\frac{Aw + 3}{8})</td>
</tr>
<tr>
<td>(Aw \leq 4)</td>
<td>(\frac{4Aw}{4})</td>
</tr>
<tr>
<td>(Aw \geq 4)</td>
<td>(Aw + 3)</td>
</tr>
</tbody>
</table>

The goal was to decrease the acceleration (the positive as well the negative which is the deceleration). To perform this with a change in the target headway, the target headway should
increase. Table 3.4 shows that this only can be reached by lowering the mean aggressiveness or by increasing the mean awareness. The other parameters are network or traffic mix dependent and are not adjustable. There is spoken about a mean aggressiveness and mean awareness, because the level of aggression and awareness is always drawn out of a distribution when the vehicle is released into the model. The default distribution for the aggression as well the awareness is a standard distribution of integers with a minimum of zero and a maximum of eight.

There for in the series of simulation runs it is recommendable to:

- Increase the default target headway
- Decrease the mean level of aggression which will result in a longer target headway
- Increase the mean level of awareness which will result in a longer target headway
- A combination of the three options above

**Model parameters \( k_1, k_2, k_3 \) and \( k_4 \)**

Before determining how the model parameters \( k_1, k_2, k_3 \) and \( k_4 \) should be adjusted, must be mentioned that the documentation provided by Quadstone regarding the used car-following model is minimal and contains some errors. Especially the documentation part about the model parameters \( k \) contains some errors. For this reason the presented model parameters in this report are not identical to the ones in the Quadstone documents, since they are removed from their errors and adjusted where necessary.

\( k_1, k_2, \) and \( k_3 \)

These parameters determine the influence relation between \( \Delta V \) and \( \frac{\Delta v}{g} \) on the acceleration. Model parameter \( k_1 \) is two hundred times smaller than \( k_3 \). This results in that \( \Delta V \) and \( \frac{\Delta v}{g} \) are equally dominant in the calculation of the acceleration in area B, but in area A the acceleration is almost only determined by \( \Delta V \).

\( k_4 \)

Model parameter \( k_4 \) is different from the other three. Where the other determined the influence factor of \( \Delta V \) and \( \frac{\Delta v}{g} \) on the acceleration, is \( k_4 \) for region D the acceleration.

The problem with adjusting these model parameters in the simulation run lies in the fact that they all influence one or two zones. From the FCCTDAS-data is known that the accelerations on average are too high, but cannot be derived if this is the case in all areas. Also cannot be determined out of the FCCTDAS if the influence of the \( \Delta V \) or \( \frac{\Delta v}{g} \) is too large on the acceleration.

**Implementation from the proposed adjustments in PARAMICS 6.0**

Now it is theoretically clear how parameters of the PARAMICS car-following-model should be adjusted to get the desired results out of the series of simulation runs, it is time to see if these adjustments can be made in version 6.0 of PARAMICS. The possibility to adjust the model parameters \( k \) has never existed in any version of PARAMICS. Regrettably is it since version 6.0 also not longer possible to adjust the distribution the level of awareness and aggression. This means that the target headway is the only remaining adjustable parameter from the study of the used car-following model.
An increase in headway will most likely result in a lower because it reduces the term \( \frac{g-1}{g} \) and so also the acceleration.

Although the research on the car-following model only lead to one adjustable parameter, are there still more parameters which can be adjusted to achieve the goal. As already mentioned in the section 2.3, literature suggest that adjusting the reaction factor might help as well. Logically a decrease in reaction time should result in lower acceleration since a high reaction time will lead to a over and under compensation accompanied by high accelerations and decelerations.

A third and final option to achieve lower accelerations, decelerations and speeds is lowering the maximum speed-acceleration and speed deceleration profiles. Since the aggression and awareness distributions cannot be adjusted is looked into what they influence. As already showed in section 3.4.2 they influence the target headway, but they also influence the used acceleration. A low level of aggression or a high level of awareness results in a longer headway and a lower maximum acceleration and deceleration. The point of departure was that the level of aggression was too high and the level of awareness too low. Since the aggression and awareness cannot be adjusted, the headway and acceleration-speed and deceleration-speed profiles are adjusted.

### 3.5 Simulation data

The simulation data is created in PARAMICS with a default time step of half a second. Fortunately the ISST-TS already possessed a fully operation model of the Adelaide CBD, which saves a lot of time. The model resembles the situation in 2005. Nowadays the situation is different, because of an extension of the tramline over King William street in 2007. With the completion of the tramline extension all traffic lights along the King William road were reconfigured. To filter the necessary data out of
PARAMICS a plug-in called qpVPosition was used. The plug-in needs a list of links, which form together the to be researched route(s), what is in this case King William Street limited by North and South Terrace. The plug-in has been given the same time span, from 7:45 to 9:00, as the real life FCTTDAS-data collected with the instrumented Commodore. The PARAMICS simulation however starts fifteen minutes earlier to make sure the network is filled by 7:45.

There are multiple series of ten runs performed with different behaviour settings, which can be divided over four groups. These four groups are completed with two series of default runs. For each run is shown what is changed compared to the default settings (DS 1). All alterations are shown in relative differences in comparison to the default values. The reason for showing relative alterations instead of absolute alterations is to maintain a clear overview. The acceleration-speed and deceleration-speed profiles, for example exist for multiple vehicle classes and each class has two times seventeen values. Showing every time all these values when they are changed would not benefit the surveyability of this report. Similar arguments apply for the other parameters, because they are often drawn out of a distribution for each vehicle which enters the network.

Table 3.5: Overview of the series of simulated runs and their adjustments in comparison to the default values.

