Scaling of traffic safety indicators using microscopic traffic simulation

A validation and scaling study on a use case of the ring road of Tilburg

DELFT UNIVERSITY OF TECHNOLOGY

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MASTER THESIS

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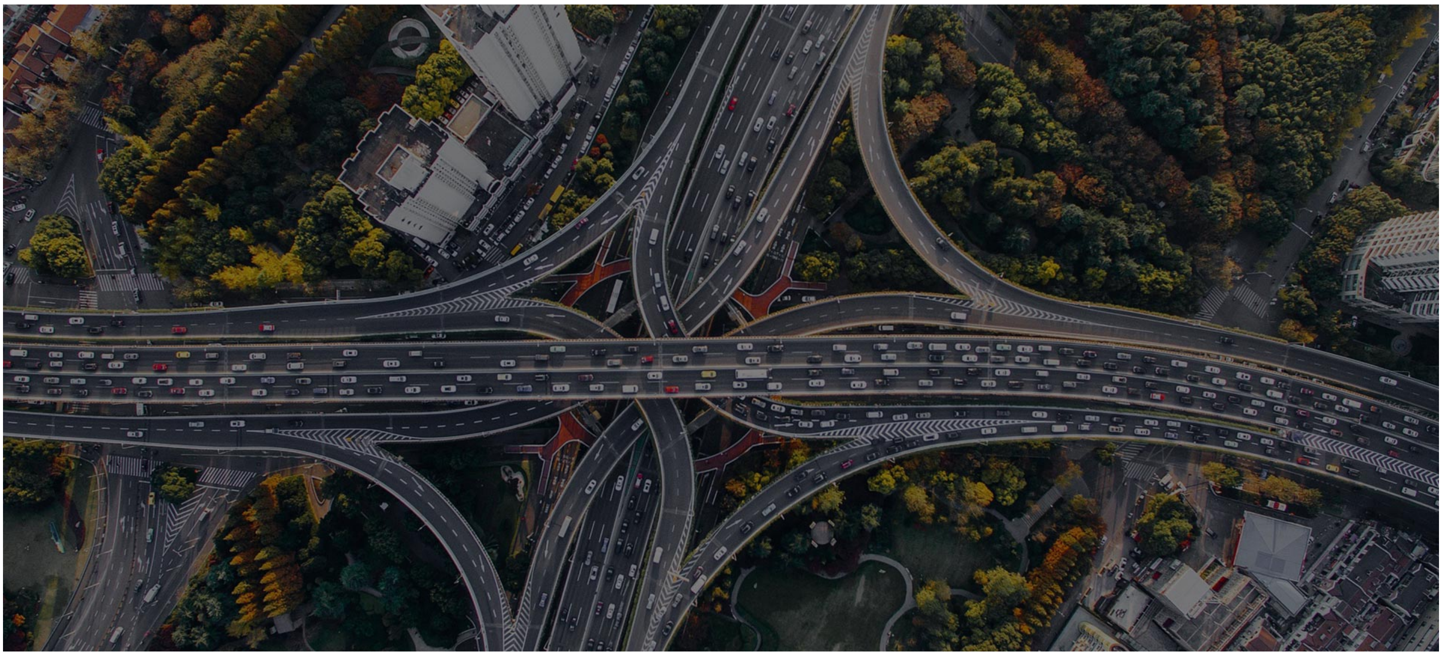

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Preface

This Master's thesis is part of the curriculum for the Master of Science Transport and planning, with the specialization road traffic systems. This research was conducted to contribute to effort needed to analyse traffic safety. My goal was to investigate the ways traffic safety can be quantified at network level and how these methods could be substantiated by using microsimulation, I believe I succeeded.

I think that the last step in obtaining something of value is always hard, especially if that something took more than seven years to obtain. While writing this preface I know for sure that I will obtain my master degree in civil engineering and when I started this journey seven years ago I did not think I would come to learn so much along the way. It started as more of a social education but became much more than that during the masters. I think the TU Delft is the place where I learned that there is always going to be people that are smarter, more motivated or people that work more efficient, but combining those qualities can lead to very nice pieces of work. I think that is also the reason why the process of this thesis was hard on me sometimes. Without someone smarter on some topics, more motivated at some times and more efficient during some part of the days, doing so much work is just a lot less fun. That's why I would like to thank the people in my masters, Marko especially, for making me realise how nice it is to work on assignments with other people.

During the time I was writing my thesis I was lucky enough to have a lot of people that were able to distract me from it. Madelief, thanks for keeping your patience and teaching me to take a break more often than I was used to. Thanks for going to Dalfsen with me when I needed to take a step back. Thanks mom and dad, for simply always being there for me. And thanks to all my friends, you know who you are, for distracting me with a beer, playing squash, going kite surfing and for listening to my complaints.

Obviously, this research would have been impossible without the help of my graduation committee. Firstly, I would like to thank Haneen Farah for her continuous patience and support throughout the whole project and for being a very nice person. Secondly, a big thank you to both Kingsley Adjenughwure and Narayana Raju for their weekly availability and time put into this project. Thirdly, I would like to thank both Wouter Schakel and Eleonora Papadimitriou for their feedback and being a part of my graduation committee. Lastly, I would like to thank the sustainable urban mobility and safety department at TNO for the opportunity to graduate at their department and for the help of many colleagues at SUMS during the last 9 months.

Executive summary

Introduction

Ever since the introduction of motorized vehicles, the lack of road traffic safety has been an issue worth investigating.Governments often use the number of (deadly) crashes that occur as a traffic safety performance indicator. The data covering these crashes is often limited and prone to underestimation, since not every crash is recorded, (Derriks and Mak [2007]). Another problem with making policy using crash data is that it will always be done in hindsight. Since the crashes have already occurred. Within this study a solution to this problem is being researched. This solution would consist of using surrogate safety measures (SSM) in combination with micro simulation. SSM are indicators of safety that use surrogate data types to quantify traffic safety. An example of SSM are conflicts. Conflicts can be seen as near crashes, and are possible to simulate in a micro simulator. Different types of conflicts can be distinguished and by using a threshold value for the proximity or severity of a conflict one can gain detailed insights in the aspects that play a role in traffic safety. Another form of surrogate safety would be to look at for example traffic volume as an indicator of safety. This could be done in the form of a safety performance function. A safety performance function uses the traffic volume on a certain type of infrastructure to predict the number of yearly crashes on that certain type of infrastructure.

The two examples mentioned above are different in their nature and give an example of the variety in SSM that exist. The conflicts can be used at a very small scale, and can quantify traffic safety of the interaction between two vehicles. The safety performance function, and some conflict indicators are more suitable for quantifying traffic safety at a larger scale. This could be 10+ vehicles, but also a complete road network. It is known that the use of SSM has both advantages and disadvantages over using traditional safety indicators. The SSM in combination with micro simulation offer a possibility to investigate infrastructural designs before they are even build. One does not have to wait for a large period of time to gather crash data in order to be able to quantify the safety. Then again, SSM need to reflect reality and are therefore also subject to certain data needs. The traffic volume, speed distribution, driving behaviour, weather and congestion state are examples of what is needed to create a realistic simulation of the true traffic situation. The question is what data is needed to be able to predict the traffic safety good enough to replace the use of traditional traffic safety indicators with SSM. But also, in what way the SSM should be used to predict this traffic safety.

In order to investigate this topic, the following research questions were posed:

- *Which methods are available to scale traffic safety indicators from microsimulation from vehicle to network level and how do these methods perform when applied in a use case consisting of a large-scale network?*

With sub questions:

- *Which indicators exist to quantify safety at vehicle level and at a network level, and how do these relate?*
- *How can the used network in combination with the surrogate safety assessment module* [1] *be validated?*
- *What is the result of different threshold values on the performance of the surrogate safety assessment module?*
- *Can methods be combined to increase their individual performance?*

Within this study the weather conditions and driver behaviour model will not be changed in order to control the scope of the project. The focus will be on the types of conflict indicators and their most suited threshold value to predict the crashes on the selected network.

[1] The SSAM is a model used to analyse traffic conflicts by processing the trajectory data from microsimulation using a set of surrogate safety indicators, (Shelby [2008]).

Literature review

Previous studies have successfully simulated the traffic safety of signalised, Huang et al. [2013], and unsignalised, Astarita et al. [2019] intersections. Micro simulation has been proved a valuable tool for substantiating surrogate safety measures (Tarko [2018]). The relation between conflicts from microsimulation and crashes from historical data has also been researched and multiple relationships were found for different scenarios, (Dijkstra et al. [2010], Gordon et al. [2011]). The same goes for the relationship between simulated and real conflicts (Huang et al. [2013], Essa and Sayed [2015]). Problems occur when scaling up the micro simulations to a network level, or better said, when using the simulations to analyse larger networks. Within Ariza [2011] a network was simulated that consisted of multiple arterials. The conflict based surrogate safety assessment module (SSAM) was used to analyse the traffic safety. It proved to be inconsistent when comparing the simulated data to empirically gathered historical crash data of that network. So, intersections can be modelled and analysed for traffic safety using surrogate safety measures, but it is unknown to what extent traffic safety indicators at vehicle level have an impact on traffic safety performance at a network level. Alsalhi and Dixit [2015] researched this effect using traffic volume and found relations between the traffic density and the unsafety of a network. Alonso et al. [2020] compared the SSAM to their own Zombie driver software in order to incorporate single vehicle conflicts from simulation. They found that their Zombie driver software outperformed the SSAM when comparing them with historical crashes.

Within the literature review three topics were covered: conflict based surrogate safety indicators, safety at macro level and the relations of traffic safety based on microsimulation. Consisting of the relations between conflicts and crashes and the relations between different types of conflict indicators. From the second literature review section it became clear that the surrogate safety assessment module is a promising tool for analysing conflicts from microsimulation. The zombie driver software can be a very nice addition to the surrogate safety assessment module as it is able to predict and analyse single vehicle conflicts. A framework for evaluating the relative safety of a network using the surrogate safety assessment module does not exist yet, while it could be beneficial if every study that uses the SSAM would also use the same method to asses the level of safety. Both the use of safety performance functions as well as safety performance indicators are a useful addition to assess relative safety but are both subject to large data requirements.

Method

The research methodology is found in figure 2 and represents the input data (green rectangles) and the methods (red rectangles) applied to that data. Historical crash data was gathered from the national government (BRON data) and was analysed to find out more about the properties and time stamps of crashes that occur on the ring road of Tilburg. A previously calibrated VISSIM network was used to simulate the traffic during the morning and evening peak after which the vehicle trajectories were used to analyse the conflicts. The conflict analysis was performed by using the surrogate safety assessment module. The traffic volume was used to predict the crashes on the same network using a safety performance function for 3- and 4-legged signalised intersections form the U.S. federal highway administration. The conflicts analysed by the surrogate safety assessment module were then compared to historical crashes on the same intersections in order to validate the simulation. For this, the intersections were ranked, and the rankings were compared using the Spearman rank coefficient. After the validation a scaling methodology was proposed to investigate the influence of each surrogate safety indicator used within the surrogate safety assessment module. This consisted of a linear framework that was solved using a least square estimate. Within this linear framework all the surrogate safety indicators within SSAM were used to model the number of conflicts which were compared to the number of crashes on the network.

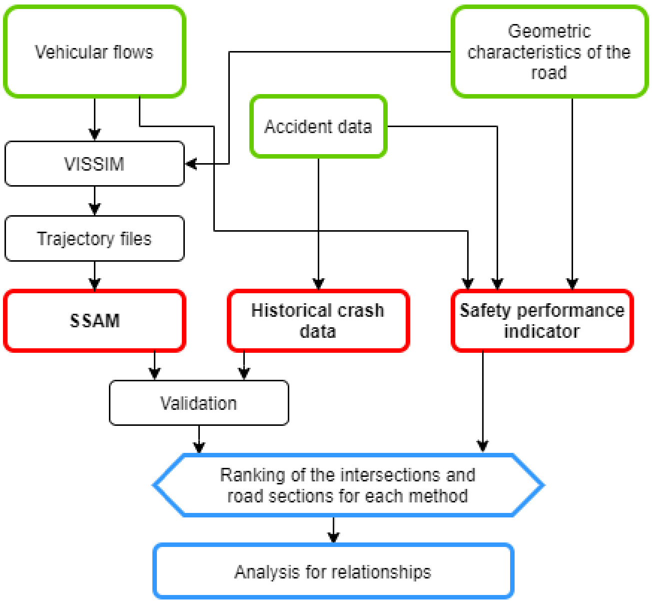

Figure 2: Research methodology

Results

An overview of the dangerous locations of the studied network is seen in figure 3. It shows the historical crashes on top and the simulated conflicts indicated by the TTC and/or PET subject to an upper threshold of 1.5 seconds below. From this figure it can be seen that the conflicts from micro simulation and the historical crashes have a very similar geographical distribution. The intensity of conflicts and crashes is also similar for each intersection.

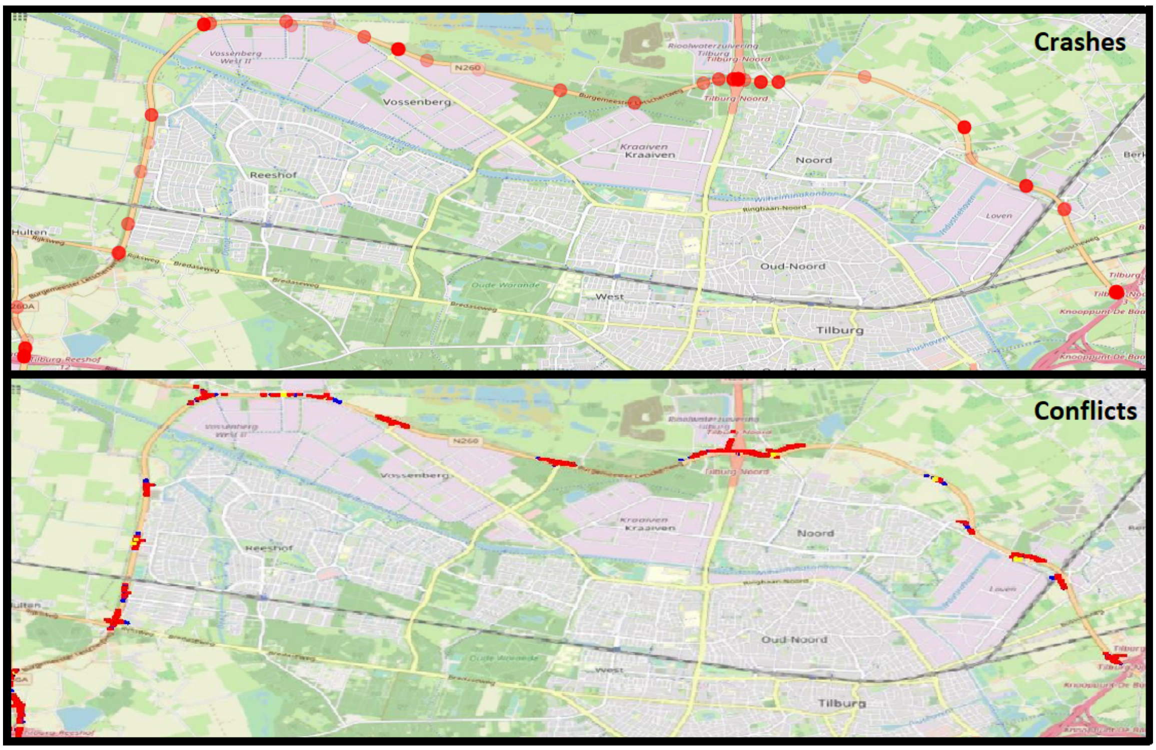

Figure 3: Historical crashes compared with simulated conflicts

When validating the conflicts using the historical crash data it was found that the conflicts from the AM peak simulation are moderately good at predicting the weekday crashes on the Tilburg network for all threshold values. The Threshold value of 1 second performed the best. For this relationship, a Spearman coefficient of up to 0.576 was found, depending on the threshold settings as seen in table 1.

Table 1: Results of the validation

Conflicts	Crashes	*TTC* low	*TTC* high	*PET* low	*PET* high	Conflicts	Crashes	Spearman coefficient	P-value	Significance within:
PM peak	*PM peak*	0.01	1.5	0.01	4.5	4722	35	0.274	0.243	Not significant
AM peak	*AM peak*	0.01	1.5	0.01	4.5	9161	25	0.481	0.031	95% confidence interval
Peak sum	*Peak sum*	0.01	1.5	0.01	4.5	13883	60	0.310	0.184	Not significant
Peak sum	*All*	0.01	1.5	0.01	4.5	13883	216	0.284	0.225	Not significant
PM peak	*PM peak*	0.01	1.5	0.01	1.5	2775	35	0.275	0.240	85% confidence interval
AM peak	*AM peak*	0.01	1.5	0.01	1.5	5089	25	0.570	0.009	95% confidence interval
Peak sum	*Peak sum*	0.01	1.5	0.01	1.5	7864	60	0.360	0.120	85% confidence interval
Peak sum	*All*	0.01	1.5	0.01	1.5	7864	216	0.362	0.116	85% confidence interval
PM peak	*PM peak*	0.01	1.0	0.01	1.0	287	35	0.182	0.443	Not significant
AM peak	*AM peak*	0.01	1.0	0.01	1.0	374	25	0.576	0.008	95% confidence interval
Peak sum	*Peak sum*	0.01	1.0	0.01	1.0	661	60	0.259	0.271	Not significant
Peak sum	*All*	0.01	1.0	0.01	1.0	661	216	0.406	0.076	90% confidence interval
PM peak	*PM peak*	0.01	0.5	0.01	0.5	78	35	0.208	0.380	Not significant
AM peak	*AM peak*	0.01	0.5	0.01	0.5	90	25	0.411	0.072	90% confidence interval
Peak sum	*Peak sum*	0.01	0.5	0.01	0.5	168	60	0.176	0.458	Not significant
Peak sum	*All*	0.01	0.5	0.01	0.5	168	216	0.498	0.0255	95% confidence interval

When predicting the crashes on the Tilburg network using the safety performance function, no reliable results were obtained. The results were tested to have a correlation with the historical crashes but no significant relation was found. The results of the safety performance function are dependent on the traffic volume.

Table 2: Estimated coefficients from linear least square estimation

Indicator	Coefficient estimate *all 3 legged*	*Random 3 -legged*	all 4-legged	*All*
N	10	5	7	17
C_{TTC}	0.0204	0.001	0.2222	0.014
C_{PET}	0.000	0.000	0.0140	0.000
C_{MaxS}	0.000	0.000	0.000	0.000
C_{Delta_S}	0.000	0.000	0.000	0.087
C_{DR}	0.000	0.000	0.000	0.000
C_{MaxD}	0.000	0.000	0.000	0.000
$C_{MaxDeltaV}$	0.0662	0.072	0.0146	0.000
Residuals	30.9	28.6	9.34	19.1

Four different estimations were performed to be able to check the consistency of the method. From these three estimations the TTC, $Delta_S$ and $MaxDelta_V$ turn out to be the best predictors of the crashes on the network. The PET only has a share in the prediction of the 4-legged intersections. All the other SSI's are estimated to have no share in the prediction of the least square estimate. Since no SSI coefficient can be zero, these values turn to zero. The TTC is the only indicator that has a share in predicting the crashes for all of the four estimations. Within table 14 it can be seen that the estimations are different for the four different estimation types. Whereas the TTC and $MaxDelta_V$ combination is within three of the four estimations, the TTC and Max_S is in only one. When looking at the residuals, the third estimate performs the best, with the residuals under 10. These residuals can be seen as the difference between an observed value, and the fitted value provided by the model. So, the residuals should be looked at in perspective to both the number of intersections used within the estimation and the number of crashes within that estimation.

Discussion and Conclusions

Within this study the use of surrogate safety measures to evaluate safety at a network level was investigated. The focus was on methods that used microsimulation as a base. From the literature review it has become clear that there were no established methods for evaluating safety at a network level using micro simulation. The most promising method or tool is the surrogate safety assessment module. This software developed by the Federal highway administration in the united states offers a tool for analysing the conflicts that occur within a micro simulation. Though, this tool on itself is not a method for evaluating traffic safety. It provides multiple surrogate indicators but does not poses a framework which can be used to measure relative safety. The Surrogate safety assessment model was validated for the use case of Tilburg, in which it proved to have significant relationships with the crash count at this network for all the AM peak scenarios. The simulation did show a lot of zero second conflicts which would suggest that crash are simulated within the simulation. For this research these zero second conflicts were deleted from the data set but it is worth investigating in more depth what could have lead to these zero second conflicts. The crashes predicted by the SPF do not correspond well to the historical crashes on the network. The safety performance function is only dependent on volume, which does give the insight that micro simulation was able to predict the conflict crash relationship better than just the volume. These functions were estimated with crash and volume data from the U.S., which is probably the reason for the lack of correlation. When correlating the predicted crashes with the historical crashes no significant relation was found. Four different translation estimations were performed to be able to check the consistency of the method. From these three estimations the TTC, $Delta_S$ and $MaxDelta_V$ turn out to be the best predictors of the crashes on the network. The framework proposed in the translation section can be a very useful tool when wanting to combine different indicators of safety.

Future directions

In order to take the work that was done within this study to the next level, a number of future directions were determined. These are split up into future scientific research recommendations and future practical recommendations.

Future scientific research recommendations

- Safety performance functions have been developed that take observed real life conflicts into account. A promising direction could be to investigate the development of a safety performance function that takes conflicts from micro simulation into account.
- Apply the proposed framework to multiple networks with more available data on historical crashes and information on volume, speed distributions and other useful indicators. This could lead to stronger conclusions on discovered relationships when using the proposed framework

Future practical recommendations

- Use more sophisticated driver behaviour models. Implementing these driver behaviour models in the simulation could lead to more realistic behaviour of drivers in the simulation which could lead to a better representation of reality.
- Develop a similar network and investigate the relative safety. Within this study it was not possible to compare but if another similar VISSIM network is available the results can be even further validated by comparing the two networks.
- Develop a more stable gap acceptance model that leads to no 0.0 seconds conflicts. This is not as straight forward as it sounds since changing the gap acceptance model could lead to new problems. Like more congestion due to an increase in the average accepted gap. The simulation model might become less suitable for traffic flow analysis but more suitable for traffic safety analysis.