<table>
<thead>
<tr>
<th>Name</th>
<th>Speed-acceleration</th>
<th>Headway</th>
<th>Reaction factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Default settings 0</td>
<td>n/a</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Default settings 1</td>
<td>DS 0</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Adjusted settings: acceleration-speed profile 50%</td>
<td>AS AP-50%</td>
<td>50%</td>
<td>100%</td>
</tr>
<tr>
<td>Adjusted settings: acceleration-speed profile 30%</td>
<td>AS AP-30%</td>
<td>30%</td>
<td>100%</td>
</tr>
<tr>
<td>Adjusted settings: acceleration-speed profile 25%</td>
<td>AS AP-25%</td>
<td>25%</td>
<td>100%</td>
</tr>
<tr>
<td>Adjusted settings: acceleration-speed profile 20%</td>
<td>AS AP-20%</td>
<td>20%</td>
<td>100%</td>
</tr>
<tr>
<td>Adjusted settings: headway 20%</td>
<td>AS HW-200%</td>
<td>100%</td>
<td>200%</td>
</tr>
<tr>
<td>Adjusted settings: headway 20%</td>
<td>AS HW-150%</td>
<td>100%</td>
<td>150%</td>
</tr>
<tr>
<td>Adjusted settings: reaction factor 200%</td>
<td>AS RF-200%</td>
<td>100%</td>
<td>200%</td>
</tr>
<tr>
<td>Adjusted settings: reaction factor 150%</td>
<td>AS RF-150%</td>
<td>100%</td>
<td>150%</td>
</tr>
<tr>
<td>Adjusted settings: reaction factor 75%</td>
<td>AS RF-75%</td>
<td>100%</td>
<td>75%</td>
</tr>
<tr>
<td>Adjusted settings: reaction factor 50%</td>
<td>AS RF-50%</td>
<td>100%</td>
<td>50%</td>
</tr>
<tr>
<td>Adjusted settings: combination of acceleration-speed profile 30% &amp; headway 200%</td>
<td>AS CB-AP30&amp;HW200</td>
<td>30%</td>
<td>200%</td>
</tr>
<tr>
<td>Adjusted settings: combination of acceleration-speed profile 30% &amp; headway 150%</td>
<td>AS CB-AP30&amp;HW150</td>
<td>30%</td>
<td>150%</td>
</tr>
<tr>
<td>Adjusted settings: combination of acceleration-speed profile 50% &amp; headway 200%</td>
<td>AS CB-AP50&amp;HW200</td>
<td>50%</td>
<td>200%</td>
</tr>
<tr>
<td>Adjusted settings: combination of acceleration-speed profile 50% &amp; headway 150%</td>
<td>AS CB-AP50&amp;HW150</td>
<td>50%</td>
<td>150%</td>
</tr>
</tbody>
</table>

The combinations of parameter adjustments are already shown here for surveyability reasons. In practice the combinations were only put together after the other series of runs were analysed in section 3.7. A similar process is followed by the determination of the level of change that was needed for each parameter in the groups one to three. After comparing the results of the default runs with the results of the FCTTDAS-data (table 3.3) an initial logical adjusted value was tried. After analysing those runs, the adjustment in the parameter was decreased or increased till the local optimum of that parameter was found (figures 3.11, 3.14 and 3.17). This also explains why for the headway three adjusted values were tried and for the reaction factor and the acceleration-speed and deceleration-speed profiles four adjusted values. More over the local optimums can be find in section 3.7.

The adjustments in the parameters in the headway and reaction factor are made locally on a link level whereas the acceleration-speed and deceleration-speed profiles could only be made for the whole PARAMICS model. Adjustments on a local level have the preference over network wide adjustments, since the network was already successfully calibrated on macroscopic data. Hence
changing as few parameters as possible has the preference. There for the parameters that are adjustable on a link level were only changed in the researched area. So during the calibration these parameter were only adjusted on King William street and for the validation only on Pulteney street.

### 3.6 Splitting simulation data

Splitting the simulated data proved to be much more challenging then splitting the FCTTDAS-data collected with the instrumented Commodore. This is because the Drive Cycle Splitter was programmed for handling output from older plug-in. This plug-in was developed by the ISST-TS and only worked with an older version of PARAMICS (version 5). In the new version of PARAMICS (version 6), Quadstone included a plug-in similar to the ISST-TS’s one, but the structure of the output file was different. Besides the problem of the different outputs of the plug-in, there was also a problem with the functionality of the plug-in itself. The plug-in records all vehicles on the selected links per time step, while for this research only the passenger vehicles which travelled the whole street without any detours are taken into account. The method chosen for solving these problems consists of a number of database queries, batch scripts and manual procedures. The used queries, batch scripts, manual procedures and an explanation how they work can be found in appendix III.

### 3.7 Statistical comparison

In this section the results of the different series of simulations are compared mutually with each other and with the FCTTDAS data. This is primarily done by comparing the means of the duration and the magnitude of the phases. A second order score is based on the fit of the standard deviations of the duration and magnitude of the phases. If necessary a third order fit could be performed based on a KS-test or T-test, but this proved not to be required since the differences on primary level were still substantial. So performing a KS-test or T-test would not have had any added value. The first variable on the x-axis is the mean duration of the error phase. This variable does not need to be calibrated but serves as a safety check. If all steps in the simulation and the analyse have gone well this value should maintain roughly constant for the different series of simulations.

Because the mean duration of the different phases varies a lot and the magnitude of the phases is not always the same quantity is was not possible to determine a score of a particular parameter setting directly. This is because a score is based on the summed differences of the mean durations and magnitudes between the simulation average over ten runs and the FCTTDAS-data. For the duration problems occur due to the length of the duration differs a lot between the phases. For the idle phase a difference of two seconds would be called a reasonable good result since its is less than 7% off, however it is a bad result for the acceleration phase since their two seconds results in deviation of 22%. Differences in magnitudes cannot even be added since they are often expressed in different quantities. To overcome all these problems all the results are indexed. After indexing the results they can summed up to a comparable score. A disadvantage of this scoring method is that it does not show how the score is being built up. For example a score of hundred twenty could be built up by twelve times ten indexed points difference or two times sixty indexed points difference. In the first case all durations and magnitudes deviate by ten percent while in the second case ten durations and magnitudes have a perfect match while the other two are deviate by fifty percent. To cope with this problem a second score was introduced by taking the summed squared difference instead of the summed difference. In the case of the shown example this would lead to a score of 1,728 for the first situation while the second situation would have a score of 7,200. This shows that although the
summed indexed difference of the means is equal, the spread over the difference in the second case is bigger. Although these scores give a good indication on how a certain parameter setting scores, one should always keep looking at the differences at the phase level. This is because the score does not show if the simulation overestimates or underestimates. But even more important is that it needs to be known which phases are off before adjusting the parameters for the following simulation. A third aspect is that similar errors in different phases do not have the same influence on the emission predictions. Errors in the acceleration phase will result in worse predictions than errors of similar magnitude in the in deceleration phase. The comparisons between the standard deviations is preformed in a similar way, although that score is of less importance then the score derived from the mean values.