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List of Abbreviations

WHO – world health organization
SSAM – Surrogate safety assessment module
SSM – surrogate safety measure
SSI – Surrogate safety indicator
TTC – Time to collision
TET – Time exposed time to collision
TIT – Time integrated time to collision
MTTC – Modified time to collision
CI – Crash index
TA - Time-to-accident
H – Time headway
PET – Post encroachment time
PICUD – Potential index for collision with urgent deceleration
PSD – Proportion of stopping distance
DSS – difference of space distance and stopping distance
TIDSS – Time integrated difference of space distance and stopping distance
UD – unsafe density
DRAC – Deceleration rate to avoid a crash
CPI – Crash potential index
CIF – Critically index function
CS – conflict severity
SPI – safety performance indicator
DRL – daytime running lights
RSR – rank sum ratio
SPF – safety performance function
AADT - annual average daily traffic
CMF - crash modification factor
EVT – extreme value theory
FD – fundamental diagram
MSD – Macroscopic fundamental diagram
FHWA – Federal highway administration
ZD -zombie driver
ACPM – Aggregate Conflict Propensity Metric
RDW – rijksdienst voor het wegverkeer- national road traffic services
BRON – Bestand geregistreerde ongevallen – database of recorded accidents
STAR – smart traffic accident reporting
JTE – junction
WVK – wegvak
NWB – Nationaal wegen bestand – national road database
GPS – Global positioning system
HGV – heavy goods vehicle
AM – Ante meridiem – before the afternoon
PM – Post meridiem – After the afternoon

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1 Introduction

Ever since the introduction of motorized vehicles, the lack of road traffic safety has been an issue worth investigating. Governments often use the number of (deadly) crashes that occur as a traffic safety performance indicator. The data covering these crashes is often limited and prone to underestimation.Since, not every crash is recorded, (Derriks and Mak [2007]). Another problem with making policy using crash data is that it will always be done in hindsight. Since the crashes have already occurred. Improvement of infrastructure and traffic regulations are still needed since each year 1.35 million people die as a result of a traffic accident, (WHO [2020]).

These problems can be overcome by using another way of assessing traffic safety. By using surrogate safety measures (SSM) it is possible to assess traffic safety without the use of historical crash data. SSM exist in multiple forms and are surrogates for quantifying traffic safety. Perkins and Harris [1967] were the first to use an alternative in the form of Surrogate safety measures (SSM). These surrogate safety measures are used to replace the crash or accident data and are a well-established method of quantifying traffic safety. Three benefits of traffic conflicts and other surrogate measures are: 1) Detecting the excessive risk of crashes on the road; 2) Improving the knowledge of conditions leading to a crash or increasing the crash probability; 3) Estimating the effectiveness of the experimental and existing countermeasures, (Tarko [2018]). Surrogate safety can be measured at micro (vehicle) level, but also at macro (network) level, using surrogate safety indicators (SSI). At micro level these indicators are derived from conflicts. A traffic conflict is the occurrence of two or more road users that would crash into each other if they would not change their direction. Within micro simulation it is not possible to simulate crashes without dedicated models that make many assumptions. Other forms of interaction or conflicts between vehicles do occur in simulation. When these conflicts are analysed it is possible to objectively quantify the traffic safety at micro level (Johnsson et al. [2018]). On a macroscopic level one could for example look at speed dispersion or the traffic flow to investigate dangerous traffic situations. Using surrogate safety measures also has a downside. It can be questioned if the number of conflicts, though mostly used in previous literature, truly reflects the level of safety, (Wang et al. [2018]). Within subsection 4.2 this will be discussed more in depth. It would be possible to reflect the level safety to a larger extent if conflict severity would be taken into account, which is the case for some conflict indicators discussed in this chapter.

Micro simulation in combination with surrogate safety measures (SSM) offer an even wider solution to the problem and has multiple advantages. Microsimulation is suitable for simulating new infrastructure before it is even built, which allows for safety analysis of new proposed infrastructure before building it. This could help policy makers with making decisions. Another advantage is the fact that every occurrence in micro simulation is saved. So even the smallest traffic conflict will be noted. Another obvious advantage is the time it takes to gather data. By using micro simulations, it is possible to gather data much faster than having to wait for empirical data to be complete. Disadvantages of micro simulation are the lack of random occurrences and the fact that it is challenging to capture human driver behaviour in a computer model.

Previous studies have successfully simulated the traffic safety of signalised, Huang et al. [2013], and unsignalised, Astarita et al. [2019] intersections. Micro simulation has been proved a valuable tool for substantiating surrogate safety measures (Tarko [2018]). The relation between conflicts from microsimulation and crashes from historical data has also been researched and multiple correlations were found for different scenarios, (Dijkstra et al. [2010], Gordon et al. [2011]). The same goes for the relationship between simulated and real conflicts (Huang et al. [2013], Essa and Sayed [2015]). Problems occur when scaling up the micro simulations to a network level, or better said, when using the simulations to analyse larger networks. Within Ariza [2011] a network was simulated that consisted of multiple arterials. The conflict based surrogate safety assessment module (SSAM) was used to analyse the traffic safety. The SSAM is a model used to analyse traffic conflicts by processing the trajectory data from microsimulation using a set of surrogate safety indicators Shelby [2008]. It proved to be inconsistent when comparing the simulated data to empirically gathered historical crash data of that network. So, intersections can be modelled and analysed for traffic safety using surrogate safety measures, but it is unknown to what extent traffic safety indicators at vehicle level have an impact on traffic safety performance at a network level. Alsalhi and Dixit [2015] researched this effect using traffic volume and found relations between the traffic density and the unsafety of a network. Alonso et al. [2020] compared the SSAM to their own Zombie driver software in order to incorporate single vehicle conflicts from simulation.

The motivation behind scaling up the surrogate safety measures would be to apply them in quick full-scale safety analysis. Envision a macroscopic model of a city consisting of a road network. When making plans to change certain infrastructure in this city the traffic safety consequences should be known. If a macroscopic model exists, these infrastructural changes could be applied in the model and its influence on the safety of the network could be analysed. Even a change in vehicle types or an increase in for example automated vehicles could be modelled to look at their effects on traffic safety within a network. This could be very use full for municipalities looking to make their infrastructure future proof, but also to be able to compare different networks so showcase their strengths and weaknesses.

The problem at this point is that these macroscopic models can be validated for traffic flow, but not for traffic safety. The question is whether microsimulation can be a backbone for such a macroscopic model, and if so, how this should be applied. For this to become reality, the relationship between traffic safety indicators at vehicle level and traffic safety indicators at a network level needs to be researched. Little research is available on screening traffic networks for traffic safety using microsimulation. For this reason, the methods that exist to analyse a network for safety have been compared to a limited extend. The safety analysis using microsimulation has not been compared to a safety analysis using safety performance indicators. No common indicator is used for quantifying traffic safety on a network level using microsimulation.

The objective of this research is to compare methods that analyse traffic safety at a network level. If possible, to find a way to combine these methods into one indicator. This is needed to gain more insight into how micro simulation can substantiate macroscopic traffic models. For this, a translation needs to be made from microscopic indicators to a level of safety at macro level.

The research gap and objective described above lead to the following research questions and sub questions:

- *Which methods are available to scale traffic safety indicators from microsimulation from vehicle to network level and how do these methods perform when applied in a use case consisting of a large-scale network?*

With sub questions:

- *Which indicators exist to quantify safety at vehicle level and at a network level, and how do these relate?*
- *How can the used network in combination with the surrogate safety assessment module be validated?*
- *What is the result of different threshold values on the performance of the surrogate safety assessment module?*
- *Can methods be combined to increase their individual performance?*

The first sub question will be answered by the literature review. Within the literature review a variety of methods will be discussed. The most suitable methods depend on the available use case and data. The validation of these methods will depend on the selected methods and will therefore be discussed in the methodology. By varying the threshold settings when applying the method, the performance will be researched . The relationship between the safety performance function and surrogate safety assessment module will be investigated by proposing a linear framework to assess their predictive qualities.

Within micro simulation there are a lot of key aspects that should be regarded. The simulated network should be calibrated in such a way that it represents the real network, both in traffic volume and crashes. The correct driver behaviour model should let the simulated drivers behave in a similar manner to real drivers. The settings of traffic lights and speed limits should be similar to the real network and even the weather conditions like wind and rain can play a major role in the simulation of traffic and the effect on traffic safety. The scope of this research is to find the methods that have been applied so far to translate surrogate safety indicators for use of network analysis. A number of methods will then be applied in a use case in order to analyse the performance of these methods and their applicability. The end of this research will be an investigation of a merge of these methods. The focus will not be on the driver behaviour model or on the calibration of the microscopic model. The model selected for this research has already been calibrated for traffic volume and the driver behaviour models are standard Wiedemann driver behaviour models. The weather conditions are assumed to be constant in this study.

Within the literature review chapters of this thesis the previous work on this topic is elaborately discussed. The first literature review chapter discusses surrogate safety indicators used to quantify traffic conflicts and therefore the safety at micro level. Chapter three governs the literature that discusses safety at a network level and the last chapter of the literature review, chapter 4, elaborates on the relations within traffic safety. Within this chapter the first two research questions are answered. Within chapter five the methodology is found which discusses the gathering of historical crash data, the simulation of a large scale network, the validation of the simulation, the application of a safety performance function and the translation of the previous into a complete safety analysis tool. Within chapter 6 the results of this research are visualised and discussed which are concluded on within chapter 7. Within that same chapter the limitations of this thesis and future research questions are discussed.

2 Surrogate safety at micro level

Within this chapter the surrogate safety at micro level is addressed by explaining the variety of ways to calculate the (un)safety of a conflict. Firstly, an explanation is provided on what is meant by a conflict situation. This is followed by four subsections in which the different kinds of surrogate safety indicators are subdivided in four categories: temporal proximal indicators, distance based proximal indicators, deceleration based proximal indicators and "others".

2.1 Conflict situation

The conflicts on which the conflict indicators discussed in this chapter are based, can be grouped in seven different conflict situations. Within figure 4 the four types of conflicts that occur at an intersection are visualised, namely crossing, merging, diverging and rear-end. Within figure 5 the three types of conflicts are visualised that occur on straight road sections, namely lane change, overtaking, car-following.

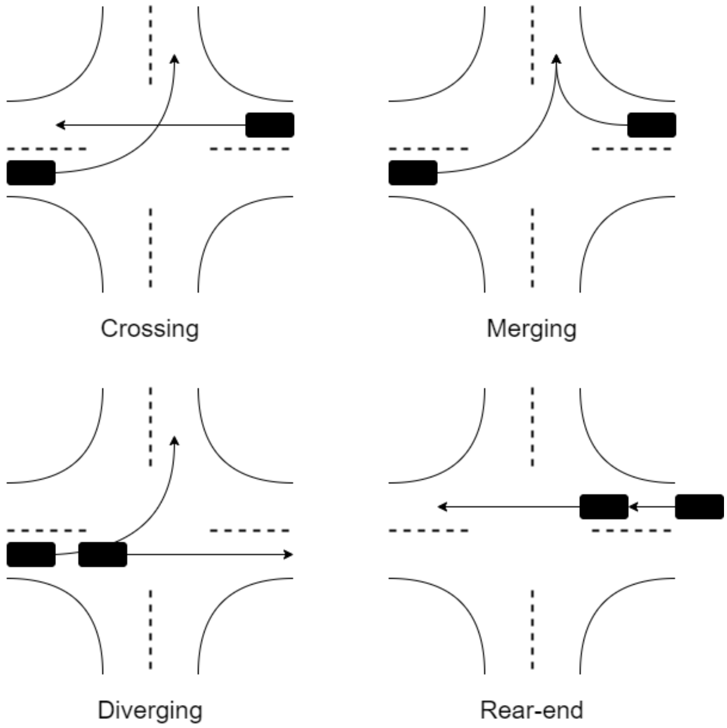


Figure 4: The four conflict types at an intersection

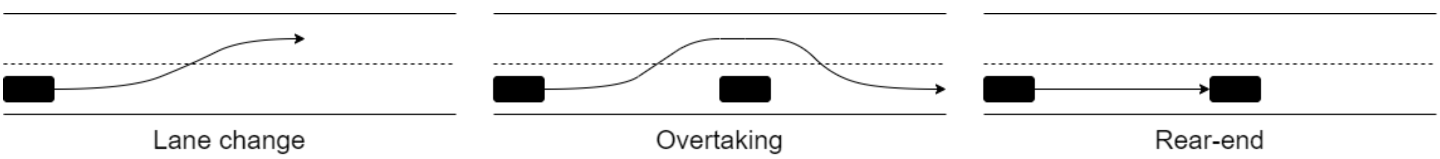


Figure 5: Three conflict situations on a straight road

2.2 Temporal proximal indicators

Temporal or spatial proximity-based indicators are based on the assumption that the closeness to another vehicle is related to the proximity of a collision. Alongside this assumption, it is good to notice that a collision is always preceded by a conflict. Proximal temporal indicators are more popular compared to the other proximity indicators since it takes the spatial proximity, direction and speed into account.

Time to collision (TTC)

The time to collision at an instant t is defined as *'the time that remains until a collision between two vehicles would have occurred if the collision course and speed are maintained'* (Hyden [1987]). The lowest value the TTC has reached during a manoeuvre can be taken as an indicator for the severity of the encounter, where a higher level of collision is indicated by a lower minimal TTC value. Within microscopic traffic simulation modelling the TTC is mainly calculated by extrapolating position and speed of vehicles from trajectory files, (Essa and Sayed [2015]). The TTC can be calculated by:

$$TTC_i(t) = \frac{\Delta X_{i,j}(t)}{\Delta V_{i,j}(t)} \tag{2.1}$$

With:
$\Delta X_{i,j}(t)$ = Bumper-to-bumper distance [m] between vehicle i and j at time t
$\Delta V_{i,j}(t)$ = Relative speed $\frac{m}{s}$ between vehicle i and j at time t

The minimal TTC value is the lowest value of all the recorded TTC values within the time window of the manoeuvre.

Time Exposed Time-to-Collision (TET)

The TET is part of the Extended time to collision. It was first proposed by Minderhoud and Bovy [2001]. The TET measures the length of time that a TTC event is below the set threshold. This way it indicates the time a vehicle was in a critical situation, rather than if the vehicle was in a critical situation yes or no.

$$TET_i^* = \sum_{t=t_0}^{t_n} \delta_i(t) \cdot \tau_{sc} \tag{2.2}$$

With:
$\delta_i(t) = \begin{cases} 1, & \text{if } 0 \leq TTC_i(t) \leq TTC^* \\ 0, & \text{else} \end{cases}$
τ_{sc} = Small time step [s]

Time Integrated Time-to-Collision (TIT)

The probability of a collision varies with the value of TTC, therefore Minderhoud and Bovy [2001] introduced the TIT, which takes the impacts of the different TTC values into account. It uses the integral of Equation 2.3 to express a relative probability of conflict.

$$TIT_i^* = \sum_{t=t_0}^{t_n} ([TTC^* - TTC_i(t)] \cdot \delta_i(t) \cdot \tau_{sc}) \tag{2.3}$$

With:
$\delta_i(t) = \begin{cases} 1, & \text{if } 0 \leq TTC_i(t) \leq TTC^* \\ 0, & \text{else} \end{cases}$
τ_{sc} = Small time step [s]

At this point the TET and the TIT might seem quite identical, the difference is visualised in figure 6. It is seen that the TET only measures the time for which the TTC threshold was exceeded, whereas the TIT measures the time for which the TTC threshold was exceeded and multiplies it with the corresponding TTC value of each time step. This results in a quite simple indicator in the form of the TET, which can be used to indicate length of time for which an unsafe situation occurred. The TIT is somewhat more sophisticated since it gives a measurement unit in the form of the severity to the time for which the unsafe situation occurred. For example, if the TTC threshold value is exceeded with just 0.01 seconds for a large amount of time, the TET would indicate this as very unsafe. If this same occurrence would be measured by the TIT, it would show up as quite safe since the multiplier (the magnitude of the exceedance) is very low.

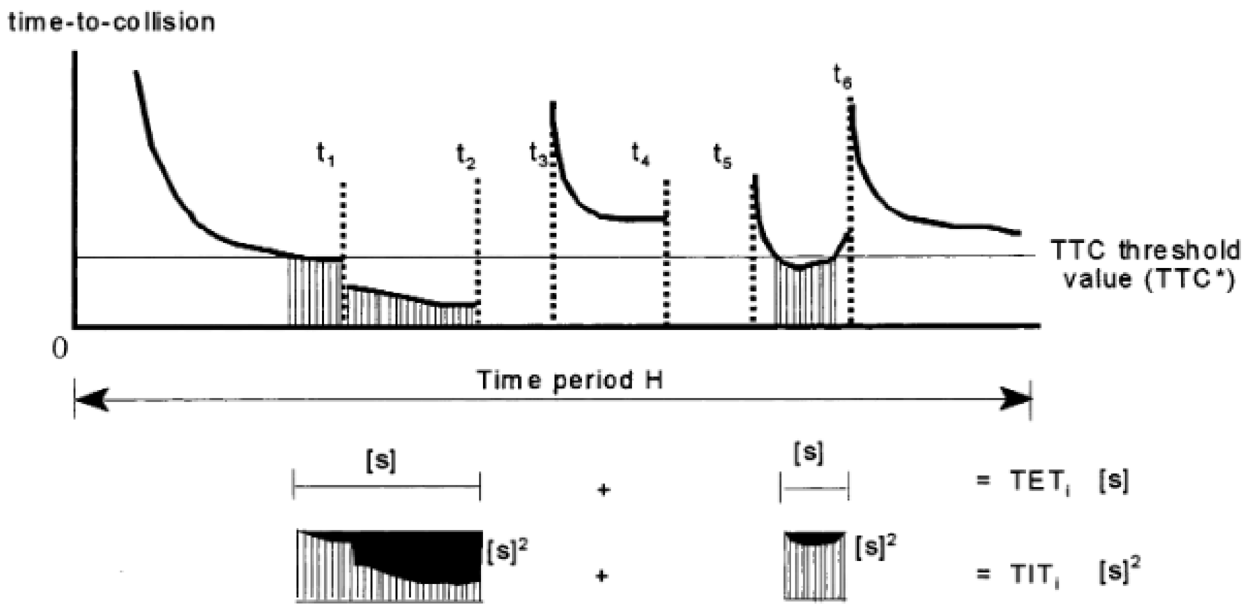


Figure 6: Safety evaluation by using TIT vs. TET (adapted from Minderhoud and Bovy [2001])

Modified TTC (MTTC)

For calculating the TTC values mentioned earlier it is assumed that consecutive vehicles will keep constant speeds until the collision occurs. Another assumption that is made is that the speed of the following vehicle has to be greater than the speed of the leading vehicle for a collision to occur. Ozbay et al. [2008] introduced the modified time to collision (MTTC) which takes relative speed, distance and acceleration into account. The MTTC therefore better represents the time left before a collision would occur compared to the normal TTC. The MTTC is calculated with the following equations:

$$td_{1,i}(t) = \frac{-\Delta V_{i,j}(t) - \sqrt{\Delta V_{i,j}^2(t) + 2 \cdot \Delta a_{i,j}(t) \cdot \Delta X_{i,j}(t)}}{\Delta a_{i,j}(t)} \tag{2.4}$$

$$td_{2,i}(t) = \frac{-\Delta V_{i,j}(t) + \sqrt{\Delta V_{i,j}^2(t) + 2 \cdot \Delta a_{i,j}(t) \cdot \Delta X_{i,j}(t)}}{\Delta a_{i,j}(t)} \tag{2.5}$$

With:
$\Delta X_{i,j}(t)$ = Bumper-to-bumper distance [m] between vehicle i and j at time t
$\Delta V_{i,j}(t)$ = Relative speed $\frac{m}{s}$ between vehicle i and j at time t
$\Delta a_{i,j}(t)$ = Relative acceleration $\frac{m}{s^2}$ between vehicle i and j at time t

$$MTTC_i(t) = \begin{cases} \min\begin{pmatrix} td_{1,i}(t) \\ td_{2,i}(t) \end{pmatrix}, \text{ if } td_{1,i}(t) > 0 \text{ and } td_{2,i}(t) > 0 \text{ and } \Delta a_{i,j}(t) \neq 0, \\ td_{1,i}(t), \text{ if } td_{1,i}(t) > 0 \text{ and } td_{2,i}(t) \leq 0 \text{ and } \Delta a_{i,j}(t) \neq 0, \\ td_{2,i}(t), \text{ if } td_{1,i}(t) \leq 0 \text{ and } td_{2,i}(t) > 0 \text{ and } \Delta a_{i,j}(t) \neq 0, \\ TTC_i(t), \text{ else.} \end{cases}$$

This MTTC included a table which includes all the longitudinal conflict scenarios, this is visualised in the table below. In this table, P represents a possible conflict, C indicates a conflict and I indicates that a conflict is impossible.

V	$V_F > V_L$			$V_F \leq V_L$		
a	$a_L > 0$	$a_L > 0$	$a_L > 0$	$a_L > 0$	$a_L > 0$	$a_L > 0$
$a_F > 0$	P	C	C	P	C	P
$a_F < 0$	P	P	P	I	P	I
$a_F = 0$	P	C	C	I	C	I

Crash Index (CI)

MTTC alone cannot give enough indication of the level of severity of a conflict. It is only possible to define conflicts by comparing to the threshold value. Therefore, different combinations of speeds and relative distances could result in the same MTTC value for two vehicles that have a probability of colliding. To overcome this problem, Ozbay et al. [2008] introduced the Crash Index (CI). With this indicator the level of severity can be analysed. It quantifies the kinetic energy involved in collisions by measuring the speed, acceleration and modified time to collision and combines them as seen in Equation 2.6 where the crash index is measured in $\frac{m}{s^2}$.

$$CI_i(t) = \frac{(V_i(t) + a_i(t) \cdot \mathrm{MTTC}_i(t))^2 - (V_j(t) + a_j(t) \cdot \mathrm{MTTC}_i(t))^2}{2} \cdot \frac{1}{\mathrm{MTTC}_i(t)} \tag{2.6}$$

With:
$V_i(t)$ = Speed of following vehicle i at time t $[\frac{m}{s}]$
$V_j(t)$ = Speed of leading vehicle j at time t $[\frac{m}{s}]$
$a_i(t)$ = Acceleration of following vehicle i at time t $[\frac{m}{s^2}]$
$a_j(t)$ = Acceleration of leading vehicle j at time t $[\frac{m}{s^2}]$
MTTC = Modified time to collision as in section 2.2

Time-to-Accident (TA)

Time-to-Accident (TA) is defined as 'the time that remains to an accident from the moment that one of the road users starts an evasive action, if they had continued with unchanged speed and directions, (Hyden [1987]). This definition is also valid for situations with only one road user. It was introduced by Hyden [1987] and is also known as the Swedish traffic conflict technique (STCT). It is calculated using Equation 2.7.

$$TA_i = TTC_i(t_a) \tag{2.7}$$

With:
t_a = Time of action [s]

The advantage of the TA is that it records the safety level at the precise moment of the start of an evasive action, although it is hard to identify the precise moment of the start of the evasive action.

Time headway (H)

Time headway indicates the difference in time that passes before two following vehicles reach the same location. This indicator is one of the simplest conflict indicators since it only measures the time gap between two cars without taking the speed of the following vehicle into account.

$$H(s) = \frac{\Delta X_{i,j}}{V_j} \tag{2.8}$$

With:
$\Delta X_{i,j}(t)$ = Bumper-to-bumper distance [m] between vehicle i and j at time t
$V_j(t)$ = Speed of leading vehicle j at time t $[\frac{m}{s}]$

Post Encroachment Time (PET)

The Post encroachment time indicates the difference in time between the moment that the offending vehicle leaves the conflict zone and the moment when the vehicle that has right of way enters the conflict zone. The PET is represented by only two points in time which makes it a very robust indicator. It was first researched by Allen et al. [1978] and is calculated as in Equation 2.9.

$$PET = t_{cp,1} - t_{cp,1} \tag{2.9}$$

With:
$t_{cp,2}$ = leaving time of conflict point [s]
$t_{cp,1}$ = Arrival time at conflict point [s]

2.3 Distance based proximal indicators

Potential Index for Collision with Urgent Deceleration (PICUD)

This scenario involves two consecutive vehicles. This indicator assumes that the leading vehicle applies its emergency brake during a lane change, so that the maximum deceleration rate of the vehicle is used. It uses this assumption to see how likely it is that two vehicles will collide. The value is calculated by using Equation 2.10 and is defined as the distance between the two vehicles when they have come to a stop, (Iida et al. [2001]).

$$\mathrm{PICUD(m)} = \frac{\mathrm{V}_j^2 - \mathrm{V}_i^2}{2\alpha} + \Delta X_{i,j}(0) - \mathrm{V}_i \Delta \mathrm{t} \tag{2.10}$$

With:
$\Delta X_{i,j}(0)$ = Bumper-to-bumper distance [m] between vehicle i and j at time 0
V_j = Speed of leading car $[\frac{m}{s}]$
V_i = Speed of following car $[\frac{m}{s}]$
$alpha$ = deceleration rate to stop $\frac{m}{s^2}$

Proportion of Stopping Distance (PSD)

The proportion of stopping distance is the ratio between the Remaining Distance (RD) and the Minimum Stopping Distance (MSD) as seen in Equation 2.12, (Allen et al. [1978]). Kitajima et al. [2009] stated that the threshold value of this indicator is 1. If the value of the ratio is lower than 1, a collision is unavoidable.

$$PSD_i(t) = \frac{RD}{MSD} = \frac{X_{i,c}(t)}{MSD_i(t)} \tag{2.11}$$

With:
$X_{i,c}(t)$ = Position [m] of following vehicle i at time of collision t.

With the MSD being calculated as:

$$MSD_i(t) = \frac{V_i^2(t)}{2 * d_{i,max}} \tag{2.12}$$

With:
$d_{i,max}$ = Maximum deceleration rate of following vehicle i in $\frac{m}{s^2}$

Difference of Space distance and Stopping distance (DSS) and Time integrated DSS (TIDSS)

The DSS is calculated as seen in Equation 2.13. It is the available space minus the stopping distance. If the sum of these two values is lower than zero, it means the situation is unsafe. A downside of the DSS is the fact that no severity level is available and that the duration of the conflict is not considered. (Okamura et al. [2011]). If this situation would occur in real life every car following situation could be seen as unsafe, but

$$\mathrm{DSS} = \left(\frac{\mathrm{v}_j^2}{2 * d_{j,max}} + \Delta X_{i,j}(t) \right) - \left(\mathrm{v_i(t)} * \mathrm{t_r} + \frac{\mathrm{v}_i^2}{2 * d_i, max} \right) \tag{2.13}$$

With:
V_i = Speed of following vehicle i in $\frac{m}{s}$
V_j = Speed of leading vehicle j in $\frac{m}{s}$
$d_{i,max}$ = Maximum deceleration rate of following vehicle i in $\frac{m}{s^2}$
$d_{j,max}$ = Maximum deceleration rate of following vehicle j in $\frac{m}{s^2}$
$\Delta X_{i,j}(t)$ = Bumper-to-bumper distance [m] between vehicle i and j at time 0

t_r = reaction time

Okamura et al. [2011] overcame this problem by introducing Time Integrated DSS (TIDSS). This new indicator provides a level of (un)safety. It integrates the value gap between DSS and the threshold value over time by using Equation 2.14 so it can evaluate the safety of traffic flow as seen in figure 7

$$\mathrm{TIDSS_i} = \int_0^t \{\mathrm{TH} - (\mathrm{DSS})\}\tau_{sc} \tag{2.14}$$

With:
TH = Threshold value
τ_{SC} = Small time step [s]

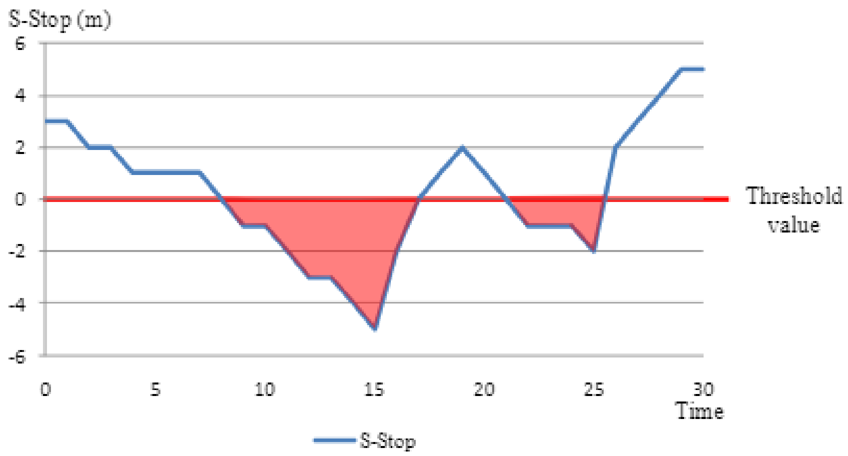


Figure 7: Safety evaluation by using TIDSS (adapted from Okamura et al. [2011])

Unsafe Density(UD)

The unsafe density by Barceló et al. [2002] is based on vehicle speeds, relative position between the lead and the following vehicle and the reaction time of the following driver. It was presented for car following models using micro simulation. The unsafe parameter from Equation 2.15 does not provide the global safety of a network. To assess safety of multiple links within a network, Equation 2.17 was introduced. It calculates an unsafe density parameter by summing all unsafety parameters of the vehicles in the simulation. So this indicator can be scaled to macro level, or makes the first step within this scaling process, as it takes the unsafety indicator which is a microscopic conflict indicator and proposes a way to use it at a higher level by summing over all vehicles. This indicator is limited to car-following since it does not take the direction of the conflict into account at would therefore not perform well when used for indicating safety of lane change or crossing conflicts.

$$\mathrm{Unsafety}_i(t) = \Delta V_{i,j}(t_c) * V_i(t) * R_{d,j}(t) \tag{2.15}$$

With:

$$R_{d,j} = \frac{-a_j(t)}{d_{j,max}} \tag{2.16}$$

And:
$\Delta V_{i,j}(t)$ = Relative speed $\frac{m}{s}$ between vehicle i and j at time t
$V_i(t)$ = Speed $\frac{m}{s}$ of following vehicle i at time t
$a_j(t)$ = Deceleration $\frac{m}{s^2}$ of leader vehicle j at time t
$d_{j,max}$ = Maximum deceleration $\frac{m}{s^2}$ of leader vehicle j

The unsafe density then becomes:

$$\text{Unsafe Density } = \frac{\sum_{\mathrm{s}=1}^{S_{\mathrm{t}}} \sum_{\mathrm{V}=1}^{V_{\mathrm{t}}} *\text{unsafety}_{V,S} * \mathrm{dT}}{\mathrm{T} \cdot \mathrm{L}} \tag{2.17}$$

With:
S_t = Number of simulation steps within aggregation period
V_t = Number of vehicles in link
T = Aggregation period duration [s]
L = Section length [m]
dT = Simulation step duration [s]

2.4 Deceleration based proximal indicators

Deceleration Rate to Avoid a Crash (DRAC)

DRAC considers the influence of speed differentials and deceleration in a conflict. It was first introduced by Almqvist et al. [1991] and is defined by Equation 2.18. It can be seen as the minimum deceleration that is required from the following vehicle to avoid a crash with the leading vehicle. Within the equation the indicator uses the difference in speed between the following (FV) and the leading (subject) vehicle (SV). The previous divided by the closing time gives the DRAC. The SV initiates the potential conflict by braking/ changing lanes/ accepting gap. The FV needs to take action to avoid such a potential conflict. The relevance of DRAC is widely recognized since it takes the role of both differential speed and decelerations in traffic flow into account (Astarita et al. [2012], Gettman and Head [2003], Qu et al. [2014]). Nonetheless, DRAC as an indicator cannot truly identify the potential conflict since it makes a lot of assumptions regarding the braking process, (Cunto and Saccomanno [2007]). It assumes that the deceleration is constant over the entire time of braking and does not take a reaction time into account. It also neglects the effects of a possible intervention by the automatic braking system which would lead to inconsistent deceleration pattern.

$$DRAC_i(t) = \frac{\Delta V_{i,j}^2(t)}{2 * \Delta X_{i,j}(t)} \tag{2.18}$$

With:
$\Delta V_{i,j}^2(t)$ = Relative speed [$\frac{m}{s}$] between vehicle i and j at time t
$\Delta X_{i,j}(t)$ = Relative position [m] between vehicle i and j at time t

Crash Potential Index (CPI)

As stated before, Cunto and Saccomanno [2007] stated that DRAC is not sufficient as an indicator on itself. For this reason, they came up with the CPI, which is defined in Equation 2.19. It calculates the probability that a given vehicles' DRAC is higher than its maximum available deceleration rate (MADR) during a given time interval. CPI is the ratio between the sum of the time steps for which DRAC is higher than MADR and the total time that vehicle i occupies the time-space domain. If a vehicles DRAC exceeds its assigned MADR, the vehicle is assumed to be in conflict. This measure provides a better understanding of the order of events before a crash occurs, but it is generally only applicable at intersections for rear-end conflict analysis. It is not suited to analyse conflicts that happened due to lateral movements. The application of this index relies on the significant collection of vehicle tracking data in highly disciplined traffic environments, (Mahmud et al. [2019]).

$$CPI_i = \frac{\sum_{t_0}^{t_n} P\left(d_{i,\max} < DRAC_i(t)\right) \cdot \tau_{sc} b_i(t)}{\Delta t_i} \tag{2.19}$$

CI
With:
$$b_i(t) = \begin{cases} 0, & \text{if no interaction with } j, \\ 1, & \text{if interaction with } j. \end{cases}$$
$d_{i,max}$ = Maximum deceleration $\frac{m}{s^2}$ rate of vehicle i
$DRAC_i(t)$ = Deceleration rate to avoid a crash for vehicle i
τ_{sc} = Simulation time step [s]
Δt_i = Total travel time for vehicle i

Critically Index Function (CIF)

The CIF, introduced by Chan [2006], uses two hypothesis to estimate the severity of a potential collision. The first is stated as: "The higher the collision speeds, the more severe the resulting consequences will be." And: "The longer time available for evasive manoeuvre, the more likely a collision can be avoided." The CIF is calculated according to Equation 2.20.

$$\text{Critically Index Function}_i(t) = \frac{V_i^2(t)}{TTC_i(t)} \tag{2.20}$$

With: $V_i(t)$ = Speed of the following vehicle in $\frac{m}{s}$

2.5 Other indicators

Delta V

Delta V represents the change in speed in the trajectories before and after a conflict, it also provides an indication of the severity of the conflict. It was researched by Shelby [2011] and is considered a prominent predictor of crash severity. It assumes a conflict that is not elastic which means that the momentum is conserved during the conflict. This assumption is not very realistic since there are many factors that will influence the momentum during a crash, but it has been found to be a useful and complete indicator. The indicator is calculated through Equation 2.21 which is adapted from Bagdadi [2013].

$$\text{Delta V}_i = \frac{m_j}{m_i + m_j} * (V_j(t_c) + V_i(t_c) * cos(\alpha)) \tag{2.21}$$

With:
$m_{i,j}$ = Mass of vehicle i resp. j
$V_{i,j}$ = Speed of vehicle i resp. j
α = Angle of approach

Conflict severity (CS)

Bagdadi [2013] went on a search for an indicator that was applicable to all conflict types. In this search the conflict severity (CS) was introduced. It combines Delta V, TA and maximum deceleration. This leads to an indicator that is able to capture crash risk and severity. The implementation of mass, impact angle and deceleration rate lead to a realistic indicator. The formulation of this indicator is found in Equation 2.22. $d_{i,max}$ is the estimated deceleration of the vehicle during the evasive braking, TA is the available braking time, i.e. time-to-accident and m_j and m_i are the corresponding weights of the involved road users. So the conflict severity could be defined as the delta V minus the time available to avoid a crash, which takes into account the decrease in speed before the predicted collision would take place.

$$CS_i = \text{DeltaV}_i - (\frac{m_j}{m_i + m_j})(TA_i \cdot d_{i,\max}) \tag{2.22}$$

With:
DeltaV_i = Delta V for vehicle i
$m_{i,j}$ = Mass of vehicle i resp. j
TA_i = Time to accident for vehicle i
$d_{i,max}$ = Maximum deceleration rate $\frac{m}{s^2}$ of vehicle i

Extended Delta V

Laureshyn et al. [2017] went on a search to improve the use of crash severity of injuries as an indicator. Before the introduction of this indicator only time or space were used to express the severity. It refers to change in velocity when a crash occurs, just like the normal Delta V indicator. The extended Delta V, however, is calculated as the expected change of velocity experienced by a road user if the conflict would have resulted in a crash. It is calculated by using Equation 2.23.

$$\Delta V_j = \frac{m_i}{m_j + m_i} * \sqrt{V_j^2(t_c) + V_i^2(t_c) - 2 * V_j * V_i * cos(\alpha)} \tag{2.23}$$

With:
$m_{i,j}$ = Mass of vehicle i resp. j
$V_{i,j}$ = Speed of vehicle i resp. j
t_c = Time at collision
α = Angle of approach

Summary

Within table 15 the surrogate safety indicators described above are summarised. The conflict types for which they can be used, and their input variable are showcased. A more extensive table with the equations and threshold values can be found in Appendix A

Table 3: Summarising table of indicators

Notation	*Name*	*conflict type*							*Variables*						
Time based		**Crossing**	**Merging**	**Diverging**	**Rear-end**	**Lane change**	**Overtaking**	**Object**	**Distance**	**speed**	**acceleration**	**deceleration**	**mass**	**duration**	**angle**
TTC	Time to collision	x	x	x	x	x	x	x	x	x					
TET	Time exposed time to collision	x	x	x	x	x	x	x	x	x				x	
TIT	Time integrated time to collision	x	x	x	x	x	x	x	x	x				x	
MTTC	Modified TTC	x	x	x	x	x	x	x	x	x	x				
CI	Crash Index	x	x	x	x	x	x	x	x	x	x				
TA	Time to accident	x	x	x	x	x	x	x	x	x					
H	Time headway				x				x	x					
PET	Post encroachment time	x	x	x											
Distance based															
PICUD	Potential index for collision with urgent deceleration	x	x	x	x	x	x	x	x	x		x			
PSD	Proportion of stopping distance				x			x	x	x		x			
DSS	Difference of space distance and stopping distance	x			x			x	x	x		x			
TIDSS	Time integrated DSS	x			x			x	x	x		x		x	
U	Unsafety		x	x	x	x			x	x		x			
UD	Unsafe density		x	x	x	x			x	x		x		x	
Deceleration based															
DRAC	Deceleration rate to avoid a crash		x	x	x			x	x	x		x		x	
CPI	Crash potential index		x	x	x			x	x	x		x		x	
CIF	Critically index function	x							x	x		x			
Other indicators															
Delta V	Delta V	x	x	x	x	x	x	x		x			x		x
CS	Conflict severity	x	x	x	x	x	x	x		x			x	x	x
E Delta V	Extended delta V	x	x	x	x	x	x	x		x			x		x

3 Safety at macro level

Within this chapter the surrogate safety at macro level is addressed by explaining the variety of ways that are used to evaluate safety at the level of an intersection, network, region or country. This chapter is subdivided in four subsections. Firstly, the surrogate safety indicators at meso/macro scale are discussed. These are indicators that can be derived from microsimulation but are evaluating the safety of more than two vehicles. Thereafter, the traditional indicators using historical crash data are discussed, which gives an insight in their use and their shortcomings. In subsection three, the overview of the use of safety performance indicators is provided, these are more uncommon indicators that evaluate the relative safety of a large-scale network without looking at historical crashes. Within the fourth subsection the topic of safety performance functions will be addressed, which is a way of predicting crashes on a large scale using the traffic volume (or other explanatory variables) on traffic networks. Lastly, the methods that previously used microsimulation as a basis for evaluating traffic safety a large-scale network are discussed.

3.1 Surrogate safety indicators at meso/macro scale

The traffic volume, or traffic flow have been tested for having a relationship with crash frequency. The consensus is that a higher traffic volume leads to higher multi vehicle crash count (Abbas [2004]). also, Sayed and Zein [1999] correlated the traffic volume to accidents on 92 intersections. It can be argued that the single-vehicle crash count is higher at lower volumes since higher speeds are possible. Higher speeds can lead to higher single vehicle crash count as well as higher severity of both single and multi-vehicle crashes, (Aarts et al. [2006]). Higher variability in speeds, or speed dispersion leads to more conflicts and on its turn to a higher crash probability, (Qu et al. [2014]). Accepted gaps can offer an indication of the general safety. Higher average accepted gaps would indicate a safer environment, (Fitzpatrick [1991]). The variance in headway can be an indication of safety, If the headway is lower than 2 seconds this can indicate a dangerous situation. If the variance indicates that the headway is often lower than 2 seconds this could indicate an unsafe situation (Peng et al. [2017]). Shock waves have a strong relation with braking, since they are a result of braking. When a vehicle brakes there will be a delay until the following vehicle brakes, this will lead to a shock wave of braking cars. Braking on its turn can indicate a level of safety, since drivers would brake to avoid a collision, which can be indicated as a conflict, (Gettman and Head [2003]). The number of lane changes can also be an indicator of the number of conflicts and can therefore be used as a measure of safety, (Gettman and Head [2003]).

3.2 Indicators using historical crash data

Quantifying traffic safety is important for comparisons between different entities. There is a need for knowing if a country, city or network is safe or unsafe. The way this is determined varies. A benchmark or threshold could be used, to which the analysed entity is compared. Multiple units exist to quantify this benchmark or threshold. This is dependent on the data available and the suitability of the data. The most frequently used indicators are described in this subsection.

- Crash frequency
- Fatalities
- Fatalities per driven kilometre
- Crash severity
- Crash rates

The crash frequency can be used when the entities that are being compared are subject to the same general conditions. So, the same modal split, same traffic volume, same vehicle types. It could be seen as the most common indicator. An example of its use could be comparing different years in the same country for traffic safety. It is important to note here that number of crashes or crash frequency is not appropriate for comparing countries, because there is no common definition of a crash. On the contrary, there is a common definition of fatality in all countries, which is a person that passes away within 30 days after the crash (Montella et al. [2013]). Fatalities per driven kilometre indicate this safety measure per driven kilometre, which creates a better indicator since driving more kilometres increases the chances of a crash.

Crash severity indicates the severity of crash and can be used to measure changes in for example speed limits. Imagine the speed limit of a road section being lowered and measuring the average crash severity before and after the change in speed limit. It is often measured in number of fatalities per 100 crashes, but no common unit is used in all countries. As mentioned before, a common definition exists for a fatality as a result of a crash. This common indicator does not exist for a non-fatal crash. And since crash severity is determined by the most severe injury involved in the incident, regardless of the number of injuries, this could lead to mixed indicators of safety when it regards a non-fatal crash.

Crash per driven kilometre is an example of a crash rate. Crash rates have different denominators that try to indicate the level of exposure and that all have their advantages and disadvantages. An example is the crashes per driven kilometre. It is a useful indicator when comparing large entities like countries. When for example comparing the U.S.A to the Netherlands it would not make sense to use crash frequency since a lot more people life in the U.S.A and a lot more kilometres are being travelled there. This indicators therefore indicates the safety per driven kilometre and can give insights into the safety differences on road level. When comparing entities with a different number of inhabitants it makes sense to measure the number of crashes per inhabitant or per large number of inhabitants. This can also provide insights into the use of vehicles when combining this indicator with the crashes per driven kilometre. The crash per driven kilometre and crash per capita are close to the theoretical definition of exposure, but the methods used for gathering this data will always be subject to some form of sampling errors (Papadimitriou et al. [2013]).

3.3 Safety performance indicators

Safety performance indicators or SPI are composite indicators of road safety. These are related to three main transport components; road user, vehicle and infrastructure (Shen et al. [2020]). The concept of composite road safety index is a popular concept among road safety experts around the world. There is a constant need for comparison among different units: countries, municipalities, networks, roads, etc. This need leads to the necessity of a comparing method that is fair to all compared units. Comparisons that only use one specific indicator or parameter describing safety or unsafety can end up with totally different ranking of compared units. The purpose of SPI's is to reflect the current safety conditions of a road traffic system. The most important feature of SPI's is that they are considered "intermediate outcomes", i.e. they will be observed before actual crashes are observed. This is very useful since it offers an evaluation method that is faster than having to gather crash data over a long period of time. SPI's can be used to measure the influence of various safety interventions and to enable comparisons between different road traffic systems (Yannis et al. [2013]). It was concluded by Shen et al. [2020] that SPI's allow quicker and more local analyses and monitoring than crash data do. Also, SPI's can incorporate quantitative and qualitative information on specific aspects that are known to have influence in the safety levels and, not only measure the influence of various safety interventions but also enable comparisons between different road systems (Viera Gomes et al. [2018]).
The search for a composite safety index lead to the categorization of SPI in the following categories:

- Alcohol and drugs
- Speed
- Protective systems
- Daytime running lights (DRL)
- Vehicle
- Road
- Emergency

Within this list, alcohol indicates the use of alcohol by drivers. Speed regards the speeds driven by drivers compared to the speed limit. Protective systems govern the use of for example seat belts. DRL takes count of the people that ignore traffic lights. Vehicle information is used to indicate the vehicle type, length, weight, etc. The Road concerns the correct use of infrastructure for the right purpose, design wise, this is elaborated below. Lastly emergency indicates the management of trauma on the road, (SWOV [2006]).

Hermans et al. [2008], investigated five weighting methods for the combination of the seven SPI's. Whereafter, Hermans et al. [2009] created a computational model to find aspects of road networks to lack safety. Within a thorough literature review by Persaud and Ariza [2014], a relationship between the problem area and road safety was ascertained. Crash related data should normally be avoided for the estimation of SPI's. The SPI are supposed to reflect the operational conditions of the system. But they can be used for comparison. The road safety performance index is an established tool used in road safety to make country comparisons, identify the "best in class" practices and define the earlier goal-oriented actions (Tešić et al. [2018]).

Yannis et al. [2013] took it upon themselves to investigate the road safety performance indicators for the interurban road network. Within their paper two methods are presented which evaluate the road network SPI to assess the level of safety of the inter urban network. It was found that mixing the road design with the road network performance indicator could potentially allow for a more complete assessment. The road network SPI aims to measure whether the right road is on the right location. It is defined as the percentage of appropriate road category length per road category. Based on four definitions; centres, sizes of centres, demand, level of unsafety based on accident density. It could be interesting to apply this as a method.