In the upcoming four sub-sections the calibration results are presented. They are grouped in the same groups as shown in section 3.7.5. Each parameter section starts with two graphs which display the mean respectively the standard deviation of the duration and magnitude of the phases. The indexed counterparts of these graphs can be found in appendix III. The first three groups also contain a sensitivity analysis to determine the local optimum for the researched parameter in that section. The fourth sub-section does not contain a sensitivity analysis, because combinations of parameter changes are tested here. In the last section the optimal parameter setting is selected which is tried to be validated in the next chapter.
3.7.1 Parameter: Acceleration-speed and deceleration-speed profile

In this section the optimal adjustment of the default acceleration-speed and deceleration-speed profiles is tried to be found. In figure 3.5 (and also in figure 3.11) can be seen that with the default values in PARAMICS result in durations which are too short and magnitudes which are too large. The too large magnitudes cause the too short durations, because the product of mean duration and mean magnitude should be roughly constant. The acceleration-speed and the deceleration-speed profiles show the maximum values of acceleration and deceleration. These values are rarely used in urban congested traffic. For this reason the profiles needed to be lowered drastically to see any effect. In figure 3.11 and figure 3.12 an improvement can be seen with the adjusted acceleration-speed and deceleration-speed profiles. However since the AS AP-50% run score best for the mean duration of the ‘acceleration from idle’ phase and AS AP-20% runs score the best for the mean duration of the cruise phase it is hard to determine which adjustment is the best one. For that reason the scores for all adjusted settings are plotted in figure 3.13. Figures a and b show respectively the summed absolute indexed error and the summed squared absolute indexed error. In both figures three errors are plotted. An error-score based on the mean durations and magnitudes of the phases, an error-score based on the standard deviation durations and magnitudes of the different phases and an error-score of both combined. In figures c and d the error-score based on the mean duration and magnitude of the phases from figure a and b is split into an error-score of the mean durations of the phases and the mean magnitudes of the phases. Similar to a and b, c is here the summed absolute indexed error and d is the summed squared absolute indexed error. For these figures applies, how smaller the error is the better the simulation data matches with the FCCTDAS-data. However if two points in the graph are more or less equal the point closest to the default parameter

Figure 3.11: Mean duration and magnitude for the trajectory phases of the FCCTDAS-data, the default simulation series and the simulation series with an adjusted acceleration-speed and deceleration-speed values.
Figure 3.12: Standard deviation of the duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with an adjusted acceleration-speed and deceleration-speed values.

Figure 3.13: Sensitivity analysis acceleration-speed profile parameter:

a) Summed absolute difference between the indexed 12 mean and/or 12 SD parameters as shown in table x.

b) Similar as fig. a only with the summed squared difference.

c) Summed absolute difference between the indexed 7 mean duration and 5 magnitude parameters as shown in table x.

d) Similar as fig. c only with the summed squared difference.
value (100%) is preferred. This is because it is desirable to stay as close as possible to the default value of the parameter in aspect to maintain a realistic simulation.

Another thing that figures c and d show is that mean magnitudes of the phases are far more sensitive to changes in the acceleration-speed and deceleration-speed profiles than the mean duration of the phases. Based on the results shown by figures in this section can be concluded that runs out the series AS AP-30% perform the best. Although its results are not optimal, it shows significant improvement over the default values. Although on some indicators the series AS-AP-25% and AS-AP-20% score slightly better, they were not believed to be realistic anymore.

3.7.2 Parameter: Headway

The second parameter which is adjusted in order to try to calibrate the PARAMICS model is the headway. It was not totally clear whether an increase in headway would result in the desired outcome of longer durations and smaller magnitudes or the inverse. Because of this uncertainty an increase as well as a decrease in headway is tested. Figure 3.14 and figure 3.15 however show that difference between the series of runs are marginal, but shows a slightly better performance of the series with a higher headway is detectable.

Figure 3.14: Mean duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with an adjusted headway parameter.

Figure 3.16 confirms that increased headway performs slightly better. Figures a and b show that in the overall score the improvement is mainly caused by the adjusted standard deviations of the durations and magnitudes over the phases. From the figures c and d can be seen that improvement in the error-score of the mean in a and b is caused by lower magnitudes.
Figure 3.15: Standard deviation of the duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with an adjusted headway parameter.

Figure 3.16: Sensitivity analysis headway parameter:

a) Summed absolute difference between the Indexed 12 mean and/or 12 SD parameters as shown in table x.
b) Similar as fig. a only with the summed squared difference.
c) Summed absolute difference between the indexed 7 mean duration and 5 magnitude parameters as shown in table x.
d) Similar as fig. c only with the summed squared difference.
Because the differences between the headway adjustments are small it is hard to select an optimal value for this parameter. However the series of AS HW-150% runs was selected because it is within realistic distances of the default value and shows an increased performance over the series of default values runs.

3.7.3 Parameter: Reaction factor
The reaction factor is, after the prefaced parameters, the third parameter which is advised by Quadstone for calibrating the car-following behaviour (Quadstone, 2006). By adjusting this parameter is tried to find an optimal value for which the calibration results improves most. Unfortunately despite the recommendation by Quadstone that the parameter could be used to calibrate the car-following model, figure 3.17, figure 3.18 as well as figure 3.19 shows no significant differences between the series of runs with an adjusted reaction factor. The small differences between the different series of run that are detectable, are as likely to be caused by the different random seeds as is explained in section 0, as by the adjusted reaction factors. Because there is no significant difference recognizable between the series of runs with an adjusted reaction factor parameter that is indisputable caused by an adjustment of the reaction factor, there is decided to keep the reaction factor on its default value.

Figure 3.17: Mean duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with an adjusted reaction factor parameter.
Figure 3.18: Standard deviation of the duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with an adjusted reaction factor parameter.

Figure 3.19: Sensitivity analysis reaction factor parameter:

a) Summed absolute difference between the indexed 12 mean and/or 12 SD parameters as shown in table x.

b) Similar as fig. a only with the summed squared difference.

c) Summed absolute difference between the indexed 7 mean duration and 5 magnitude parameters as shown in table x.

d) Similar as fig. c only with the summed squared difference.
### 3.7.4 Parameter: Combinations

Before selecting the optimal parameter settings, some combinations of adjusted parameters are tested as well. This does not always have to be a combination of the optimal adjustments of the individual parameters of the previous sections. Because if one parameter causes an overestimation of a duration or magnitude of a phase, an adjusted second parameter could cause an underestimation. Individual they have a poor error-score, but both combined they perform well once the underestimation and overestimation neutralize each other. However since that in section 3.7.3 showed that changing the reaction factor results as good as no improvement, an adjusted value compared to its default value is not considered to be a part of the tested combinations. Added to this that the parameters aggression and awareness could unfortunately not be changed, only combinations of two parameters are possible. Of the adjusted acceleration-speed and the deceleration-speed parameter and adjusted headway parameter series of runs for each the best two performing adjustments were selected. Combining results in the four combinations as described in section 3.5 and shown in figure 3.20 and figure 3.21. Because the combinations do not have a sensitivity analysis is it slightly more difficult to selected the preferred combination. It is clear that combinations including the AS AP-30% parameter setting perform equal or better on all durations and magnitudes of the phases except for the mean duration of the ‘acceleration from idle’ than the combinations including AS AP-50%. This was also to be expected based on the error-scores of the individual adjustments of the acceleration-speed and deceleration-speed profiles.
Figure 3.21: Standard deviation of the duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with a combination of adjusted parameters.
3.7.5 Selection of the optimal parameter settings