Chen et al. [2016] also noticed the lack of universally agreed upon approach for road safety bench marking. Especially the two core activities: (1) developing a set of road safety performance indicators (SPI's) and combining them into a composite index; and (2) identifying a meaningful reference(best-in-class), are not easy to fulfil. To this end, a technique that can combine the safety performance indicators (SPI's) into a complete index, and can identify the 'best-in-class' is required. Within Chen et al. [2016], an Entropy-included RSR (Rank-sum ratio) methodology was investigated with the aim of combining the above two aspects. Using a combination of results from other methods (e.g. the SUNflower approach) and other measures (e.g. Human Development Index) as a relevant reference, a given set of European countries were ranked and grouped into several classes based on the composite Road Safety Index. Within each class the 'best-in-class' was than identified.

3.4 Safety performance functions

Another way of assessing safety at a network level is using safety performance functions (SPF). SPF are models that are developed to predict the number of crashes. This takes away the need for historical crash data to evaluate traffic safety. The number of crashes is predicted by developing a model for specific road sections or intersections by finding consistencies within their specific road geometry and the yearly crash count. The estimated model would take the annual average daily traffic (AADT) as input and predict the number of crashes in a year on a certain (part of a) network. By using crash modification factors (CMF) general models can be extended to better predict the crash frequency at road sections.

In order to develop a safety performance function a lot of data is needed, the collection time and effort needed for gathering this data are extensive. The federal highway administration dedicated a lot of time to the development of safety performance functions in the united states. From the highway safety manual three large projects were derived that focused on SPF's. Within Srinivasan et al. [2013b] a strategy is derived that discusses the option of developing a new SPF or calibrating an existing model. These two options exist since the transferability of SPF's for use in different countries or jurisdictions are not straight forward. This is a result of differences in driving behaviour, speed limits, vehicle types etc. (Farid et al. [2018]). The option of developing a new SPF is further discussed within Srinivasan et al. [2013a]. The option of calibrating an existing model is further discussed within Lyon et al. [2016]. The main takeaway is the amount of time and data that is needed to either develop or calibrate a SPF.

Since the use of foreign SPF's is not straight forward, Schermers and Van Petegem [2014] tried to develop a SPF for rural 80 km/h roads in the Netherlands. The development of this SPF was not successful due to multiple reasons. First of all, limited data was available regarding the road geometry and traffic on the selected roads. Secondly the shortcomings of crash registration in the Netherlands became apparent when analysing the crash data and lastly the relatively low crash density in the Netherlands lead to a small number of data points. From the failed attempt it became clear that roads were too heterogeneous to determine a base road type suitable for SPF use with the data that was available.

Within Wang et al. [2020] exposure measures and functional forms are investigated for SPF's used for signalised and stop controlled intersection in urban and suburban areas. Generalized Negative Binomial – P models were estimated for the crash prediction on those intersections. I was found that there is a strong correlation between overdispersion of the spf's and the traffic volume on the minor road ($AADT_{minor}$). This overdispersion was parameterized to account for data heterogeneity. It was concluded that exposure measures (like traffic volume) and functional forms vary across intersection types and crash types.

Another interesting research direction is prediction of conflicts using a safety performance function. Within Essa and Sayed

[2018] a conflict-based safety performance functions for signalized intersections at the cycle level was developed. The explanatory traffic variables (traffic volume, queue length, shock wave speed and area, and the platoon ratio) were collected during video analysis. Essa and Sayed [2019] built upon the research topic by investigating multiple conflict indicators (TTC, MTTC and DRAC) and using them to for a real time safety evaluation model at these signalised intersections. This is still be subject to time as one would need to visually analyse the infrastructure so it would already need to be build and will still be performed in hindsight.

3.5 Methods for analysing traffic safety at network level using microsimulation

Within this section multiple methods are described that aim at analysing traffic safety at a network level using micro simulation. These methods can be grouped into different categories and within those categories often show similar results. Within this section, the methods have been grouped into volume based methods (which use the volume on a network to predict the crashes on that same network), Extreme value theory (EVT) methods (which use the EVT to extrapolate the number of conflicts or crashes to a network level). Followed up by post processing software's, SSAM and Zombie driver, which use trajectory data from microsimulation to compose the number of conflicts and other indicators on the simulated network. Lastly there is a subsection consisting of the methods that either use a combination of the previous methods or a method that did not fit into one of the groups.

3.5.1 Volume based

The first method found in literature was first researched by (Alsalhi et al. [2018]). Within this study a novel mathematical model was created which calculates the probability of a crash. This probability is calculated for each traffic state interval and is dependent of speed, flow or density. By using this crash probability, a Macroscopic Safety Diagram (MSD) can be composed which can be used to indicate traffic safety at a network level. This MSD is based on the Fundamental diagram (FD). The model takes the output of SSAM as input. A right skewed, bell shaped curve was found when the relationship between traffic density and crash probability was analysed. The study uses one 10 by 10 grid toy network and one two-mile by one-mile network of congested arterials and saturated freeway. The relationship is validated using empirical data from video images of a major arterial road in Saudi Arabia. The shortcomings of this study are twofold. Firstly, no empirical data was available of heavily congested roads, so the relationship that was found could not be validated for heavily congested roads. The other shortcoming was the lack of sensitivity analysis. More scenarios should be run with a variety of parameter settings to see how this affects the MSD.

Wagner et al. [2021] investigates the relation between volume (traffic flow) and crash frequency, without taking microsimulation into account. Within this research the crash frequency N is related to the exposure (traffic flow) Q on the macroscopic level of a whole city. When the data set of the crash frequency and the data set of the exposure were related it was found that the relation N(Q) is not a linear relation. If Q is small, N takes the shape of a second order polynomial, while it shows an S-shaped relationship under larger values of Q. This research substantiates the conclusion provided in Alsalhi and Dixit [2015], where the crash rate increases if the density increases, with a stabilization at higher densities.

3.5.2 Post processing software's

SSAM

SSAM is short for Surrogate safety assessment model. This is a model that was developed by Shelby [2008]. It build upon Gettman and Head [2003] and was part of a project together with Federal Highway Administration (FHWA). SSAM is a post processing software program that analyses traffic conflicts from traffic simulation using trajectory data.

The SSAM used four micro simulating software types: AIMSUM, Paramics, TEXAS and VISSIM. It identifies conflicts within micro simulation. These conflicts are identified when the trajectories of two vehicles would collide if they do not change their direction. A threshold TTC value of 1.5 seconds was used initially. The focus was oriented on evaluating intersections, interchanges and roundabouts. Nevertheless, SSAM can identify conflicts on any type of roadway where two vehicles travel in proximity. The conflicts that were researched are based on three manoeuvre types: Path-crossing, rear-end and lane changes. The software then computes corresponding SSM: TTC, PET, initial DR, Max DR, maximum speed and a hypothetical collision severity measure: Delta-V, (Shelby [2008]).

The SSAM was validated in three steps. Firstly, a theoretical validation was performed, secondly a field validation was completed and lastly a sensitivity analysis took place. Within the theoretical validation it was found that if the same traffic conditions were simulated, both simulated intersections lead to different number of conflicts and conflict severity, and these differences were statistically significant. However, if these numbers were used, no clear preference for infrastructure design was concluded on. This was a result of a trade-off of SSM's. The results pointed out the need for future research to develop a conflict index or safety index, Shelby [2008].

From the field validation it became clear that the simulation conflict data of the lane changes and rear-end conflicts provided by SSAM were significantly correlated with the crash data collected in the field. To conclude this, 83 field site data sets were used. These were all four-leg, urban, signalised intersections, which were also modelled in VISSIM. It has to be noted that the volume-based crash prediction models performed better in terms of correlation than the surrogate measures in all test cases. Shelby [2008]

Within the sensitivity analysis five intersections were reassessed using all four simulation software types. It was found that when using different simulation models for the same traffic infrastructure a wide range of results can be obtained. VISSIM showed a conflict frequency that was almost ten times lower than TEXAS. Rear end conflicts had by far the largest share within the total number of conflicts at all evaluated TTC thresholds (0.5, 1.0, 1.5 seconds), Shelby [2008].

After the final report on the SSAM by Shelby [2008], the SSAM has been used in varies studies. However, SSAM does not directly outputs a benchmark indicator for simulation-based safety studies, so this should be investigated further Wang et al. [2018].
Within Ariza [2011], research was conducted to see if the SSAM is applicable to analyse traffic safety of a network of arterials. At this time, the SSAM was only used to analyse intersections. The main objective of this study was investigating the transferability of the SSAM conflict based crash prediction model to other study areas. Both volume- and conflict-based crash prediction models were used. The conflict-based models performed badly for modelling the arterials. This could have been a result of a high agent to driver ratio or a result of the chosen driver behaviour model since drivers behave differently on arterials compared to intersections. Very limited computational power was available which lead to few final conclusions.

Zombie driver

Alonso et al. [2020] wanted to develop a post processing software that could also take into account single vehicle crashes as described in subsubsection 4.2.2. For this reason, they created a new post processing software that takes trajectory files as input. This new software also looks at the lateral changes in the trajectories to identify single vehicle conflicts. As an addition to the number of conflicts, the zombie driver software also gives a larger range of indicators as output. Namely, the delta V, the number of deaths, the energy of impact and the injuries. It was compared to the performance of the SSAM and was found to better reflect the number of crashes within the same study area. In order to apply the zombie driver software vehicle trajectory files are needed just as for the SSAM. These trajectory files are the output of a simulation run. To retrieve realistic trajectories, one needs to model the network according to its real network geometry (arc length, lane width, lane number, gradients, intersection management features). The signal light settings should also reflect the real settings and the vehicular flows should be calibrated according to the traffic flow on the network during the same time periods.

The Zombie driver software is than able to simulate a driver's distraction. It does so for each time instant, for every vehicle simulated in the network and saves the trajectories. In order to simulate the driver's distraction, two parameters are used:

- Δt (time interval of simulation during which the driver is distracted and moved maintaining its constant speed)
- Angle of deviation

Based on these deviated trajectories, the zombie driver software is able to evaluate various surrogate safety indicators parameters .The Zombie driver algorithm adds the factor of driver distractions to simulation. Within that same simulation, three different outcomes are determined for each modelled vehicle: No impact occurs, impact with another vehicle occurs, impact with a fixed obstacle occurs.

3.5.3 Other methods

Qu et al. [2014] aimed at assessing the performance of 3 macroscopic safety indicators (speed, speed dispersion, and volume) and two microscopic potential crash risks (time to collision and deceleration rate to avoid crash) on safety evaluation for expressways. This way the relation could be investigated between SSM on micro and macro level. Andrew et al. [2009] considers interactions between vehicles as risky events (called here, surrogate events) and estimates the risk of crash conditional on such an event based on observed separations between interacting vehicles. The EVM represents three considerable advantages over the traffic conflict technique. Barceló et al. [2002] Limited the research to unsafe density. Their research provides a statistical way to scale up but does not regard indicators at network level. Within Astarita et al. [2012] automatic video detection was combined with microsimulation in order to estimate the road safety performance through DRAC, TTC and PSD. These indicators represent interactions in real time between different pairs of vehicles in traffic. The combination of video detection and micro simulation was used to calculate and validate vehicle trajectories.

4 Relations of traffic safety based on microsimulation

Within this third chapter of the literature review and fourth chapter of the thesis, the relationship within traffic safety when using microsimulation are discussed. Within the first subsection a framework is proposed to visualise the relation of safety indicators based on microsimulation. Within the second subsection the relationship between conflicts derived from microsimulation and historical crashes is discussed in depth.

4.1 Relation between indicators at the micro and macro level

After all the information provided in the previous sections, all the conflict indicators are explained. However, it is not straight forward what the relation between these indicators is. To clarify their relation a visualisation was made of the SSM. Within figure 8 the SSM are plotted in a x-y system. Where the x-axis indicates the scale of the SSM and the y axis indicators whether the SSM is more lateral movement or longitudinal movement based. This figure is not substantiated by data. It was used to gain more insight into relationship between all the indicators. The indicators are grouped as in section 2. All the red indicators are temporal, the green indicators are deceleration based, the blue indicators are distance based and the yellow indicators are miscellaneous. The relative ranking is based on the way these indicators are used and described in literature, their input variables and their ranges of the outcomes of the formulas used to calculate these indicators. In these criteria, the lateral and longitudinal are the most straight forward indicators. A deceleration-based indicator is by this methodology very longitudinal since it is derived from the longitudinal behaviour of two vehicles. The post encroachment time (PET) can be seen as more lateral since it assumes a crossing conflict.

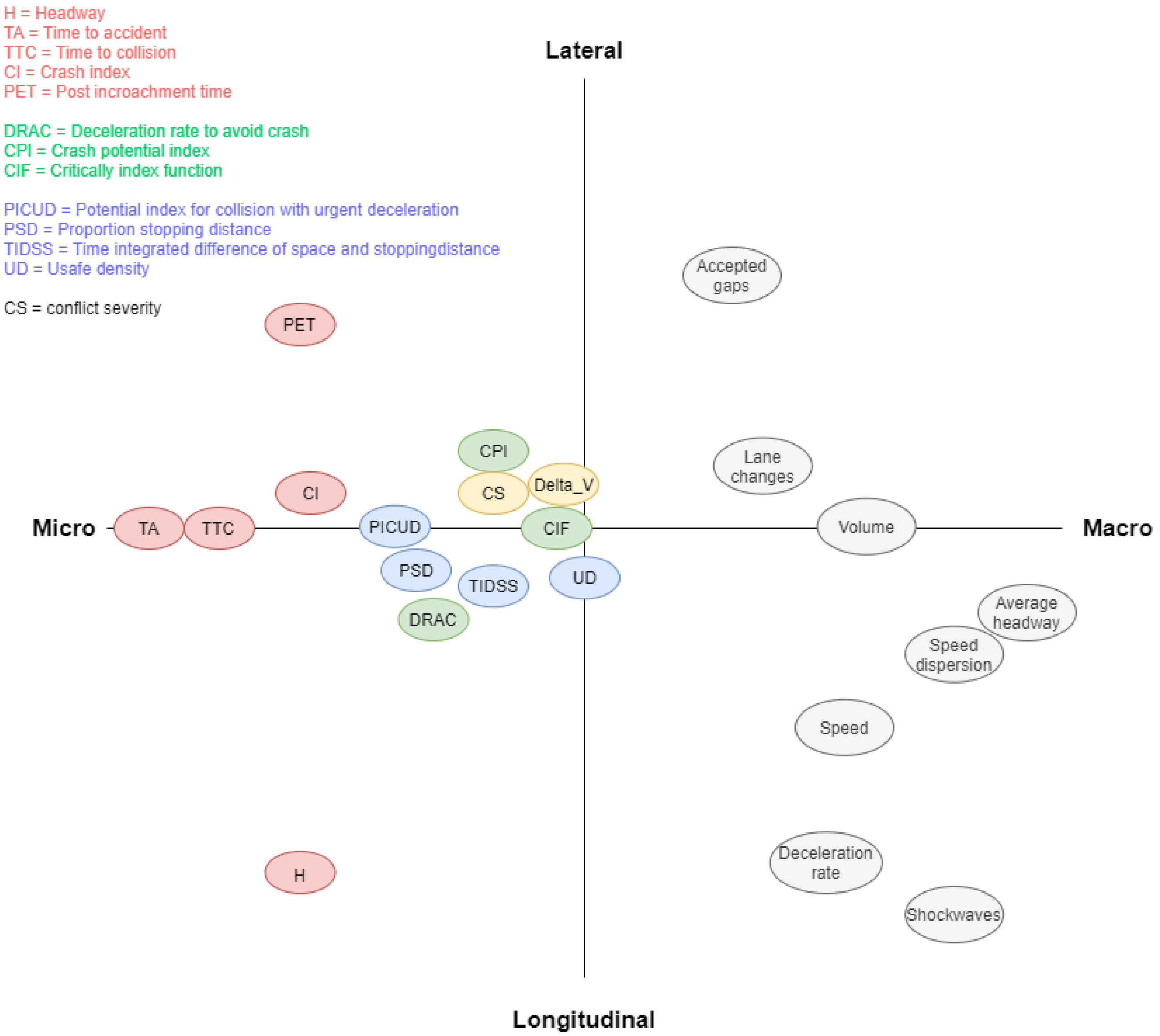


Figure 8: Relation of SSM within lateral longitudinal and micro macro framework

Within figure 9 The same was done as in figure 8 but now with the urban to highway scale on the y axis.

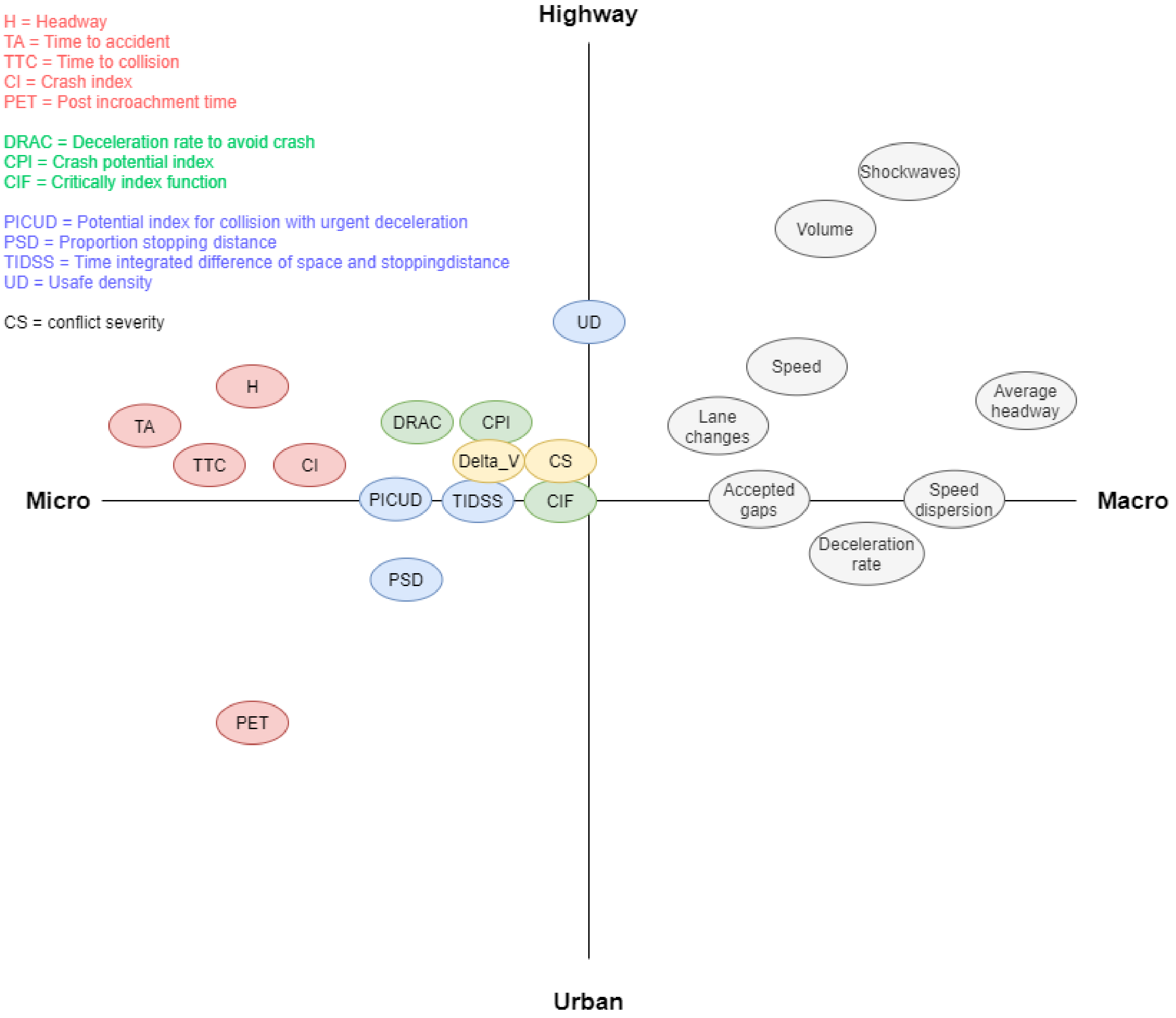


Figure 9: Relation of SSM within urban - highway and micro - macro framework

It can be seen that a lot of the macro indicators are more towards the longitudinal side of the graph. This is in line with the fact that it's hard to scale up these indicators since both the translation from lateral to longitudinal and the translation from micro to macro would have to be made. The longitudinal indicators are more applicable to more than two vehicles since deceleration patterns or ratio's between distance (space) and speed can be used. The more lateral indicators are always interaction measured between two cars, like for example the lane changes and accepted gaps.

4.2 Relation conflict to crashes

For surrogate safety indicators to be useful, it is important that there is a kind of relation between the indicators, crash rate, and severity. Real data of crashes and measured and simulated conflicts have been compared obtaining acceptable results in many papers (Caliendo and Guida [2012],Dijkstra et al. [2010] Huang et al. [2013]).

4.2.1 Multi vehicle conflicts

Dijkstra et al. [2010] considers only the quantitative relation of conflicts and crashes at junctions of regional roads. At this moment in time crashes at intersections can be imitated unlike crashes at road sections where vehicles run off the road. Crashes are the most extreme form or outcome of conflicts.
A conflict in a simulation model is not the same as a conflicts on the street. In a simulation model, vehicles follow a known route and react to other vehicles in a programmed manner. However, both in a simulation and in real streets, vehicles will

approach each other with a given speed and relative direction.
The number of conflicts and the number of passing vehicles were found to be significant. The number of conflicts at junctions and the number of passing motor vehicles appear to be statistically related to the number of observed crashes for all the junctions. A classification of crashes and conflicts into various crash types clarifies that junctions with signals show considerable differences between lateral conflicts and crashes. This difference probably occurs because the method used also calculates conflicts between two vehicles of which one is already standing still (at a red light).

Huang et al. [2013] related the conflicts measured in the field with conflicts derived from microsimulation using the SSAM. A reasonable goodness of fit was found between the simulated and real-world rear-end and total conflicts. It was also found that simulation can't properly indicate unexpected driving manoeuvres.
Young et al. [2014] provides a state of the art of the use of microsimulation for analysing traffic safety.
Tarko [2018] states that : "The required ecological consistency between conflicts and collisions can be ensured by sufficient nearness of conflicts to collisions." Within this same paper, several models of are discussed that estimate the relationship between conflicts and crashes. These models are listed in table 4.

Table 4: Overview of models that estimate the conflict to crashes relationship, adapted from Tarko [2018].

Type	Model form	References
1A	$Accidents(T,Y) = K(conflicts(t,X)$	Hauer [1982], Glauz et al. [1985], Hyden [1987]
1B*	$Accidents(T,Y) = \sum_s K_s(Conflicts_s(t,X)$	Hauer and Garder [1986], Sayed and Zein [1999], Guo et al. [2010]
2**	$Accidents(T,Y) = K(Y,X) * Conflicts(t,X)$	Wu and Jovanis [2012], El-Basyouny and Sayed [2013]
3	$Accidents(t,X) = \sum_s R_s * (X) * Conflicts_s(t,X)$	Davis et al. [2011], Campbell [1996], Tarko and Songchitruksa [2005],
4	$Accidents(t,X) = R(X) * Conflicts(t,X)$	Tarko [2012], Jonasson and Rootzén [2014], Zheng et al. [2014],
5	$\frac{\text{Accidents }(T_A,Y_A)}{\text{Accidents }(T_B,Y_B)} = \frac{\text{Conflicts }(t_A,X_A)}{\text{Conflicts }(t_B,X_B)}$	Sacchi et al. [2013]

- $Accidents(T,Y)$ = expected number of accidents during period T and under conditions Y;
- $Conflicts(t,X)$ = number of conflicts during period t (much shorter than T) and under conditions X
- $Conflicts_s(t,X)$ = number of conflicts of severity s during period t and under conditions X.
- K = conflict-crash conversion coefficient;
- K_s = conflict-crash conversion coefficient for conflicts with severity s.
- $R_s(X)$ = risk (probability) of crash given risky event of severity s.
- $R(X)$ = risk (probability) of a crash given risky event
- T_B, T_A = period of counting crashes before and after improvement, respectively.
- t_B, t_A = period of counting conflicts before and after improvement, respectively.

*The model's form is linear $Accidents(T,Y) = K_o(Y) + K_1(Y) * Conflicts(t)$, but the authors have estimated different models for different conditions Y.
**The model is probabilistic and it estimates the probability of a crash given conflict conditions (true positive).

Within model type 1A there was trouble with collecting crashes because it takes very long and the collection of conflicts is very expensive, so the period T of the crashes is much longer then conflict period t and the conditions Y of crashes are therefore different from conditions X of conflicts. Model type 1B is an extension of type 1A because it considers the conflict severity s. Model Type 2 assumes that different relationships exist between conflicts and crashes for different conditions. It was estimated with count models and the conflict rates are included among the explanatory variables. The conditions of X and Y can still be different. The model Type 3 estimates the expected number of crashes in the same period as the earlier occurring events. This means that the conflicts precede a crash with different probabilities. The mechanism takes various conflict severity's s and conditions X as input parameters and outputs probabilities of precipitation $R_s(X)$. This model needs a long observation period in order to obtain reliable results, since precipitating events with a high collision probability do not occur frequent and do not generally appear in a short period. This can lead to underestimation of the number of crashes. Within the type 4 model conflicts are defined as the same event as a collision, while assuming the continuity of severity S.

This leads to the type 4 model being more applicable for estimation using only short periods, since the observed events can be extrapolated. Both the type 3 and 4 model can be estimated without historical crash data if either extreme value theory or exceedance-based statistics are applied (Songchitruksa and Tarko [2006], Tarko [2012], Tarko and Songchitruksa [2005]). Zheng et al. [2014] found that the exceedance-based estimation is more efficient compared to the extreme value estimation. The type 5 model is mostly useful for estimating crash modification factors. These can express relative changes in safety. In the setting of this model, the changes in safety can be explained by certain traffic treatments.

Astarita et al. [2019] created a concept where the actual risk of crashes can be investigated using traffic simulation and sampling of safety performance indicators instead of real traffic data. Many of existing surrogate safety measures are based on trajectories of vehicles that will not intersect. These SSM establish a number of potential conflicts based on a from proximity. They state that the closer the vehicles are to each other, the more likely they are to have a collision. The proximity is calculated using quantitative measurements derived from vehicle trajectories. The majority of these conflict indicators do not consider conflicts between moving vehicles and fixed road-side barriers and obstacles, which in reality make up a large share of the crashes

Guido et al. [2019] offers a comparison analysis between real accident locations and simulated risk areas in an Urban road network. It aims to assess how the microscopic simulation is a useful tool to identify potentially unsafe vehicle interactions and how high-risk locations identified by a microsimulation technique are similar to the ones identified by using historical crash data. The high-risk locations identified through SSAM correspond with those from accident data.

$$RiskRate_i = \frac{PotCon_i}{TotFlow_i} \tag{4.1}$$

$$AccidentRate_i = \frac{AccCounts_i}{AADT_i} \tag{4.2}$$

The correlation consists of the ratio between risk rate and accident rate. A significant relationship was found when investigating this ratio. This result represents a validation of the proposed equation, providing a link between the microsimulation and observed data.

4.2.2 Single vehicle conflicts

As mentioned earlier, single vehicle crashes are a large share of all crashes and are not taken into account within a lot of simulations of safety. Gordon et al. [2011] specifically addresses road departure crashes involving a single vehicle. Surrogates should be based on the lateral control of the vehicle. Within this research naturalistic driving data from a field operational test were spatially joined with highway data and crash data from the same area, and a set of candidate crash surrogates was tested. Estimated time to road departure was found to show the correct statistical dependencies, consistent with the crash data. Simple lateral lane position did not provide a satisfactory surrogate. Within Alonso et al. [2020] a new software named the zombie driver software is introduced to overcome the statistical shortcomings and to overcome the fact that single vehicle crashes are not being modelled in micro simulation. Zombie driver takes roadside objects into account. As well as more additional parameters, as posted in fig 4 of Alonso et al. [2020]. SSAM is used as well as the zombie driver software to investigate the safety at multiple intersections. The Zombie driver software allegedly outperformed the SSAM software when validated with real crash data.

5 Method

Within figure 10, the data flow of the research is presented. This data flow shows the main outline of this study. The traffic volume, or vehicular flows, together with historical accident data and the geometric characteristics of the network are the input to this methodology. With this input, three methods will be applied to rank all intersections and road sections on the network. With that ranking, the goal is to construct a new metric that uses the relation between these methods. To get to this comparison, a validation will be performed on the outcome of the SSAM conflicts by performing statistical tests on the correlation between the simulated conflicts and the historical crash data. After this validation safety performance function will be adapted to assess the same network. The goal is to be able to assess the relative safety of a network without having historical data. And to be able to see how certain changes in policy, e.g. speed and changes in circumstances, e.g. traffic flow effect the relative safety of a network.

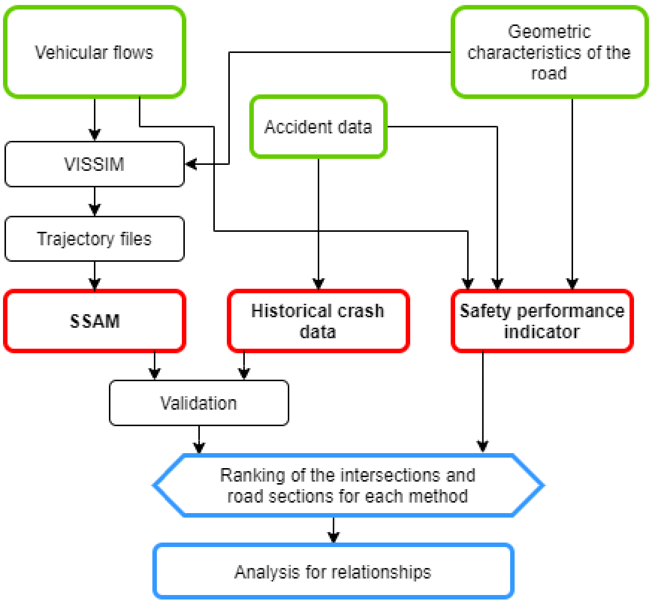


Figure 10: Data flow of this research

Within the rest of this chapter, the methodology will be elaborated on in six sections. The first section covers the way the historical crash data was gathered and analysed. The second section covers the details of the simulation after which the third section will explain the way the conflicts from simulation were analysed. In the fourth section the validation procedure will be discussed and in sections five and six the application of safety performance function and the translation are explained.

5.1 Historical crash data

5.1.1 Sources

Historical crash data is available for this network. That data is recorded and stored by multiple sources; Dexter RDW cloud, BRON data, dataplatform.nl and smart traffic accident reporting (STAR). The nationaal dataportal wegverkeer "NDW" has a website called Dexter on which the accidents and incidents are recorded from multiple sources. The data from NDW is recorded since July 2019 and therefore no data points were available before that date. Dataplatform.nl is a platform that offers free data sets on many topics, including crash data. However, dataplatform.nl did not have historical crash data for this specific network. STAR is a tool that exports crash data directly from insurance companies. It is therefore a complete extended database. The STAR database was offline and it was not possible to retrieve this data from the company. The other data source considered was the Bestand geregistreerde ongevallen "BRON" data from Rijkswaterstaat. This data is available from 2010 onwards and has a clear structure which is helpful for analysing the data .

Because of the aforementioned reasons, the BRON data was the selected data source. The BRON data has multiple assets that are of value to this research. Time stamps of the accidents are available on request, which is necessary for making a time of day analysis. This time of day analysis ensures that the right periods will be simulated and compared to the accidents of that time of the day. The accidents can be traced back to individual road sections and intersections which is necessary to evaluate the road section and intersection on an individual level. The accident data set has a column which indicates the section on which the accident occurred. This is indicated by a code starting with "JTE" for intersections and "WVK" for road sections and ending with ten-digit number. The section data set then links these road section and intersections to a road name. Since only the street names of the network were known, the road names have to be linked to the corresponding road sections. The accidents that occurred on these specific road sections have to be exported from the accident data set that contain every single accident for the whole country within the selected time period. For this a python script (as seen in Appendix B) was created that links the road name to the road section and then exports the accidents that happened on the indicated street names. For this research that would be the Burgemeester Bechtweg and the Burgemeester Letschertweg.

5.1.2 Data filtering

The historical crashes data set is a raw data set which needs filtering. Firstly, the frequency of accidents per year was checked to see if it was consistent, or at least subject to a consistent increase or decrease, without any large peaks. Secondly, the number of involved parties had to be checked for each historical crash. Since the goal is to perform a validation study of the conflicts from microsimulation, crashes with only one involved vehicle were removed from the data set. This was done because crashes with only one involved vehicle would most likely have a different nature, like running of the road due to distraction or a collision with a crossing animal. The conflicts from microsimulation are a result of two vehicles interacting and would therefore have a different nature than single vehicle crashes. Single-vehicle crashes are however also of interest when considering different road designs, since single vehicle crashes could be a result of bad infrastructure design. Within this study however, the interaction between vehicles is investigated. Some historical crashes were indicated with zero involved vehicles due to limited information on the crash, these data points were therefore removed from the data set. Another question that remains is what the relation is between accidents with three or more vehicles and two vehicle conflicts. Within the SSAM manual this is not discussed.

With the filtered data set a descriptive statistics data analysis was performed to gain more insight into the data at hand. The spread of the accidents over the days of the week and the spread of the accidents over the time of day were analysed. The results gave an impression of the scenarios that should be simulated in VISSIM.

5.1.3 Location of crashes

The location of a crash can be traced back to the level of road- and intersections within the BRON data. In order to compare the locations from the data set to the links in VISSIM, a tool should be used to couple the locations. The tool at hand is QGIS. Within figure 11 the map containing all the road sections of Tilburg is displayed.

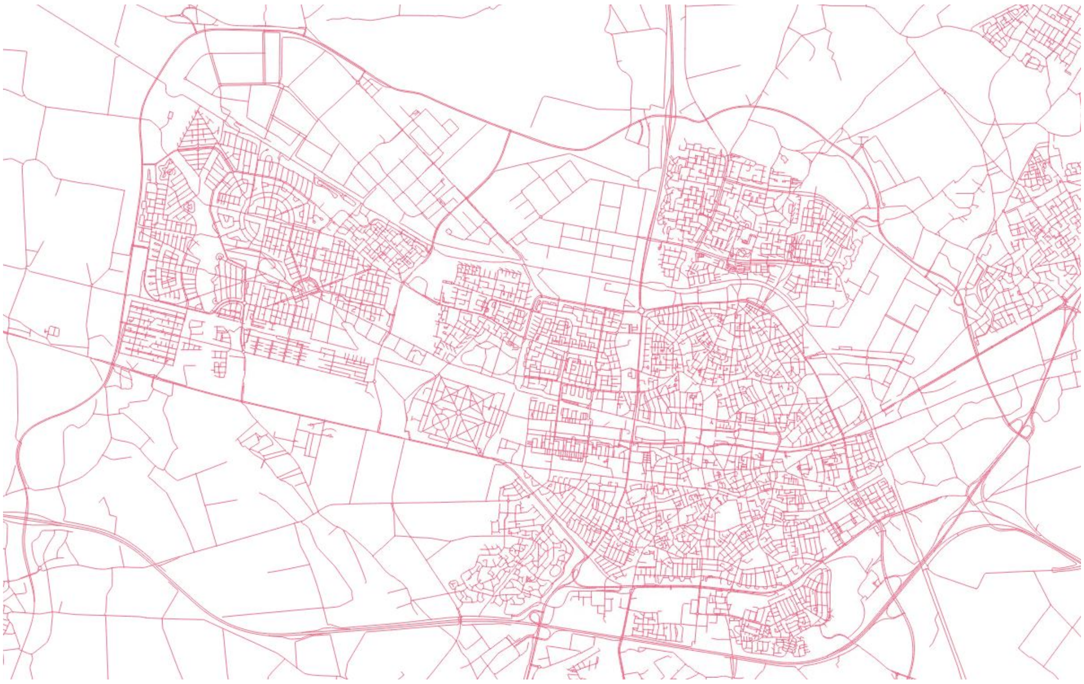


Figure 11: Tilburg network in QGIS showing the road sections

Ideally this program would also be able to indicate the hectometre point of the crashes. This is useful in case of long road sections where one would like to distinguish the location of different crashes on that long road section. The NWB offers a map of the Netherlands with almost all the hectometre points but the hectometre points for the selected network are missing. This leads to the fact that it was not possible to trace the crashes back to hectometre level.

With the use of a python script found in Appendix B, the GPS coordinates of each road section were coupled with the crashes that happened on that road section.

5.2 Microsimulation

Within this section the simulation setup will be elaborated on by showing the selected network, it's infrastructure, the used settings and the scenario's that were used for the simulation. After that, the number of runs used in the simulation study are discussed.

5.2.1 Simulation network

In order to perform the study a simulated network is needed. It was outside of the scope of this thesis to create a new network from scratch and for that reason a previously created network available at TNO was selected. The requirements were arbitrary in the sense that "a network" can mean multiple things. In this case a mix of road sections and intersections was one of the requirements, together with the requirement of having a network that is not categorised as a highway nor an urban network, so that it would not just be applicable to either one of these two. Since many surrogate safety indicators are used for either urban or highway study's it would lead to not being able to use and therefore scale many of these indicators. These requirements, together with the fact that this specific network was in a later development stage led to the selection of the northern part of the ring road of Tilburg as seen as the yellow highlighted road in figure 12. This road can be categorised as a distributor road with a speed limit of 80 km/h.

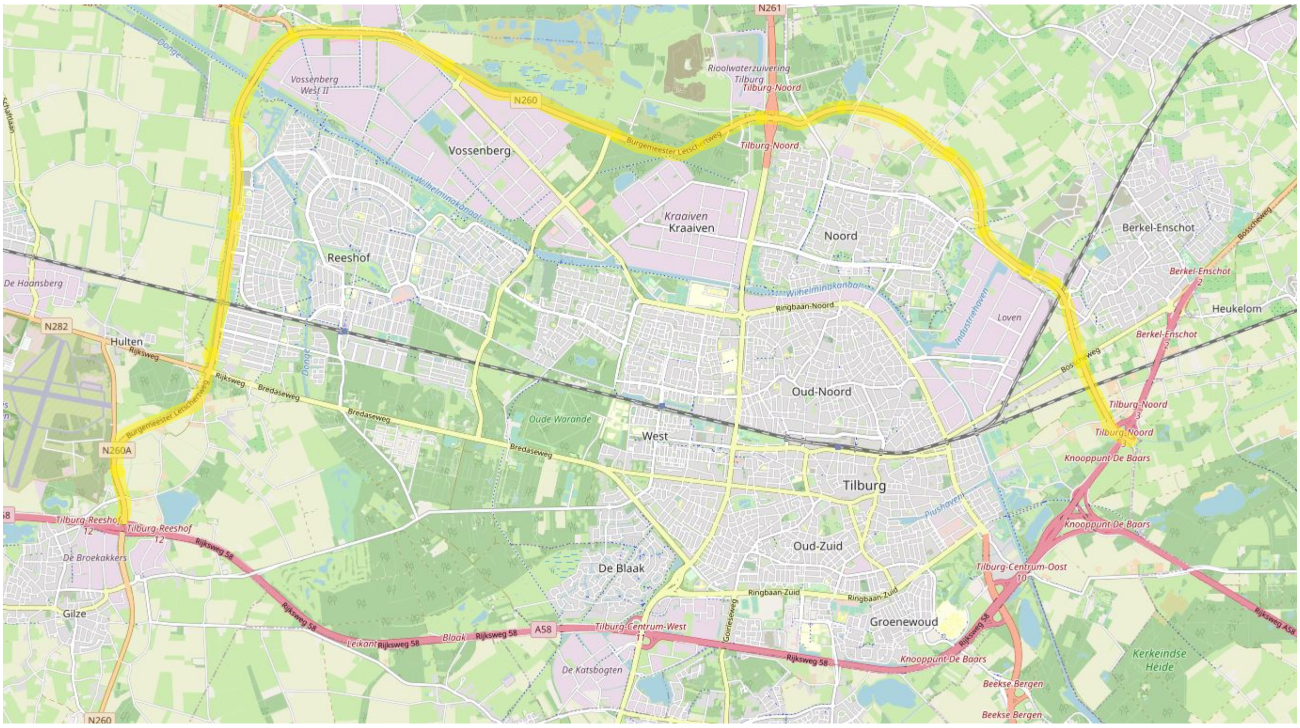


Figure 12: The selected network: The northern part of the ring road of Tilburg, consisting of the N260 and the N261.

The model for this network was created in VISSIM and is already calibrated for volume for the year 2018. This means that the scenarios within the VISSIM model accurately represent the vehicular flows from the year 2018. The signal lights have also been calibrated and reflect the real-life traffic situation on the network. The network has a length of 20,4 kilometres and consists of 20 intersections and 20 road sections. The intersections are visible in more detail in Appendix A. As seen in the visualisation of figure 13, the network consists of an elongated main section and secondary roads, which are the roads perpendicular to the main road. These perpendicular sections are not part of the safety assessment due to time limitations while processing the data. It would have been time consuming to look up all the names of the minor roads and their corresponding road sections. Partly because this step could not be automated and partly because it would be very error prone to assess where these roads (and their road sections) end with respect to the minor roads in the simulated network.

It should be noted that this network did not undergo any infrastructural changes in the past 7 years. This information was requested from the city of Tilburg.

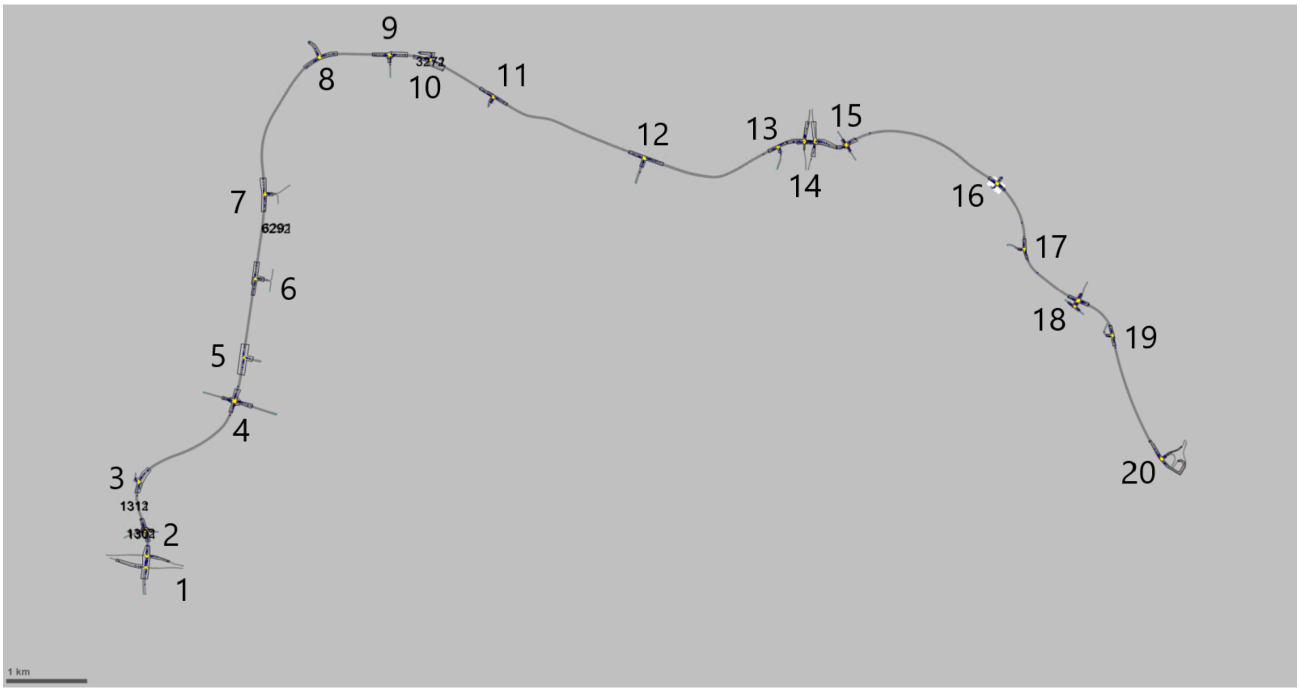


Figure 13: The selected network: The northern part of the ring road of Tilburg, consisting of the N260 and the N261 modelled in VISSIM with the corresponding node numbers.

Within VISSIM, the network consists of links and nodes. Nodes can be seen as intersections and links can be seen as road sections. But these do not correspond one to one, for the majority of the network it can be said that one road section consists of multiple VISSIM links. The way this is dealt with is discussed in Subsection 6.3. An example of a node and a link is provided in figure 14, where the link is highlighted by black arrows and the node is highlighted by the black line surrounding the two intersections. Within Appendix D An overview of all the nodes in the network can be found.