Now the series of runs of the parameter adjustments and combination of parameter adjustments are performed an optimal series can be selected. To make this process more transparent all results are plotted in the figure 3.22. This figure contains six bar charts. The bar charts in the left column shows the total indexed error compared to the FCTTDAS-data and the bar charts in the right shows the total indexed squared error compared to the FCTTDAS-data. Similar as has been done previous in the sensitivity analysis. The bar charts in the first row show the error build up out of the mean of the durations and magnitudes combined with the error out of the standard deviations. Although this gives a good impression of which series of runs perform better than others the charts are not correct. This is because the error of the first order is added to the error of the second order. Adding both errors without additional measures which ensure that first order error weights heavier then the second order is incorrect. Also is this second order error larger than the first order error as can be seen in figure c, d, e and f. This results that in an case of the small than average first order error and

![Figure 3.22: Summed Indexed errors between the FCTTDAS data and the simulations:](image)

- a) Summed absolute difference between the indexed 12 mean and 12 SD parameters as shown in table x.
- b) Similar as fig. a only with the summed squared difference.
- c) Summed absolute difference between the indexed 12 mean parameters as shown in table x.
- d) Similar as fig. c only with the summed squared difference.
- e) Summed absolute difference between the indexed 12 standard deviation parameters as shown in table x.
- f) Similar as fig. e only with the summed squared difference.
larger than average second order error, the good first order error-score would not be recognised since it is added to the large second order error-score. Therefore the first and second order errors are also plotted separately. This is done in row two for the first order error caused by the mean of the durations and magnitudes of the different phases. Row three shows respectively the second order error caused by the standard deviation of the durations and magnitudes of the different phases.

Figure 3.22 shows clearly that the following five series of runs perform better than the other series of runs; 'AS AP-30%', 'AS AP-25%', 'AS AP-20%', 'AS CB-AP30&HW150' and 'AS CB-AP30&HW200'. However the performance of these five is fairly equal, in earlier sections was already concluded that the series of runs 'AS AP-25%', 'AS AP-20%' and 'AS CB-AP30&HW200' were not realistic enough. Because the scores of 'AS AP-30%' and 'AS CB-AP30&HW150' are so close each other, that it is not clear which is preferable since minor deviations could as well be caused by the used random seeds. Due to this both settings are tried to validate in the next chapter. Although both series do not perform optimal table 3.6 shows in comparison with table 3.3 better results. Where the mean duration of phases before the calibration (table 3.3) showed an average deviation of 29% this is after the calibration reduced to an average deviation of 19%. Also for the mean magnitude of the phases an improvement can be observed. Where before the calibration the average deviation was 97% this is after the calibration reduced to an average deviation of 35% and 31%. The emission predictions made from these trajectories will most likely improve more than proportional. This is because in particular the magnitudes from the deceleration phases score poorly. But as already mentioned in the literature study have the acceleration phases significantly less effect on the amount of emissions produced than the acceleration and cruise phases have. Due to this the improvement after the calibration is larger than it initially looks like. Remarkable is the situation of the phases ‘acceleration’ and ‘cruise’. Although the magnitudes are almost equal to the measured FCTTDAS-data magnitudes, the durations are still too short.

All results were already presented divided over several bar charts of the previous sections, but table 3.7 shows in a single overview all results.
Table 3.7: Results of all series of simulation runs

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Chapter 3: Calibration of the PARAMS model
3.8 Conclusions and recommendations regarding the calibration

After evaluating the calibration process some conclusions and recommendations can be drawn about the results as well about the used method. This is done in two sections, where the first section deals with the conclusions and the second section with the recommendations. In both sections first is dealt with the used method and is continued with the actual results. By separating the calibration method and the calibration results, it becomes more transparent what the causes of the poor calibration results are.

3.8.1 Conclusions of the calibration

Conclusions concerning the calibration method:

- The method is extremely dependent on large quantities of adequate data
  The method relies heavily on availability of an adequate dataset. If the used dataset, as the FCTTDAS-data used in this research, has shortcomings in quantity or quality than the probability of successful calibration decreases rapidly.

  The FCTTDAS-data which is used to calibrate the PARAMICS model shows shortcomings in quantity as well in quality. The number of available runs recorded with the probe vehicle are significantly too low to have any statistical relevance. Also the fact that the runs where performed by only one driver makes it highly unlikely that the behaviour of this driver reflects the average behaviour of all drivers in the study area. Besides it was only one driver, it was also an inexperienced driver who was non familiar to the Adelaide traffic circumstances. This makes the reliability of the mean and standard deviation of the durations and magnitudes of the phases even more questionable. In section 4.3 is therefore looked into the influence that the driver of the probe vehicle has on the mean durations and magnitudes of the FCCTDAS-data.

- The calibration method is too elaborate
  The calibration method and in particular the analyses of the series of runs are too elaborate. This is mainly due to the number of procedures that need to performed manually. This gives the results a higher uncertainty than if the steps as described in appendix II were fully automated. Besides reducing the possibility of errors in the results, automation would also most likely reduce the time that is needed for the analyse of a single series of runs. An automated analysis will open the opportunity to generate and analyse more different series of runs or generate and analyse more runs per series.

- It is unclear if the calibration method works
  Although the calibration was not successful, this does not mean that the calibration method does not work. The absence of a good dataset and the impossibility to adjust key parameters like aggression and awareness makes it impossible to determine if the calibration method works for calibration urban traffic microsimulation models.

Conclusions concerning the calibration results:

- Overall calibration result are poor
  The first thing that can be concluded when looking at the calibration results, is that it is challenging to converge the simulated datasets to the recorded trajectories collected with the ISST-TS's probe vehicle. Even when taking in consideration that the used FCTTDAS data set is not
optimal, and therefore the accuracy of the mean and stand deviation of the duration and magnitude is questionable, it is still hard to adjust the selected durations and magnitudes correctly. Especially the phases 'deceleration to idle' and 'acceleration' are hard to calibrate with the available options and show poor results.

- **The simulations with parameter setting AS CB-AP30&HW150 performs the best**
  The best calibration result is reached with 30% of the defaults values of the acceleration-speed and deceleration-speed speed profiles combined with a headway of 150% of the default value. This combination combines a relative good error-score with adjustments in parameters which still can be justified. Although the calibration result is not optimal, runs with adjusted performs without a doubt better than the default parameter values.

### 3.8.2 Recommendations

**Recommendations concerning the calibration method:**

- **A further automation of the calibration process is recommended**
  A further automation of the calibration process is desirable, because it makes the results more reliable and most likely allows more simulation runs to be analysed in the same time span.

- **Calibrate the model with an improved dataset to determine if the calibration method works**
  The poor calibration data and the impossibility to adjust all desired parameters that are recommend by literature and arise from studying PARAMIC's car-following model, has a significant influence on the calibration result. This makes it hard to criticize the applied phase-based calibration method, except for the fact that is very dependent on adequate data. After a calibration with proper calibration data and the possibility to calibrate the aggression and awareness as well, it is possible to deeply criticize the used calibration method.

**Recommendations concerning the calibration results:**

- **Acceleration-speed and deceleration-speed profile should to be adjusted separately**
  Although the acceleration-speed and deceleration speed profiles are both initially overestimated with the default settings in PARAMICS it is recommended to adjust them separately. In figure 3.11 can be seen that when the profiles are being lowered, the acceleration and deceleration reach at different moments their optimal value. Although both parameters are determined in one file is possible to adjust them independently.

- **Finding a manner to adjust the aggression and awareness parameters**
  Since literature suggests and poor calibration results indicate that it is necessary to find a way to adjust the aggression and the awareness parameters as well. This can be performed by manual adjustments in the core files of PARAMICS. It would be however more desirable that Quadstone allows researchers to adjust the aggression and awareness parameters through a graphical user interface in PARAMICS.
- **Acquire a FCTTDAS-dataset with a more reliable quality and a higher quantity**
  The calibration is performed with a dataset of questionable quality and a low quantity. For further research a bigger and more reliable dataset is desirable.

- **Step size between the adjusted settings of the same parameter should be smaller**
  The sensitivity analysis gives a reasonable insight where the optimal values of the parameters lie through plotting a line through the known points. However this method only gives an estimate of points in between. If the analysis of the simulations becomes more automated it recommendable to create more known points. Especially in the neighbourhood of the suspected local minimum more known points would have an additional value.

- **Calibrate the model again with an improved dataset for a more reliable calibration result**
  The poor calibration data and the impossibility to adjust all desired parameters that are recommend by Quadstone has a significant influence on the calibration result. With proper calibration data and the possibility to calibrate the aggression and awareness as well it is recommendable to calibrate the model again. Results will be different and most likely be better.
Chapter 4: Validation of the PARAMICS model

In this chapter the calibration results of the previous chapter will be validated. Although the calibration results were not optimal, a successful validation would still be useful. Because if the results can be validated the calibration method can be used for relative comparisons if the errors in the durations and magnitudes are consistent. It would also prove that it is useful to continue to search for a parameter setting which gives a better result than the best parameter setting found in this report. The chapter starts with an introduction of the validation case. In the second section the results from the validation are compared with the calibration. The chapter ends with a section about the influence that the driver of probe vehicle has on the durations and magnitudes of the phases of the FCTTDAS-data.

4.1 Validation data

The calibration data is used for validating the PARAMICS Adelaide CBD model. The validation data comes from the same TSC research project (Chang, 2006) as the calibration data (section 3.2). For the validation process the Pulteney Street, limited by North and South Terrace, is chosen. In figure 4.1 Pulteney Street (highlighted in green) and King William Street (highlighted in red) look similar since both are North–South orientated, are almost equally long and have a similar capacity. However there are also some differences. The first is that King William Street is an on-going road which crosses the Adelaide CBD where Pulteney is frontage road which enters the CBD from the south.

Figure 4.1: Overview of the Adelaide CBD with in red King William street used for the calibration and in green Pulteney street used for the validation.
and ends at the northern border of the CBD. The second is that the relative and absolute amount of public transport on King William street is significantly higher than on Pulteney Street. The final difference is that King William Street has one traffic square (Victoria Square) where Pulteney Street has two squares (Hurtle Square and Hindmarsh Square). The Victoria Square consists of King William Street, where the other two squares are build around Pulteney Street and do not influence the geometry of the road.

Besides using a different road and there for consequently a different dataset for the validation the procedures performed to make the dataset ready for the splitter are almost identical to the calibration procedure. The period of the day on which was validated is again the morning peak from 7:45 to 9:00. The dataset was also plotted in Mapinfo to determine correct start and end times. There are also only northbound runs used due to the fact that travel times northbound and southbound are dissimilar. However the FCTTDAS-data of Pulteney Street consists out of four northbound runs. This is the double amount of runs that were available for the King William Street. In the report of Chang (2006) it was not clear that there more useable runs for Pulteney Street than King William street. This became only clear once the raw data was plotted into Mapinfo. If however this had been known in advance Pulteney Street would be used for calibration and King William for validation. This because the durations and magnitudes over four runs are more reliable than over two.
4.2 Statistical comparison

Figure 4.2 and figure 4.3 show the results after FCTTDAS-data and the simulated series of runs ‘AS AP-30%’ and ‘AS CB-AP30&HW150’ have been put through the Drive Cycle Splitter. Although it is logically that the mean durations and magnitudes of the FCTTDAS-data are different for the Pulteney Street than for the King William Street, differences between the FCTTDAS-data and the simulations should be of the same order if the method is consistent. This is however if the bar charts are compared with bar charts from chapter 3 not for all phases the case. The mean duration of the idle phase was underestimated in the calibration simulations and is overestimated in the validation simulations. An inverse switch from overestimation to underestimation can be seen in the mean duration of the acceleration phase. Another deviation that stands out is the mean and standard deviation of the duration of the error/indeterminate phase in the FCTTDAS-data. These are both higher than expected. Usually the mean duration and magnitude of the phase error/indeterminate are mainly determined by existence of indeterminate phases which cannot be larger than three seconds. The FCTTDAS-data contains also a rare error with a long duration which explains the higher mean and standard deviation. Nevertheless most of the durations and magnitudes show similar deviations between the FCTTDAS-data and the simulation series in the calibration as well the validation.
When the results of table 3.1 are compared with results of table 3.6, it can be seen that the absolute differences as well as the relative differences do not match. Therefore, the method cannot be used for relative comparisons. It is possible that the result of the poor FCTTDAS-data or the method and the FCTTDAS-data is not clear yet.

Table 4.1: Absolute and relative difference between the mean durations and magnitudes of the phases between the FCTTDAS-data and the AS AP-30% and AS CB AP30&HW150 simulation runs.