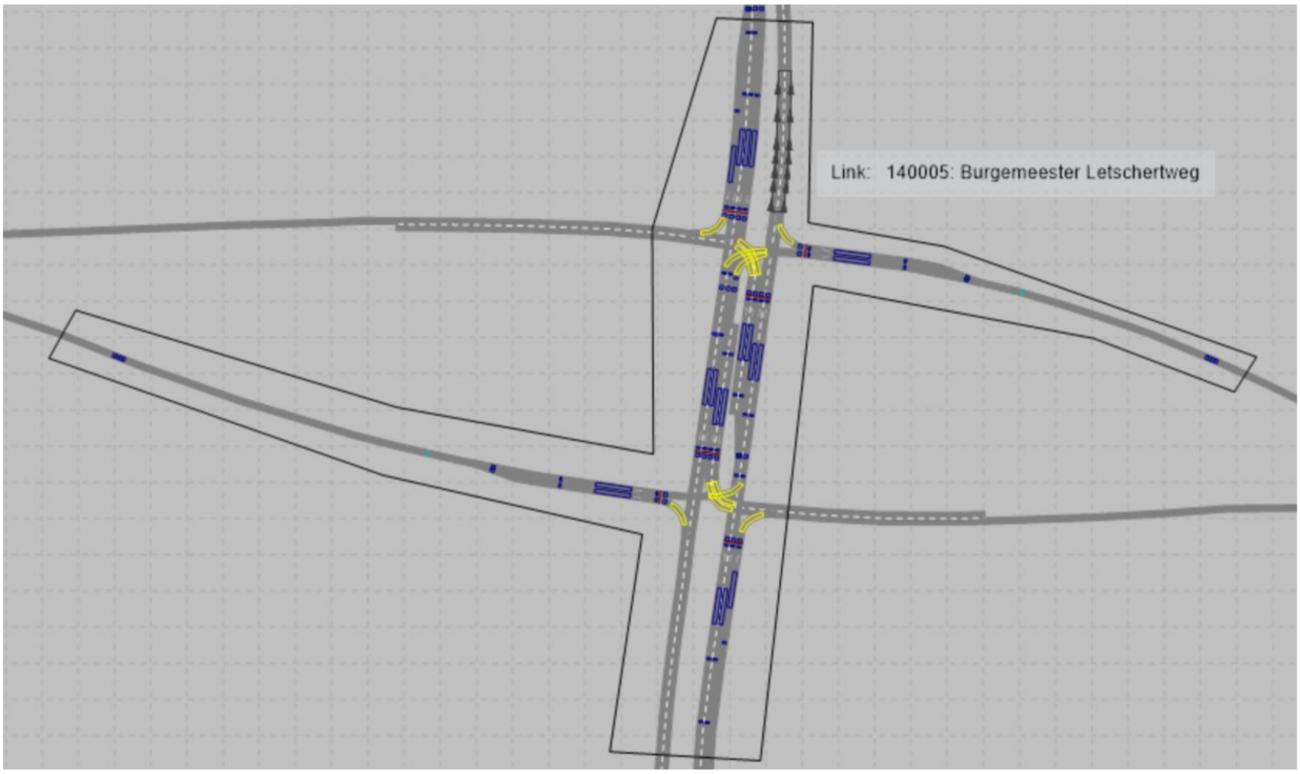


Figure 14: Node 1 with link 140005 in VISSIM

5.2.2 Settings

The VISSIM simulation was calibrated previously by TNO. No changes were made to the settings in the program. The driver behaviour model will play a large part in the outcome of the results, but this is not part of the scope of this project and was therefore not investigated. The traffic lights are programmed according to the naturalistic settings and should therefore reflect the reality closely. The traffic lights on the Tilburg network are in reality dynamically controlled by Dinniq. Dinniq is a company that offers "smart traffic lights". These smart traffic lights can adapt to the current traffic flow and adapts the timing of the traffic lights to guarantee the optimal traffic flow. This means that the traffic lights in reality do not have a fixed cycle. They do optimize towards a green wave and can also be vehicle actuated. The traffic signals within the VISSIM network will not adapt to optimize the traffic flow. They can therefore be seen as green wave traffic signals without vehicle actuation.

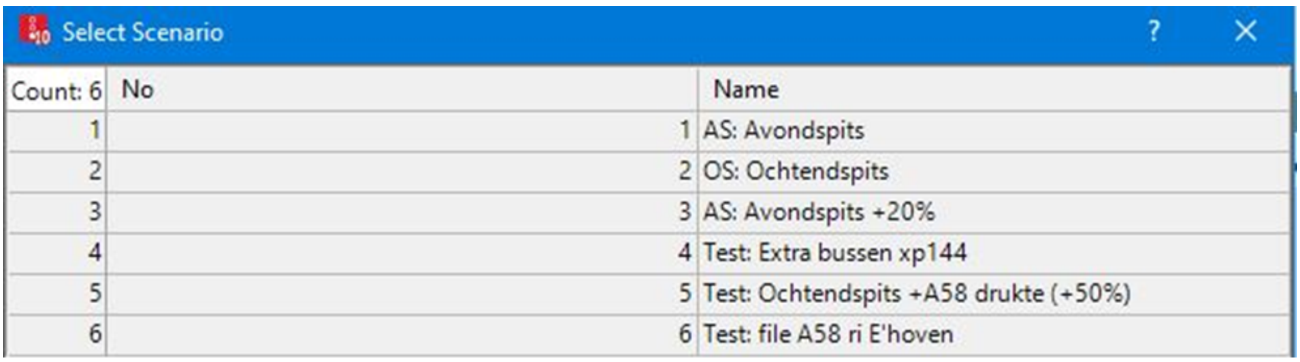
The driver behaviour models used in the vissim model are the Wiedeman 74 and the Wiedemann 99 model. The Wiedemann 74 model is used for describing the urban driving behaviour and is used in for example merging areas. The Wiedemann 99 model is used for the freeway traffic behaviour.

The model has two vehicle types as input which are car and HGV (Heavy goods vehicle). For the car 5 different cars with different dimensions are used as input in the model. For the HGV there's one vehicle available. The desired speed for both these vehicles is set to 80 km/h with a normal distribution. 5% of all vehicles is an HGV. The model also has PT lines in the form of busses, these share the same characteristics as HGV's. Pedestrians and cyclists are also modelled within the network, but their interactions are not saved within the trajectory files and these traffic participants can therefore be neglected.

The trajectory files from VISSIM are the output of the simulation and are the input for the post processing software. For this, it is needed to select the SSAM checkbox under the evaluation configuration tab. This selection leads to the creation of a .fzp file which contains the trajectories of the simulation when it is complete. The .fzp file is the file that is used as input for SSAM.

5.2.3 Scenarios

Six scenarios were defined to simulate the traffic at the network of Tilburg. Of these six scenarios only two scenarios reflect real life scenarios. Scenario 1 reflects the Evening peak (PM) and scenario 2 reflects the Morning peak (AM). For the sake of validation, it would be useful to have more than two scenarios, to be able to make more comparisons. The pre-programmed scenarios are calibrated for the real life volume on the network and if more scenarios would be created, assumptions would need to be made to reflect the correct traffic volume during these periods. As seen in figure 15 four more scenarios were defined; 3:Evening peak + 20%, 4:Extra busses, 5:Morning peak + A58 Traffic and 6: Congestion A58 direction Eindhoven. Scenario's 1 and 2 are used within this study, since they reflect real life volumes and can therefore be compared to real crashes.


Select Scenario

Count: 6	No	Name
1	1	AS: Avondspits
2	2	OS: Ochtendspits
3	3	AS: Avondspits +20%
4	4	Test: Extra bussen xp144
5	5	Test: Ochtendspits +A58 drukte (+50%)
6	6	Test: file A58 ri E'hoven

Figure 15: The available scenarios in VISSIM

5.2.4 Number of runs

Traffic micro simulation models are stochastic. In order to mimic the diversity in real life traffic, random numbers are generated. These random numbers are used to generate the vehicles entering the network, to determine were the vehicles go to and to select the behaviour of the simulated drivers. All these random numbers have an influence on the outcome of the simulation. In order the compensate for this randomness, a number of runs should be selected that offers simulation outcomes that are reliable. The number of runs can be calculated with Equation 5.1. Shahdah et al. [2015].

$$N = \left(\frac{t_{(1-\frac{\alpha}{2}),N-1} \times \sigma}{E} \right)^2 \tag{5.1}$$

With:
N = required number of simulation runs
σ = the sample standard deviation of the number of simulated conflicts
t = student's t-statistic for two sided error of $\alpha/2$
E = allowed error range

The allowed error range can be taken as a percentage of the mean, such that:

$$E = \varepsilon * \mu \tag{5.2}$$

With:
μ = the mean of the number of simulated conflicts on the initial set if simulation runs
ε = the allowable error specified as a fraction of the mean μ

For using this equation, a parameter should be selected that represents the data set that will be used. Within this study, that parameter is the TTC. The simulation was performed with 6 runs for both the AM and PM scenario. Which gave a mean TTC of 1.24 seconds with a variance of 0.06 seconds for all the conflicts within the the AM simulation and a mean TTC of 1.23 seconds with a variance of 0.07 seconds for all the conflicts within the PM simulation. With 5 degrees of freedom and a confidence interval of 95 % the students t statistic then becomes 2.23. With an allowed error of 10% the error range becomes 1.235. This leads to a required number of simulations runs of 2. So, 6 runs per scenario is sufficient.

5.3 Post processing software SSAM

Within this section the settings used for the surrogate safety assessment module will be elaborated on. The filter settings, conflict angle and threshold values will be discussed.

The SSAM program consists of multiple tabs which all offer different functions. Within the filter tab one can filter the conflicts by setting threshold values as seen in figure 16.

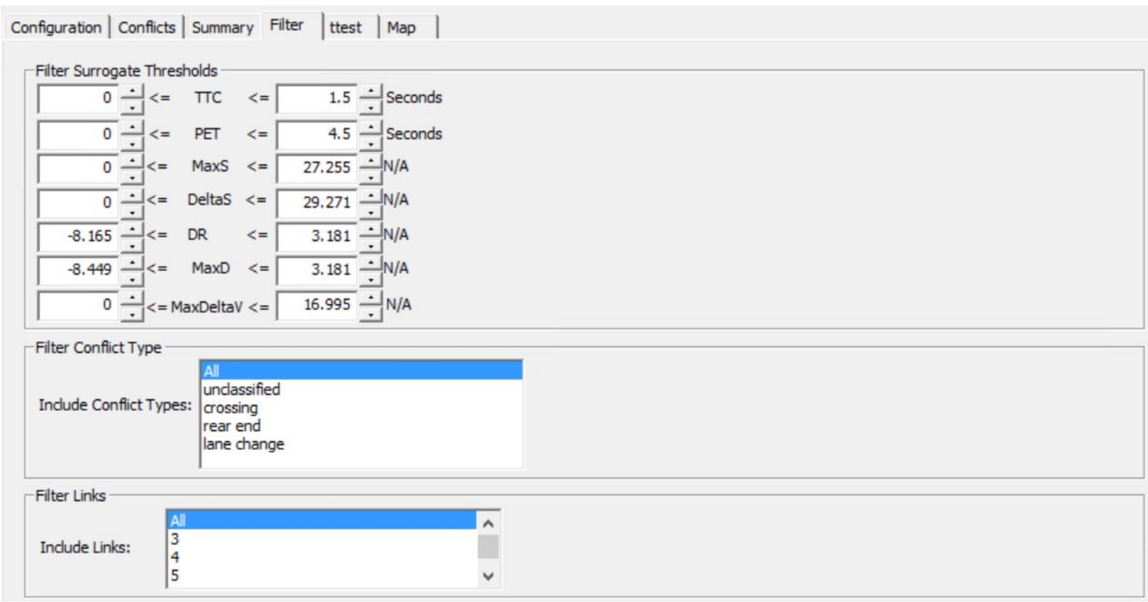


Figure 16: Filter options within SSAM

The post processing contained four different filter settings for TTC and PET as seen in table 5. The lower value was first set to 0.0 seconds instead of 0.01 seconds, but this led to a high number of 0 second conflicts due to an error in the VISSIM model. This will be discussed in more depth within subsection 6.2. No other filters were applied at this point. It is possible to filter on MaxS, which represents the maximum speed measured during a conflict. The DeltaS indicator represents the difference in speeds during the conflict. DR stands for the Deceleration Rate and Max Delta V is the maximum Delta V value of either vehicle in the conflict. Within this analysis only the PET and TTC values were filtered. This was done because these two indicators offer an estimate of the proximity of two vehicles. The MaxS, DeltaS and MaxDeltaV all indicate a level of severeness. This level of severeness was not analysed for the historical crashes, so it was assumed that PET and TTC would better explain the crashes. The values of the thresholds were chosen in such a way that the intervals were constant. Also, having multiple filters with decreasing values offers insight in which filter setting creates the best fit with the historical crashes in the later validation stage.

Table 5: Filter settings SSAM

	TTC (s)		***PET (s)***	
	low	**high**	**low**	**high**
PM_0.01_Default	0.01	1.5	0.01	4.5
AM_0.01_Default	0.01	1.5	0.01	4.5
PM_0.01_1.5	0.01	1.5	0.01	1.5
AM_0.01_1.5	0.01	1.5	0.01	1.5
PM_0.01_1.0	0.01	1.0	0.01	1.0
AM_0.01_1.0	0.01	1.0	0.01	1.0
PM_0.01_0.5	0.01	0.5	0.01	0.5
AM_0.01_0.5	0.01	0.5	0.01	0.5

Within the configurations tab, the conflict angle can be adjusted. For this study the default settings were used, which indicates a rear-end conflict at any angle smaller than 30 degrees. It indicates a conflict as being a lane change conflict for a conflict angle between 30 and 80 degrees. If the angle is larger than 80 degrees the conflict is regarded as a crossing conflict. This is visualised in figure 17, within this figure the lane change angle is set between 30 and 85 degrees. Within this research this angle is set between 30 and 80 degrees. It should be said that this is a simplification of the real situation. For example, if a vehicle would make a lane change and hit the side of a vehicle next to him, that would count as a rear-end conflict. While in reality, the vehicle was changing lanes at a low angle. This could be made more realistic by taking into account if a vehicle actually changes lanes, or if it overtakes another vehicle, but the SSAM program does not take this into account.

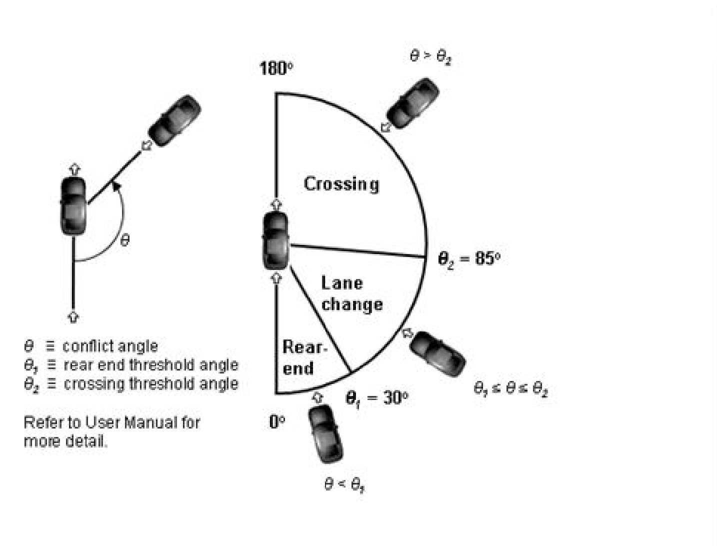


Figure 17: Conflict angle settings in SSAM

5.4 Validation

Within this subsection the methodology for the validation is found. It regards the visual validation, the conflict and crash aggregation and application of the Spearman rank correlation.

5.4.1 Conflict and crash aggregation per node

In order to perform the validation some assumptions had to be made regarding the clustering or aggregation of road sections and links. The historical crash data is provided with a corresponding location which is indicated by a road section, as previously described. The simulated conflicts are provided with a corresponding location in the form of a link number in VISSIM. The road sections do not completely correspond with the links in VISSIM, so assumptions had to be made in order to be able to compare the two data sets. An example of how the location indication of the data sets do not correspond is provided in figure 18. Every line in the left picture equals a road sections, so this image counts around 10 road sections. While the same intersection on the right side of figure 18 consists of more than 20 links in VISSIM. For this reason, intersections were seen as nodes and the number of historical crashes and conflicts were summed per node.

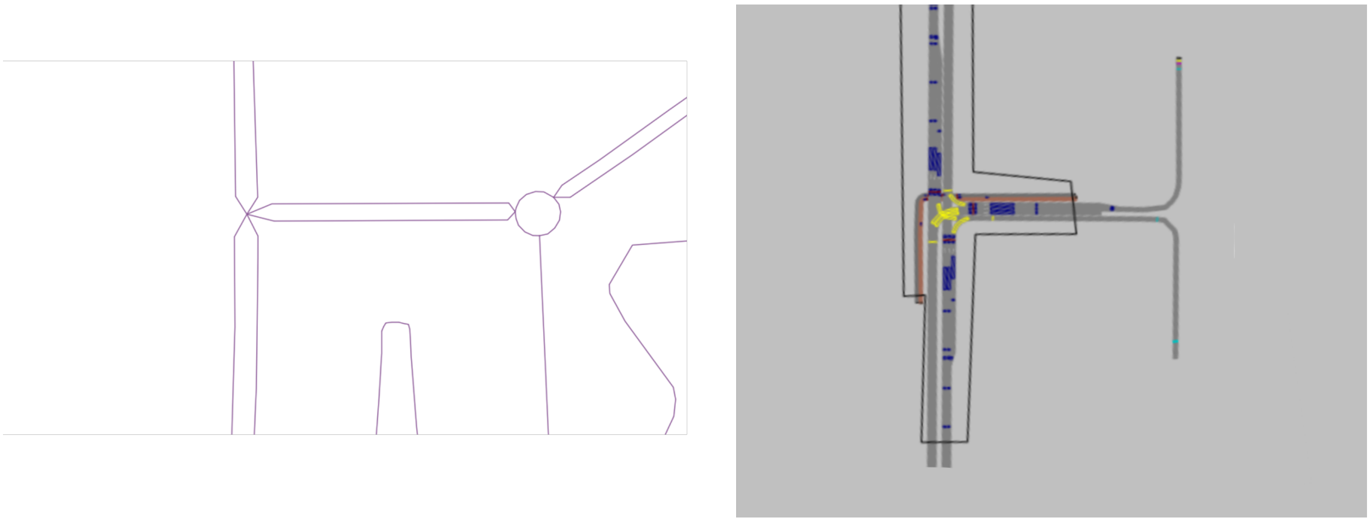


Figure 18: Example of intersection clustering with Qgis roadsections (left) and VISSIM links (right) at node 6.

The goal was to stay consistent for each individual node. Within VISSIM, the links leading up to the intersection were seen as part of the intersection, since these are a lot shorter compared to the road section leading up the intersections in Qgis. This same approach was used for every intersection. The historical crashes that occurred on road sections that could not be linked to a link in VISISM were not taken into account in the validation because it was not possible to compare them to the conflicts on the corresponding road. Out of the 275 crashes 216 could be linked to intersections.

5.4.2 Spearman rank correlation

The next step is to validate the outcome of the simulations statistically. In order to do this all the intersections were ranked based on the number of accidents and based on the number of conflicts happening on these intersections. The rankings were compared using the Spearman rank correlation coefficient. The Spearman rank correlation can be calculated by using Equation 5.3 and the rankings found in table 8. Where d_i is the difference between two rankings for node i and n is the number of items ranked.

$$\rho_s = 1 - \frac{6\sum d_i^2}{n\,(n^2-1)} \tag{5.3}$$

with:
d_i = the difference between two rankings for item i.
n = the number of items ranked.

The standard deviation can then be established by using Equation 5.4.

$$\sigma_s = \frac{1}{\sqrt{(n-1)}} \tag{5.4}$$

With:
σ_s = Standard deviation
n = Number of items ranked

And the critical Z-value can be calculated by using Equation 5.5.

$$Z = \rho_s \sqrt{(n-1)} \tag{5.5}$$

with $n = 20$, there are $20 - 1 = 19$ degrees of freedom which leads to a z value of 1.73 at a confidence level of 95%, a z-value of 2.09 at a confidence level of 90%. The Spearman rank correlations were calculated using python (see Appendix B for the script) and the results are summarized in table 9. From this table it can be seen that the AM peak conflicts and crashes have a better correlation than the PM conflicts and crashes. Multiple TTC and PET thresholds were tested to see the influence on the correlation and it can be seen that the lower the thresholds, the higher the correlation.

5.4.3 R^2 statistic

In order to substantiate the Spearman rank validation, the R^2 statistic will be used to check the relation of the conflicts and crashes for each intersection. The R^2 is the residual sum of squares of the linear regression of the earlier mentioned relation between conflicts and crashes. This statistic will be calculated for each combination of simulated conflict and historical crash data.

5.5 Safety performance function

In order to have a third way of evaluating the level of safety at the Tilburg network, a safety performance function will be used to predict the crashes at the network by using the volume, or traffic flow on the network. Safety performance functions are developed for specific countries. No safety performance functions are available for signalised intersections in the Netherlands as discussed in subsection 3.4. For this reason, a previously developed safety performance function for three and four legged, signalised intersections was selected from the safety analyst part of the highway safety manual. This SPF is based on data from the United states, which comes with limitations regarding the calibration, as discussed in Subsection 3.4. The formula of that safety performance function is found in Equation 5.6

$$Predicted\ crashes\ on\ intersection = years * Exp(-6.57) * (AADT_{major})^{0.66} * (AADT_{minor})^{0.2} \tag{5.6}$$

With:
$years$ = years for which is being estimated
$AADT_{major}$ = Average annual daily traffic on major road, two directions together.
$AADT_{minor}$ = Average annual daily traffic on minor road, two directions together.

Since only the volumes from the simulation are available the peak hour volumes needed to be translated to AADT. For this, a K factor is needed, which includes the season, weather and Time of day. Since for this research the peak hour volume is assumed constant through the year, the season and weather factor are also assumed to not play a role. To get from the AM and PM peak hourly volumes, Chen and Xie [2016], roads authority [2012] propose to average the AM and PM flows to counter the effects of a directional bias in either the morning or the afternoon. A multiplication factor is proposed ranging from 10 to 14 for regional roads.

In order to match such a SPF to a selected region it should be calibrated to fit the network or country to which it is applied. For calibration of such an SPF both minor and major roads AADT and crash count on the network are needed, of a similar network. Calibrating the SPF with data from the used Tilburg network would lead to the model being fit to the same network for which it should predict the crashes. This would not lead to useful or reliable results. No similar networks exist in the Netherlands and for the similar intersections that do exist no traffic volume data is available. For this reason, it was decided to not calibrate the model and directly translate it from the highway safety manual.

The SPF will be applied to 17 of the 20 intersections within the network, since intersection 1, 14 and 20 are very different from the other intersections when looking at their infrastructure as seen in Appendix D. Applying the selected SPF to these three intersections will not provide reliable results.

5.6 Scaling of indicators with linear model

Within this scaling section a methodology is proposed to gain more insight in the relationship between the different surrogate safety indicators of SSAM, the predicted crashes and the historical crashes of the Tilburg network. This can be useful to investigate which SSI are best at predicting the number of crashes, and should therefore be used when quantifying the safety of a network. In order to gain this insight, the simulated conflicts were analysed for each individual conflict indicator. Each conflict indicator is subject to a threshold value and by setting these threshold values in SSAM it is possible to put the focus on only one of the conflict indicators. For this application a new SSAM analysis with the AM peak simulation trajectories was performed. The AM peak simulation was used for this step in the research because it showed the best correlation with the historical crash data within the validation. Both the preliminary TTC and PET analysis values were set to 5 seconds, so that every conflict was taken into account. This made it possible to look at the lower threshold values of the other conflict indicators for conflicts that are subject to a TTC value higher than 1.5 seconds, because SSAM marks a conflict using the TTC and PET value. If the preliminary TTC and PET value are set to 1.5 seconds, this could eliminate conflicts that are only subject to for example a high deceleration rate. Next, all the bandwidths for the indicators were selected in such a way that they represent a severe conflict.