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<td>Average deviation</td>
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4.3 Driver influence on the data collection

This section gives some insight into the influence that a driver of a probe vehicle has on the collected data. The reason for looking into the drivers influence on the FCTTDAS-data are doubts during the calibration as well in the validation about the correctness of the duration and magnitude of the phases. The low number of runs has a big negative influence on the reliability of data. But it is expected that the driver has also influence on the data. Unfortunately there is no data set available of the Adelaide CBD which contains trajectories of the same route recorded by different drivers. The ISST-TS is however in the possession of another FCTTDAS-data set for a project on the South Road which is also in the Adelaide region. This data set contains trajectories of the same route, recorded with the same probe vehicle, in the same time period, but driven by three different drivers. Although the traffic conditions on the South Road are not similar to the conditions in the Adelaide CBD it proofs if inter driver differences exist. The drivers all had the same instructions. The instructions were to drive as an average driver. More details of the instructions can be found in the document “the provision of services associated with the collection and analysis of travel time data in the Adelaide metropolitan area and an option for GPS data collection for UniSA” (Kraus, 2002).

![Influence of the driver on the distribution of the phases](image)

Figure 4.4: Influence of the driver on the deviation of the phases.

Figure 4.4 shows the result of the three collection runs with three different drivers (Branko, Jeremy and Anthea). Although three runs can never be exactly the same through continuously changing traffic conditions, the differences are large enough to conclude that a driver has influence on the collected durations and magnitudes. Some durations/magnitudes are consistent over the three runs. The mean cruise speed is a good example of this. The reason for this lies in the maximum speed and the driving instructions. In other durations/magnitudes the driver has more freedom. The mean deceleration in the deceleration to idle is a good example of this. Anthea prefers to decelerate stronger and shorter where Branko prefers to decelerate slower and longer. In general the drivers
have the most influence on the deceleration and acceleration phases. This however influences the
other phases indirect since the average travel time remains constant. I.E. if you accelerate and
decelerate harder, the duration of your cruise and idle phase will increase to keep the total travel
time constant.

4.4 Conclusions and recommendations of the validation

The validation is completed and some conclusions can be drawn regarding the validity of the
calibration results. Based on these conclusions some recommendations are made for further
research and practice.

4.4.1 Conclusions of the validation

• Validation results are not consistent with the calibration results
  The results of the validation do not match for all durations and magnitudes with the results of
  the calibration. For almost all durations and magnitudes the absolute and relative differences
  between the FCTTDAS-data and the simulations are not consistent. Ten out 12
  durations/magnitudes show however an identical over- or underestimation in the calibration
  and validation. Only the difference between the duration of the idle phase and the duration
  acceleration phase give in the validation an inverse view when compared with the calibration.

• FCCTTDAS-data has an negative effect on the quality of the validation
  The poor quality of the FCCTTDAS-data makes a well-founded validation impossible. During the
  calibration poor FCCTTDAS-data among other things made a reliable calibration impossible. A
  reliable validation is also impossible, because the FCCTTDAS-data used for the validation contains
  most likely different deviations than the FCCTTDAS-data used for the calibration. This makes the
determination if the deviations are consistent difficult.

• The driver of the probe vehicle has noticeable influence on the duration and magnitude of the
  phases.
  The driver of the probe vehicle has demonstrable influence on the collected data. The influence
  is perceived directly in the duration and magnitude of acceleration and deceleration phases.
  Indirect this influences also the duration of the idle and cruise phase.

4.4.2 Recommendations of the validation

• New validation attempt with more reliable validation data is recommendable for a more reliable
  validation
  If quantitative more, and qualitative better FCCTTDAS-data is available in the future, it is
  recommendable to go over the validation process again to get more reliable validation results.

• When collecting FCCTTDAS-data on a route, it is recommendable that the probe vehicle is driven
  by multiple drivers to level out the influence that individual driver has on the durations and
  magnitudes.
  By future data collection runs it is recommendable to perform not only more runs, but also
  execute them by various drivers. By doing this personal preferences in driving styles will be
  aggregated out.
Chapter 5: Conclusions and recommendations

In this chapter conclusions are drawn with respect to possibility to calibrate traffic microsimulation models with a phase-based algorithm and microscopic data to create trajectories which are suitable for traffic emission predictions. These conclusions elaborated in section 5.1 use the research question from section 1.5 as a guideline. The conclusions are also split into three parts. A general part concerning the use of traffic microsimulation models for traffic emission predictions on a microscopic scale. After the first part the conclusions continue with a part about calibration method and results of the calibration and validation. The conclusions end with a review on the phase based calibration method. In section 5.2 some recommendations are formulated for future research and practice. These recommendations originate from the conclusions and have been split into two parts. One part gives recommendations for similar research or practice and the second part gives recommendations for possible directions of further research.

5.1 Conclusions

The goal of this research was “Acquiring insight into the behaviour of simulated trajectories and their errors, and determine if a PARAMICS model can be calibrated with a phase-based algorithm, so that the trajectories are suitable for reliable traffic emission predictions.” This goal will be reached through answering the research questions stated in section 1.5. All these questions are answered in this section and summarized in a final overall conclusion concerning the stated goal.

General conclusions regarding the usage of traffic microsimulation models for traffic emission predictions on a microscopic scale.

How well do microsimulation traffic models, and in particular longitudinal driving behaviour and car following modules, perform with respect to generating trajectories which are suitable for traffic emission predictions? And if unnatural behaviour occurs, what are the causes of these errors? Traffic microsimulation models in general, and more specific PARAMICS do still not perform as desired regarding the simulation of trajectories which are suitable for traffic emission predictions. Unnatural behaviour does still occur in the trajectories generated by traffic microsimulation models, although a phase-based calibration shows an improvement of approximately fifty percent in comparison to the default calibration. The main cause that there still exist considerable errors in the simulated trajectories lies in the fact that not all driver behaviour parameters can be adjusted. Whereas an analysis has shown that these unchangeable parameters are important for calibrating the driver behaviour, developers of the traffic microsimulation model do not allow them to be changed.

Conclusions regarding the phase-based calibration and validation of the Adelaide CBD PARAMICS model.

What are the optimal parameter settings of PARAMICS for which the phase-based calibration approach gives the most reliable predictions? The calibration and validation show that series of simulated runs ‘AS CB-AP30&HW150’ would give the most reliable prediction. In this series the acceleration-speed and deceleration-speed profiles are lowered to 30% of their initial values and the time headway is increased to 150% of the original values. This optimum is however a relative optimum, i.e. the best settings that could be found within the boundaries of this research. The results that these optimal parameter settings differs still
significantly from the desired absolute optimum, which is the situation where the simulated durations and magnitudes match the recorded durations and magnitudes.

How well is the fit of the statistical distributions of the phases found in the simulated data in comparison with the distributions of the real life data?
The fit of the statistical distributions is poor. There are however two factors which could explain this poor result. The first is the questionable quality and poor quantity of the used FCTTDAS-data. The number of recorded runs are far too low to base any statistical relevance to it. Also the fact that all runs were performed by the same driver results in a reliability problem since is shown section 4.3 that a driver has a noticeable influence on the recorded trajectories. The second cause that could explain a poor calibration result is the impracticality to adjust the key driving behaviour parameters aggression and awareness. The lack of this opportunity is somewhat strange since Quadstone as well recommends to use the aggression and awareness parameters for calibrating the driving behaviour and as well prohibits adjustments of it in its newest version of PARAMICS.

Is it possible to predict traffic emissions in urban areas, within the determined error margin, with the phase-based method?
It is not possible to predict traffic emissions in urban areas with a phase-based method yet. However, as explained in previous paragraph there are two factors which have a significant influence on the poor result. If however these issues can be overcome, the calibration result will be different and most likely improve. So the correct answer would be that it is not possible yet to predict traffic emissions in urban areas with a phased-based method under the given conditions.

Are the errors in the emission predictions consistent? I.E. can the predictions still be used for relative performance comparisons even if the absolute prediction is not correct?
This is a difficult question to answer. The validation showed some inconsistent result in comparison with the calibration. It is however not totally clear what the cause of this inconsistency is. It could be that that the errors are inconsistent, but the consistency of the errors is influenced by the poor quality of the FCTTDAS-data. However the current results are not totally consistent.

Overall conclusion
Summarizing the stated above, the following can be concluded regarding the goal which was set at the start of this research. Concerning the part of gaining insight into the behaviour of simulated trajectories and their errors the goal is reached. It is clear what their behaviour is and what needs to be done in order to make simulated trajectories suitable for traffic emission predictions. The second and most important part of the goal concerning discovering if traffic microsimulation models can be calibrated with a phase-based algorithm, so that their trajectories are suitable for reliable traffic emission predictions is not fully reached. Shown is that within the given conditions it was not possible to calibrate traffic microsimulation models such that their trajectories are suitable for reliable traffic emission predictions. However if the two main hindrances, knowingly the poor FCCTDAS-data and the impossibility of adjusting the two key driving behaviour parameters aggression and awareness can be taken away, it might be very well possible to calibrate a traffic microsimulation model successfully to use its trajectories for reliable traffic emission predictions purposes.
Chapter 5: Conclusions and recommendations

Evaluation phase-based approach

That the phase-based traffic emission calculation method is a successful manner to calculate traffic emissions was already proved in a confidential report for the South Australian government (Zito, 2003). The goal of this evaluation is to single out the strong and weaker points of the approach. This is based on the findings during this research. The evaluation starts with the weaker points of the phase-based approach and ends with the strong points.

A first weak point is that there is calibrated on the duration and magnitude of the different phases. A successful calibration and validation however does not guarantee that the model resembles the reality. I.e. the fact that the durations and magnitudes of the phases are correct, does not guarantee that the order of the phases is correct. A comparable risk lies in the time distribution over the phases. The accelerations and decelerations are logically balanced, since the amount of km/h/s that are accelerated also roughly need to be decelerated as well. But if their proportion is correct in comparison to the idle or the cruise phase cannot be determined based on only the durations and magnitudes. Information like travel time and average speed is also needed to ensure that the time distribution over the phases is correct. Another weak point of the whole approach lies in the dependency of the validity of the calibration and validation data. All calibration procedures are of course dependent of the quality of the used calibration data. The problem with the phase-based emission calculation lies in the fact that each phase has its own emission function. So if a speed or acceleration at a certain point is significantly incorrect, this will most likely result in an incorrect phase determination, by which the emission calculation is not only poor due to the wrong speed and acceleration, but also because the wrong emission function is used.

However this effect works two-sided and can also be a strong point of the method. If it is certain that a phase is correct, small errors in the accelerations (caused for example by the numerical implementation of the car-following model), have less influence because the emission function is phase based. And within a phase-based emission function a relative small error has less influence on the emission calculation than a general emission function would have. The most obvious advantage of this phase-based approach is of course that after a successful calibration and validation of the traffic microsimulation model the characteristics of the durations and magnitudes are known. This has a positive effect on the reliability of the emission calculations when compared with other methods which do not have these detailed information of the phases. Another advantage of the phase-based approach is that during the determination of the error score in the calibration and validation different weight factors can be applied to each duration or magnitude. By doing this durations which have the largest influence on the produced amount of emissions can be assigned with a higher weight factor and vice versa. Although this emission calculation might technically be an attractive option, one should be careful since from a traffic engineering view all durations and magnitudes have the same weight factor. So changing weight factors might result in more reliable emission predictions but in a worse traffic model.
5.2 Recommendations

Based on the conclusion of the previous section some recommendations are made for further research and practice. The recommendations can be split up into two groups. The first set of recommendations focuses on what should be improved when a similar kind of research is repeated. The second cluster recommendations focuses on in which directions additional research regarding this topic should go.

**Recommendations for similar research, under improved conditions**

For further research in capability of traffic microsimulation models to generate trajectories which are suitable for traffic emission predictions it is recommendable to use models where all driving behaviour parameters can be adjusted.

The ability to adjust only three out of five key parameters that were advised by Quadstone for calibrating driving behaviour and in more detail car-following behaviour in PARAMICS, has considerably restricted the search for an optimal calibration result. There for it is recommend to use for further research only microsimulation models were all important parameters can be adjusted to the researchers insights.

A qualitative and quantitative good dataset for calibration and validation purposes is recommended for a reliable outcome.

The reliability of some outcomes of this research, like if the calibration is valid or not, are questionable. The poor FCTTDAS-data is one of the main causes of these reliability problems. A quantitative and qualitative good dataset would therefore be recommendable to exclude the uncertainties caused by a poor dataset. Excluding uncertainties caused by a poor dataset will result in more solid conclusions.

**Recommendations for additional research on this topic**

It would be very interesting to research which car-following model gives the best results for a phase-based calibration of a traffic microsimulation model, under further similar circumstances.

There exists already a lot of different car-following behaviour models and multiple comparison studies are performed. These performed studies however focus almost always on the traditional use of car-following model in a traffic microsimulation model. It would however be interesting to know which model is preferable for a phase-based calibration of a microsimulation model.

Further research is recommendable to derive the true optimal parameter settings of PARAMICS for which the phase-based calibration approach gives the most reliable predictions.

For determining the true optimal parameter settings of PARAMICS for which the phase-based calibration approach gives the most reliable predictions more research is required. The optimum found in this research is an optimum within undesired boundary conditions. To succeed in further research it is recommendable to use a quantitative and qualitative better calibration and validation dataset and have the opportunity to adjust all driving behaviour parameters.
Bibliography


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Calibrating a traffic microsimulation model with a phase based algorithm to make the trajectories suitable for traffic emission predictions.