- TTC = 1 second
- PET = 1 second
- MaxS = 80 km/h or 22.2 m/s, when a vehicle is exceeding the speed limit.
- DeltaS, difficult because the speed difference can be huge if the PET and TTC are 5 seconds. Now set to 70 km/hour.
- DR = -3.35 $\frac{m}{s^2}$
- MaxD = 3.50 $\frac{m}{s^2}$
- MaxdeltaV = 10 $\frac{m}{s}$ per weight ratio and conflict angle.

For both TTC and PET the threshold value was set to 1 second. This value has been proved to have a strong correlation with crashes in the validation stage of this study. The maxS value is set to 80 km/h since this is the speed limit on the network. If a vehicle would exceed this speed limit it could lead to a dangerous situation. The DR is set to -3.35 seconds which was found to be the best fitting threshold within (Cunto and Saccomanno [2007]). The maximum deceleration is set to 3.50 $\frac{m}{s^2}$ which is considered a hard brake and is the deceleration value considered to impair the driver's comfort. Max delta V is set to 10, which is a result of an iterative process that looked at the number of conflicts for each threshold value. The unit of the deltaV indicator is not straightforward. It takes the ratio of the weights of the vehicles and the conflict angle into account and multiplies this with the difference in speed in $\frac{m}{s}$. In this way it can predict the conflict severity.

Table 6: translation framework for safety indicators

Intersection	**SPF/Volume**	**TTC**	**PET**	**MaxS**	**DeltaS**	**DR**	**MaxD**	**MaxDeltaV**	Crashes
1									
2									
3									
⋮									
n									

Table 6 is a linear system as seen in Equation 5.7, with the constraints that the coefficients of each safety predictor (the surrogate safety indicators and the safety performance function) should be positive and add up to a maximum of 1. Within this equation, m indicates the number of the intersection, C_x indicates the coefficient to be estimated. This linear system can be solved with a least squares estimate method to find the coefficient (or influence) that each conflict indicator should have to best predict the number of crashes on a network. The python code for estimating this framework is found in Appendix B. This type of framework was selected to simplify the problem. By seeing it as this linear system it is possible to estimate the weights of each indicator which can show its ability to predict crashes.

$$\begin{bmatrix} SPF_1 & TTC_1 & MaxS_1 & DeltaS_1 & DR_1 & MaxD_1 & MaxDeltaV_1 \\ SPF_2 & TTC_2 & MaxS_2 & DeltaS_1 & DR_2 & MaxD_2 & MaxDeltaV_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ SPF_m & TTC_m & MaxS_m & DeltaS_m & DR_m & MaxD_m & MaxDeltaV_m \end{bmatrix} * \begin{bmatrix} C_{TTC} \\ C_{PET} \\ C_{MaxS} \\ C_{Delta_S} \\ C_{DR} \\ C_{MaxD} \\ C_{MaxDeltaV} \end{bmatrix} = \begin{bmatrix} Crashcount_1 \\ Crashcount_2 \\ \vdots \\ Crashcount_m \end{bmatrix} \tag{5.7}$$

6 Results

Within this chapter the results of the research will be displayed. This section consists of the same subsections as the methodology. Firstly, the historical crashes on the network of Tilburg will be analysed. Secondly, an insight will be provided in the simulation results and the corresponding conflicts derived from SSAM. Within the third section the results of the validation will be shown. Within the fourth section the results of the safety performance function are posted and discussed and the last section will cover the translation.

6.1 Historical crash Data

Within this section the historical crashes are elaborated on. This section consists of three subsections. Subsection one discusses the distribution of crashes over time and the times that are of interest to this research. Subsection two covers the locations of the crashes within the Tilburg network and subsection three covers the crash types distinguished within the historical crashes data set.

6.1.1 Temporal distribution of crashes

Figure 19 shows the first step of the data analysis which was to check the crash frequency on the network for each year from 2010 to 2019. It should be noted that 2020 was not analysed in this research since the data would be biased due to the limited traffic flow during the COVID-19 lock downs. From figure 19 it can easily be seen that the crash frequency is consistent from 2015 onwards. In 2012 a large new part of the N260 was opened, Tilburg [2012], which explains the increase in crashes in this year. The reason for the large increase in crashes on the network from 2015 onwards could be a result of improved data collection or the result of the fact that multiple ways of collecting data were combined e.g. police records, hospital records and more. If the years 2015 to 2019 are combined a total of around 400 crashes are recorded. That is a large number but it should be noted that for the later comparisons and validation a large number is also required, and the data still needs to be filtered at this point.

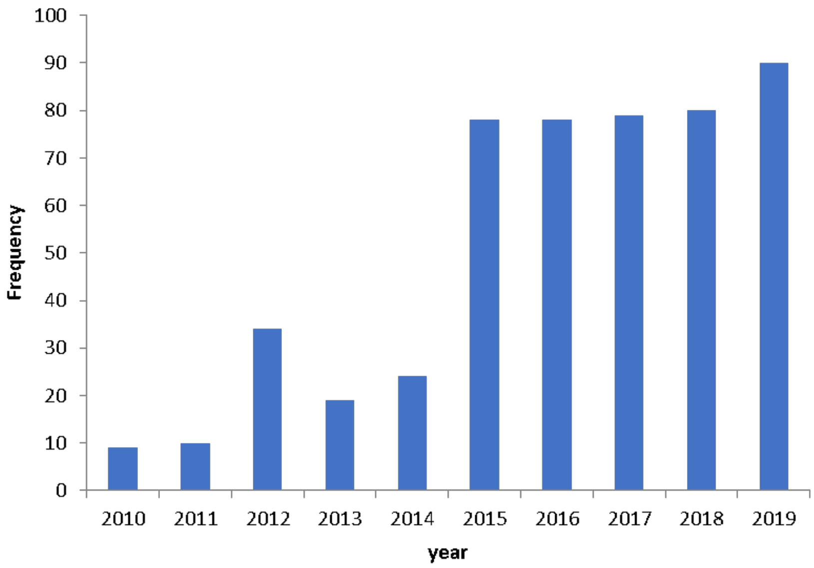


Figure 19: Frequency of historical crashes per year

Within figure 20 the percentage of crashes per day of the week are displayed for the years 2015 to 2019. It shows that the weekend days have a somewhat lower share with 13% and 11%, for Saturday and Sunday respectively. Apart from that conclusion no other trend was found which means that simulating weekdays would provide the comparison with the most crashes.

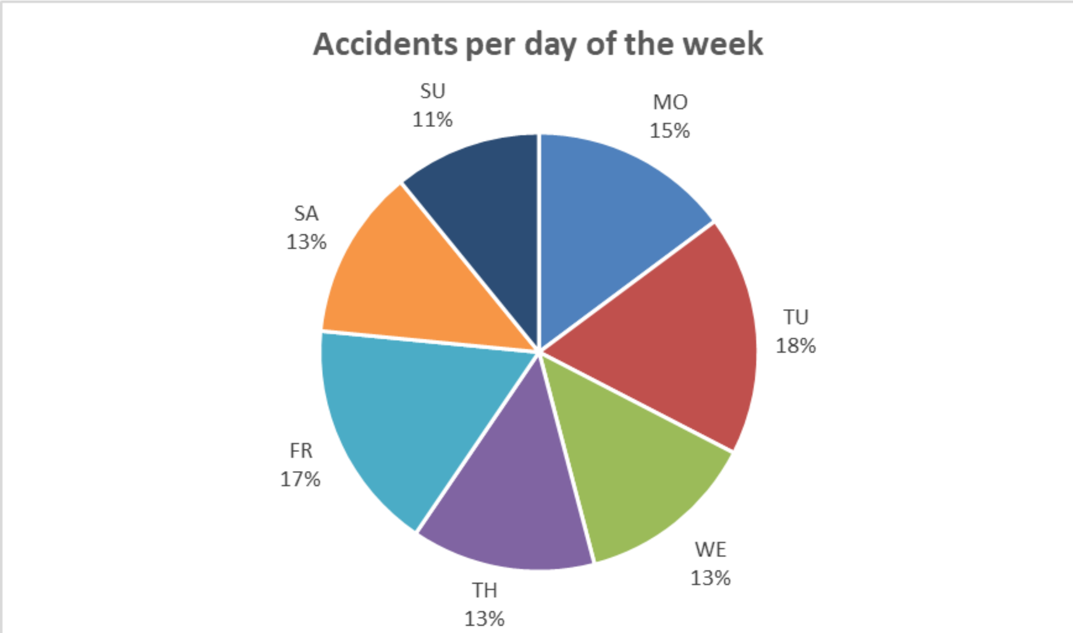


Figure 20: Division of accidents over the days of the week

Within figure 21 and figure 22 the crashes were aggregated over time periods during weekdays and weekend days respectively. This was an iterative process. It was used to substantiate the time period that represents the peak hours. The time periods were determined by maximizing the differences while keeping the known bandwidths of peak periods in mind. The figures show a clear accumulation of crashes during the morning and evening peaks on weekdays. The time periods indicated on the X-axis are not consistent since it represents different aggregations of periods, but the number of crashes is normalised per hour. So, the figures represent the average crash per hour within the given time frame for each year. From this figure it can be concluded that the crash frequency during the PM peak is generally higher than the crash frequency during the AM peak, the only exception is the year 2017 in which these frequencies were the same. Another point if interest is the somewhat equal crash frequency during the AM peak compared to the time between the AM and PM peak. During this time the crash frequency is lower, but the difference is very small.

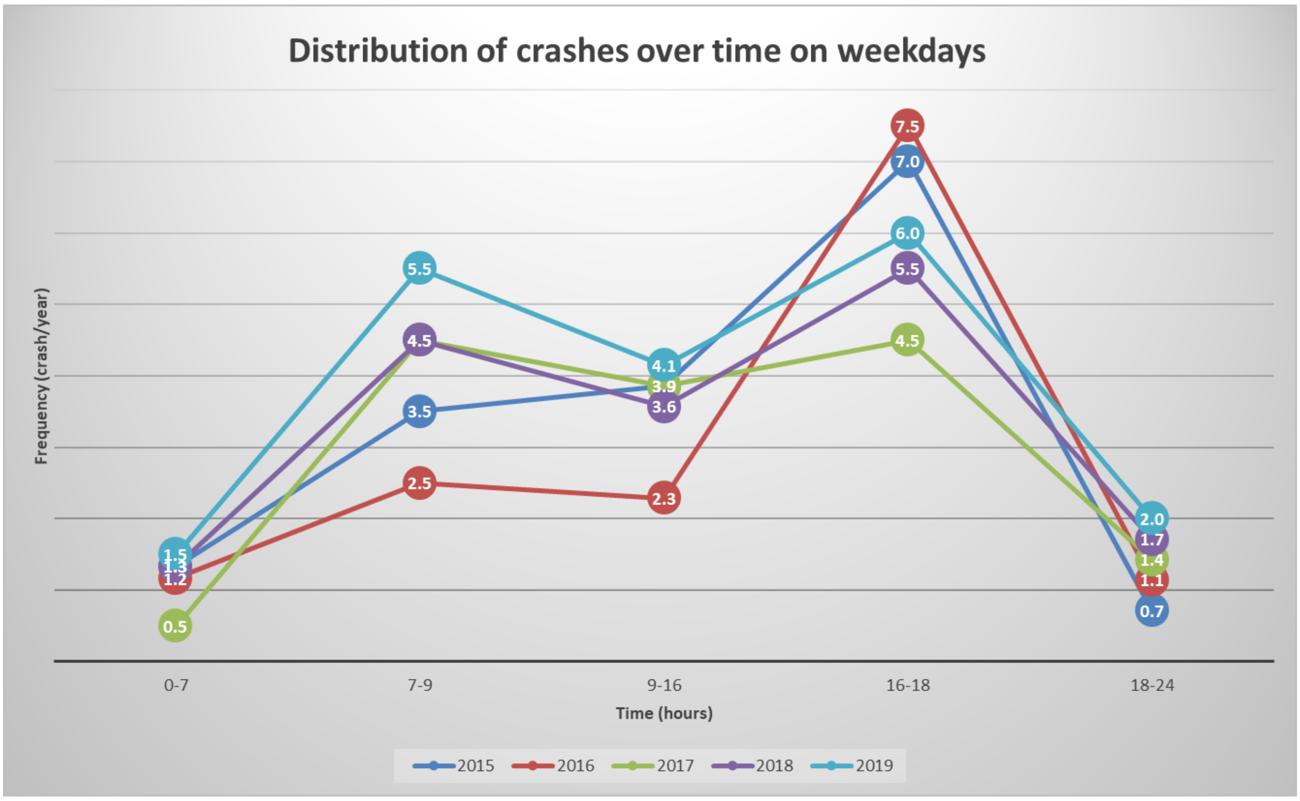


Figure 21: Distribution of crashes over the time of day, normalised per hour.

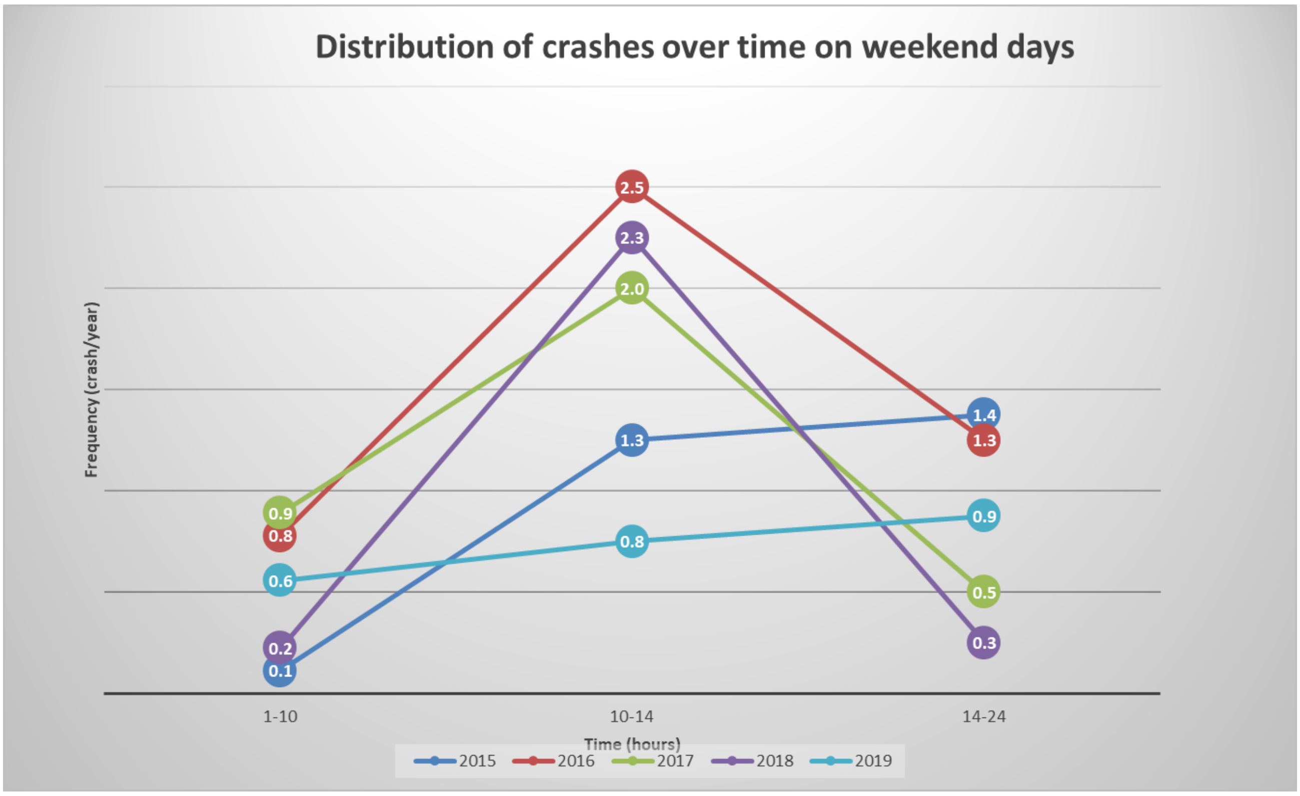


Figure 22: Distribution of accidents over the time of the day, normalised per hour.

6.1.2 Geographical distribution of crashes

Within Figure 23 the crashes are projected on the network of the ring road of Tilburg. The frequency of crashes is visualised by the density of the circles, where a darker red circle indicates more crashes compared to a lighter coloured circle indicating less crashes. A fully coloured red circle indicates over five crashes at that location. The in detail crash count can be found within Table 7 in Subsection 6.3 It can be seen that the majority of crashes occur at intersections, this makes sense since most interactions between vehicles take place at and near intersections. The three intersections with the highest crash count are the intersections that connect the distributor roads N261 and N260 with the distributor road N261, highway A58 and highway A65. The biggest difference between these three intersections and the other intersections within this network is the presence of weaving sections. This projection will be used in Subsection 6.3 to compare the locations prone to accidents with locations prone to conflicts.

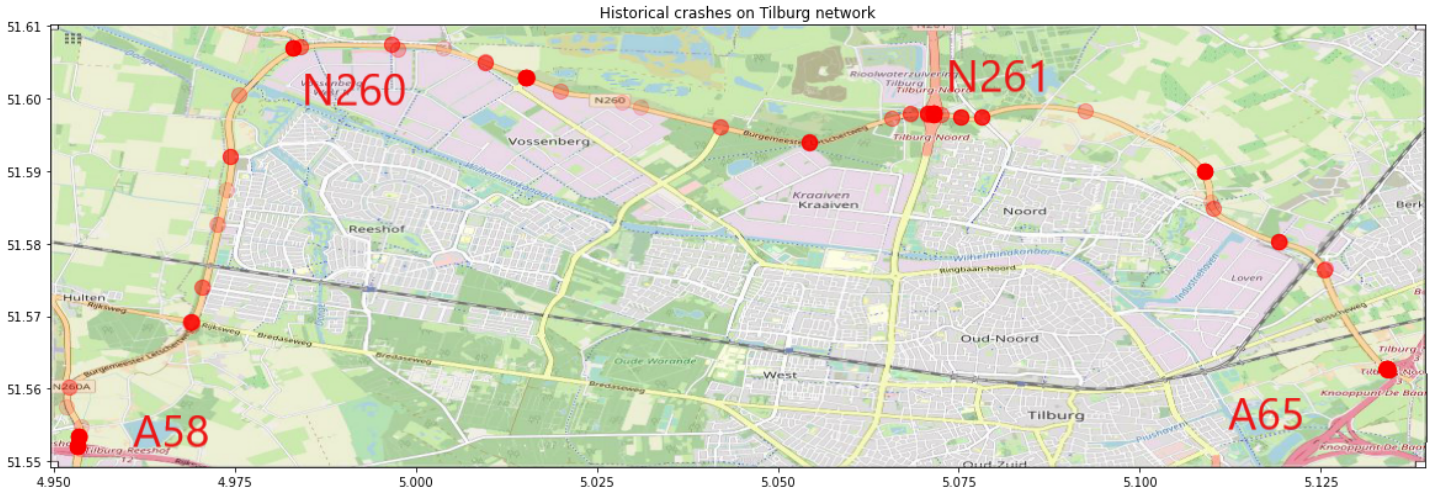


Figure 23: Historical crashes with two or more vehicles plotted in the map of Tilburg

6.1.3 Crash type

Within figure 24 the different types of crashes are distinguished for all the crashes in the data set. As seen in this figure 44% of the crash types are unknown. It is useful to know the types of crashes within the data set since this can provide clear insights in the causes of a crash. Another reason for looking at the crash types is the possibility to compare them with the conflict types later on.

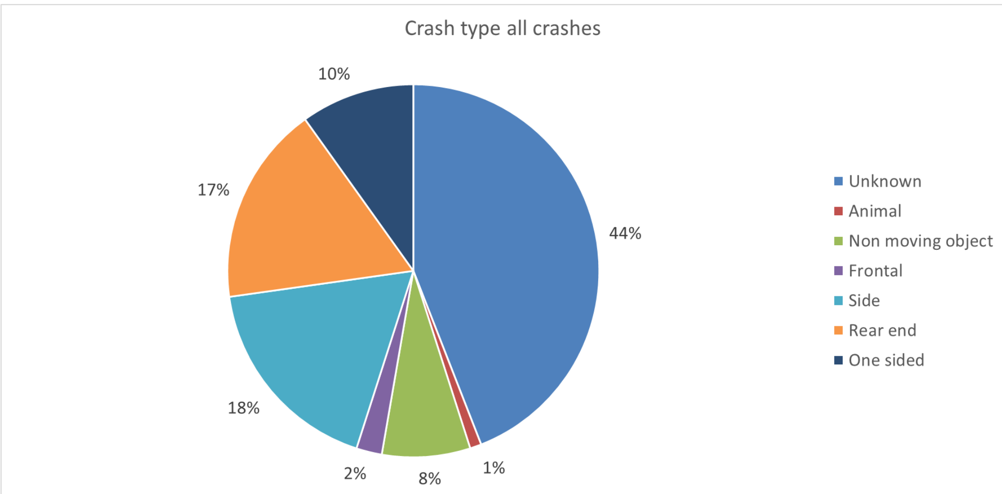


Figure 24: Crash types of the complete data set

When the single vehicle crashes are deleted Figure 25 is obtained. It is seen that the share of unknown crashes and the share of crashes with an object decrease. This leads to the conclusion that crashes in the data set which involved two or more vehicles contain more information about the nature of the crash. What is odd is that there were still one sided crashes in the data set. A one sided crash is a crash with one vehicle involved. The single vehicle crashes were deleted by deleting the data points which only included one vehicle. Apparently, some information flows are not reliable or information about the crash is not noted correctly. For the sake of homogeneous results, the one sided crashes were also deleted to obtain Figure 25.