Goals
- Correct emission predictions
- Truthful simulated trajectories

Product
- Method for reliable emission predictions
- Out of simulated trajectories

Reliable predictions
- Reliable prediction

Emissions
- CO2
- NOX
- NH3
- N2O
- PM10
- CO

Fuel consumption
- Fuel types
- Is the fuel consumption directly proportional to the emissions?
- Have all the emissions the same sensitivity?

Calibration
- Criteria
- Calibration methods
- When is a calibration good?
- What are the criteria?
- When is it reliable?
- How to formulate boundary conditions for the reliability?

Microsimulation transport models
- Predictive vs responsive
- Driver behaviour module

Trajectories
- Time-place
- Time-speed
- Time-acceleration

Phase splitting
- Different phases
- Reliability

Probe vehicles
- Number of vehicles
- Thresholds

Smoothening
- Algorithm
- Type selection

Software
- Who is going to use it?
- In which software is it programmed?

Software
- Who is going to use it?

Correct emission predictions
- Truthful simulated trajectories

MSc-diploma
- What is required for graduation?

Goals
- Are the goals realizable?

Figure A.5.1: Need to know pebbles used for exploring the assignment and setting up the research.
Appendix II: Queries and manual procedures used for fitting the simulation data to the Drive Cycle Splitter

This appendix describes roughly the queries and manual procedures, which are needed for formatting PARAMICS output data which is generated by the Quadstone designed plug-in qpVPosition, into a format which is accepted by the Drive Cycle Splitter. The queries and procedures are not literally shown, because this would not benefit the readability and the intention to explain and clarify the use procedures and queries.

**Step 1: Loading the PARAMICS output file**
Create a new Postgres database and load the PARAMICS output file ‘vehicle-positions-**.***.csv’ in as a table. An alternative method is linking the table, this will save hard disk drive space, but will increase the running time of the queries.

**Step 2: Defining routes**
To be able to select vehicle IDs of the vehicles which drive the total route, all links that form together a route need to be specified. Similar routes in the opposite direction need to be specified as a separate route, because they use different links. This is the case, because a link number consist of its start and end node. For example if certain link is named “1:2” than in the opposite direction it is named “2:1”. Besides the reverse numbering, opposite directions do not always use the same nodes. All routes are specified in the table ‘route’.

**Step 3: Decreasing table size**
The loaded table from step 1 contains a lot of data that is not used as input for the Drive Cycle Splitter. To decrease the running time of the future queries a new table ‘base table’, is created which contains only the time, vehicle ID, speed, acceleration, link number and link length for the records which contain a link number which exist in the defined routes of step 2. This query also removes the records of all non personal vehicles out of this table. This action significantly reduces the table size which results in shorter running times for future queries.

**Step 4: Determining which vehicles travel the total route.**
This query removes all vehicles which do not travel the total route. In practice this means that all records of a certain vehicle ID are removed if within the span of all records of this vehicle not all the links of a defined route exist. Because it is really complex (or impossible) to perform this action in a database, a trick is used. For each vehicle ID the number of distinct link numbers are determined. As this number matches the number of distinct links of a defined route then the vehicle ID stays in the selection, otherwise it is removed. If there exist more than one route, this procedure needs to be repeated for each route. Also an additional check is necessary to ensure if it is the desired route. This is done by checking the chronological first and last link number. They should match the start and endpoint of the route. Another problem is the problem of vehicles which travel the total route, but also use certain links other links. If this occurs they have a non-continuous timeline, since the plug-in only selects data from vehicle on the route. If a vehicle drove the total route without any detours, the number of vehicle’s records in the database should be equal to difference between the start and end time multiplied by two (dependent on the number of simulation steps per second) plus one. The function is the following: \( \text{Number of records for vehicle IDx} = 2 \times (t_{\text{end}} - t_{\text{start}}) + 1 \). If a vehicle does not meet this requirement means that is has a non continuous timeline and all corresponding records are removed from the database.
Step 5: Creating new parameter columns
The old plug-in generates two parameters, (time) headway and distance, which the new one does not generate. Since the input for the Drive Cycle Splitter should be in the same format regardless of the used plug-in, these two columns need to be added to the table. The Drive Cycle Splitter does not actually use the time headway, which is a good aspect since it can no longer be determined. Because it is not actually used, the column is filled with zeros. Distance, is in the old plug-in determined as the distance left to the end of the link. With the three existing parameters link length, speed and acceleration this parameter can be determined. This parameter is created through first calculating the distance travelled during that time step with the function \( x = v \cdot t + \frac{1}{2} a \cdot t^2 \). Then the checked if the current link ID is the same as in the previous record. If this is the case then distance travelled is subtracted from the remaining link length of the previous record (with a boundary condition that it cannot be smaller than zero). If the link ID is different than the distance is subtracted from the total link length. In a new table ‘Output’ is created were the five final parameters per record, vehicle ID, headway, distance, speed and acceleration are displayed. The vehicle ID is here renumbered from 1, based on chronological starting time.

Step 6: Transforming the data in the correct format
The table ‘Output’ is linked Access, because in Postgres it is not possible to export the table in the correct format. Once loaded in Access a query is run to ensure that each value consists of the right number of digits and decimals. The final step is to export the database table to a txt-file with a fixed width. The width of the consecutive columns should be 5, 10, 14, 15 and 15. The last procedure that needs to be done is to copy the original header into the text-file. If the created text file consist out of more than 32,000 records, it must be cut into multiple files which each contain less records then this threshold. This is necessary because the Driver Cycle Splitter cannot process files with more than 32,000 records. At this point the PARAMICS output is ready to be processed with the Drive Cycle Splitter.
Appendix III: Indexed graphs of the mean and standard deviation of the different parameter settings of the calibration.

Figure A.5.2: Indexed mean duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with an adjusted acceleration-speed and deceleration-speed values.

Figure A.5.3: Indexed standard deviation of the duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with an adjusted acceleration-speed and deceleration-speed values.
Figure A.5.4: Indexed mean duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with an adjusted headway parameter.

Figure A.5.5: Indexed standard deviation of the duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with an adjusted headway parameter.
Figure A.5.6: Indexed mean duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with an adjusted reaction factor parameter.

Figure A.5.7: Indexed standard deviation of the duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with an adjusted reaction factor parameter.
Figure A.5.8: Indexed mean duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with a combination of adjusted parameters.

Figure A.5.9: Indexed standard deviation of the duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series with a combination of adjusted parameters.
Appendix IV: Indexed graphs of the mean and standard deviation of the different parameter settings of the validation.

Figure A.5.10: Indexed mean duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series.

Figure A.5.11: Indexed standard deviation of the duration and magnitude for the trajectory phases of the FCTTDAS-data, the default simulation series and the simulation series.