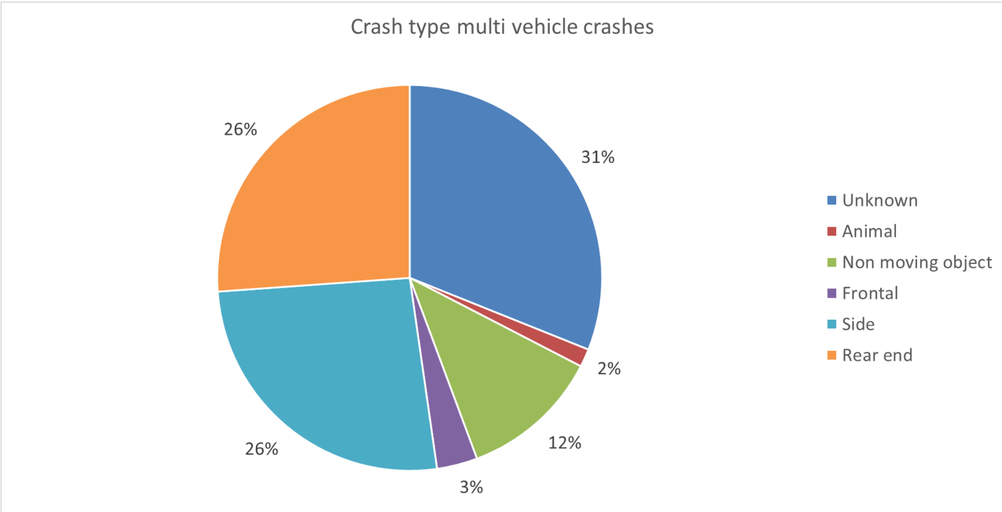


Figure 25: Crash types of the data set without single vehicle crashes

When the crashes with an unknown crash type are deleted from the data set, it can be seen that the majority of the crashes were of the rear end and side type. The usefulness of this figure should be argued. After all, the distribution of crash types within the unknown crashes could be different from the distribution of the known crash types.

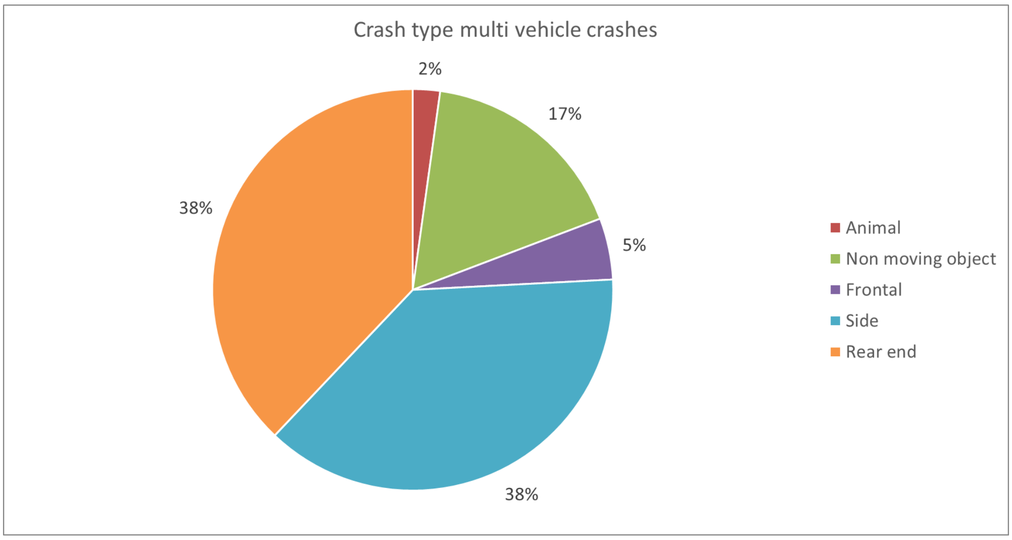


Figure 26: Crash types of the data set without unknown crash type and single vehicle crashes

In the end of the analysis of the historical crashes a selection was made of the crashes that should be taken into account for further analysis. The weekend day crashes were deleted from the data set. Which lead to a remainder of 315 crashes. Next, the crashes with 0 or 1 involved vehicle were deleted from the data set. This led to a data set of 275 crashes to be used for further analysis.

6.2 Simulation and conflict analysis

Within this section the conflicts derived from the microsimulation will be analysed. The section consists of three subsections. Within the first subsection the conflict values will be displayed to show the frequency of conflicts with a certain PET or TTC value. Within the second subsection the locations of the conflicts will be displayed and within the third and last subsection the conflict types will be analysed.

6.2.1 Conflict values

When analysing the conflict values a large number of conflicts indicated a value of 0.0 seconds for both the PET and the TTC. A conflict value of 0.0 seconds would indicate a crash within simulation, but no crashes should occur within this simulation.

Within FHWA [2008] it is described that some situations within simulation result in virtual crashes. These situations occur when physical possibility of a manoeuvre cannot be accurately represented. It is also stated that this does not occur often compared to the total number of analysed manoeuvres. SSAM identifies these occurrences as conflicts with a TTC value of 0.0 seconds. This could be the explanation for some of the 0.0 second conflicts. Within the FHWA [2008] it was also stated that for further statistical analysis these zeros are removed from the data set. When investigating the simulation, the reason for these 0.0 seconds conflicts became more evident. Some vehicles accepted gaps that are too small which causes them to "collide" with other vehicles which leads to crossing trajectories which on it's turn leads to 0.0 second conflicts when analysing in SSAM. For the AM peak 24% of all conflicts were 0.0 second conflicts. For PM peak 30% of all conflicts were 0.0 seconds. This is quite frequent and can not only be explained by the inaccurate physical representation as discussed above. The gap acceptance model of this simulation network should be further investigated because this is most probably the cause for the large number of 0.0 second conflicts.

When deleting the 0.0 second conflicts figure 27 and figure 28 are obtained, which visualise the conflict values during the simulations as found by SSAM. Within these figures, the x-axis values are the upper values of the time bands that they represent.

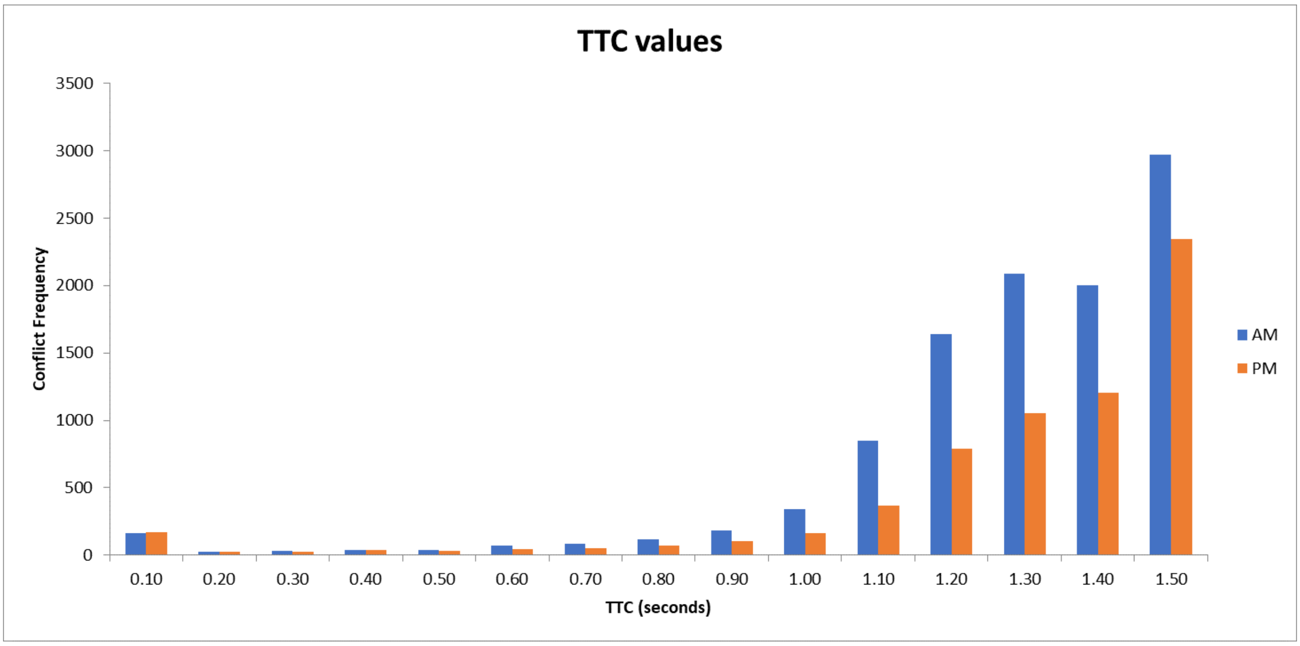


Figure 27: Distribution of TTC values

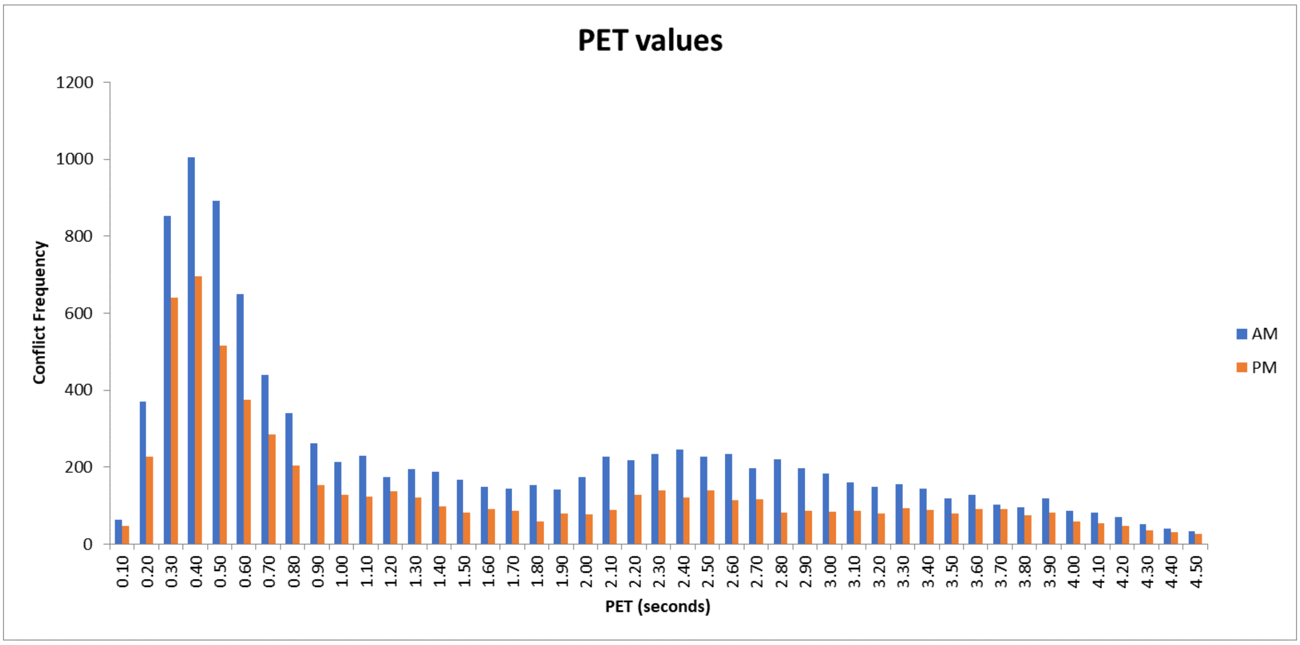


Figure 28: Distribution of PET values

One would expect both figures to follow a distribution. The TTC follows an exponential distribution and the PET follows a negative exponential distribution. For the TTC this makes sense, since in essence every manoeuvre of two vehicles in some form of proximity can be seen as a conflict and if the upper threshold is increased this will capture more conflicts. The Distribution of the PET values is harder to explain.

6.2.2 Geographical distribution of conflicts

Just as the historical crashes the conflicts were plotted on the map of the network. This was done using the map function of SSAM. If one loads the map of the network it is possible to visualise the location of the conflicts. It's possible to filter the different kinds of conflicts to distinguish between rear-end, crossing and lane change conflicts. Within the Figure 33 and Figure 30 the rear-end conflicts are shown in red, lane change conflicts are shown in yellow and crossing conflicts are shown in blue.

Figure 29: Conflicts simulated during the AM peak

Figure 30: Conflicts simulated during the PM peak

6.2.3 Conflict types

Within figure 31 an overview is provided of the type of conflicts that occurred during the simulation for both the AM and PM scenario with multiple filter settings. It can be seen that the majority of conflicts are rear-end conflicts. It can also be concluded that the types of conflicts are quite similar during the AM and PM peak. When the TTC and PET threshold values are lowered, the share of rear-end conflicts decreases. This indicates that the majority of the rear end conflicts has a relatively high TTC and/or PET value. These could be argued as being less severe since the PET and TTC value are higher. It can also be concluded that the majority of the crossing conflicts have a low TTC and PET value as their share increases when lowering the PET and TTC threshold values. The high share of rear-end conflict angles could also be a result of the settings of SSAM. Within SSAM the conflict angles are specified in such a way that every conflict with an angle of approach between 0 and 30 degrees is seen as a rear-end conflict, as seen in subsection 5.3. While in reality, a lane change conflict could also have a very small angle of approach.

Figure 31: Division of conflicts type per SSAM filter setting

6.3 Validation of historical crashes and simulated conflicts

Within the previous two sections results were shown of the historical crashes and the conflicts on the same network. Within this chapter the goal is to investigate the relationship between this empirical data set and the data set generated through simulation and analysis by SSAM. Within the first subsection the conflicts and crashes will be visually validated. The second subsection covers the statistical validation which contains descriptive statistics regarding both conflicts and crashes and which uses the Spearman rank coefficient and the R^2 value to investigate possible relationships.

6.3.1 Visual validation

The first step used to validate the results was to generate visual representations of the crashes and conflicts on the network. Within figure 32 the historical crashes that occurred during the AM peak in the years 2015-2019 are displayed. Within figure 33 the conflicts that were analysed by SSAM are displayed for the AM peak simulation. By looking at both figure 32 and figure 33 it can be seen that the crashes and conflicts accumulate at the intersections on the network. Obviously a lot more conflicts are visualised compared to the number of crashes.

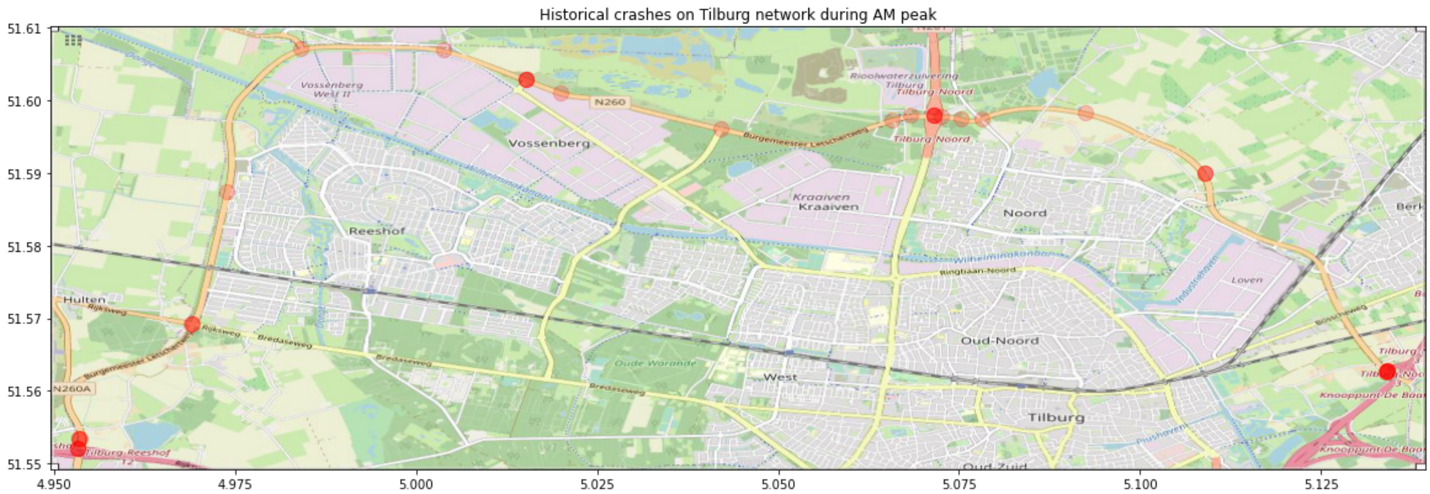


Figure 32: Historical crashes that occurred during the AM peak

Figure 33: Conflicts simulated during the AM peak

Within figure 34 the historical crashes during the PM peak are plotted and within figure 35 the conflicts that occurred in the PM peak simulation are visualised.

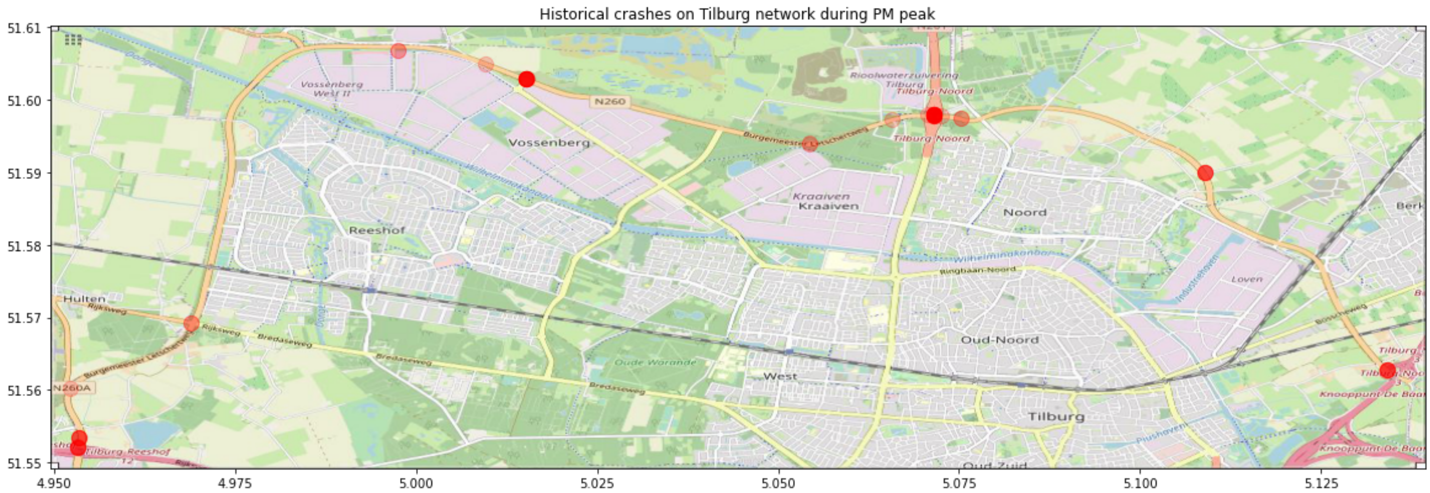


Figure 34: Historical crashes that occurred during the PM peak

Figure 35: Conflicts simulated during the PM peak

From both these comparisons it can be established that at least geographically the historical crash data corresponds with the conflicts from simulation. The magnitude of both these indicators should further be investigated to see how they correlate statistically.

6.3.2 Statistical validation

Within this section the relation between historical crashes and the simulated conflicts is validated statistically. The morning traffic flows are different compared to the traffic flows in the afternoon since the network is subject to a directional bias during these peaks. This means that the traffic volume in one direction is higher in the morning than in the evening, and the other way around for the other direction. This is a result of commuting inhabitants of Tilburg. That's why it is important to differentiate between morning peak simulation and evening peak simulation. This is also visible from the division of the crashes over the days as seen in figure 21. What is odd is that, as seen in table 7, the number of conflicts is consistently higher in the AM peak compared to the PM peak while the number of crashes is higher in the PM peak. This is worth investigating using the traffic flows in the simulations which can be found in Appendix C. When looking at these volumes the directional bias can be seen at for example intersections 9 to 11, where the traffic volume from west to east is higher in the AM peak, and the traffic volume from east to west is higher in the PM peak. This could lead to different kinds of congested states on the network which on it's turn can lead to many conflicts due to the proximity of the vehicles in the congested state. While this could lead to dangerous interactions between vehicles, a congested state does not necessarily have to be more dangerous than a non-congested state, while the conflicts do indicate this. For example, a slow moving traffic jam will lead to many conflicts due to the proximity of the vehicles. If a car accelerates while closing a gap to the following car during this traffic jam, the speed difference will be large, the distance between the two cars can be very short, but it could be a very controlled manoeuvre. This will be indicated differently by the TTC value.

Within table 7 an overview is provided of the total number of conflicts and crashes per node, per scenario and per SSAM filter setting.

Table 7: Descriptive statistics of the crashes and conflicts for different SSAM filter settings

	Crashes			*Conflicts*									
Node	**Total**	**PM**	**AM**	**AM_Default**	**PM_Default**	**AM_0.01_Default**	**PM_0.01_Default**	**AM_0.01_1.5**	**PM_0.01_1.5**	**AM_0.01_1.0**	**PM_0.01_1.0**	**AM_0.01_0.5**	**PM_0.01_0.5**
1	29	5	4	295	289	210	200	147	131	4	5	0	2
2	1	0	0	381	270	281	183	164	110	16	12	3	1
3	3	1	0	251	169	223	152	141	80	14	11	2	0
4	8	1	3	289	207	222	143	161	92	17	12	4	4
5	4	0	0	80	85	67	68	44	40	9	12	3	5
6	2	0	0	166	136	122	100	69	61	9	3	3	1
7	6	0	0	147	156	120	137	71	82	8	6	3	2
8	19	0	1	191	289	130	222	81	115	16	16	6	5
9	6	2	0	300	139	245	115	157	60	9	6	3	1
10	1	0	1	529	459	411	361	239	197	17	14	4	7
11	17	8	2	524	278	401	210	240	119	17	9	3	3
12	4	0	1	697	620	450	420	271	228	38	32	8	6
13	3	1	1	137	252	114	216	80	113	7	8	2	1
14	52	14	5	2123	912	1461	597	857	426	74	37	15	10
15	9	0	1	4226	698	3769	494	1751	305	73	20	17	7
16	0	0	0	55	76	41	62	25	32	1	6	1	1
17	0	0	0	150	421	118	324	73	173	5	18	1	3
18	11	0	0	575	520	447	349	316	235	16	23	6	5
19	6	0	0	174	163	141	136	90	65	6	10	1	3
20	34	3	6	328	336	188	233	112	111	18	27	5	11
min	0	0	0	55	76	41	62	25	32	1	3	0	0
max	52	14	6	4226	912	3769	597	1751	426	74	37	17	11
mean	10.75	1.75	1.25	580.90	323.75	458.05	236.10	254.45	138.75	18.70	14.35	4.50	3.90
STD	13.51	3.55	1.83	966.03	221.50	836.42	144.99	394.96	98.12	20.32	9.31	4.39	3.09
SUM	215	35	25	11618	6475	9161	4722	5089	2775	374	287	90	78

Within table 7 especially nodes 2 to 4 can be seen as false positives. These nodes predict many conflicts while the crash count is relatively low. So, when only looking at the conflicts as a measure of safety, it would predict that these intersections are unsafe, while in reality very little crashes occur on these intersections. These false positives would be a good thing when considering traffic safety analysis. One would rather identify an intersection as unsafe while in reality it is safe than the other way around. If a dangerous intersection would be missed this could have consequences like having more crashes than expected (false negative). When taking another look at Table 7 it can be seen that there are no false negatives within the predicted conflicts, e.g. there is no intersection with a low conflict count and a high crash count.

The results posted in table 7 lead to the rankings found in table 8. These ranking are needed to perform the validation using the Spearman rank coefficient as explained in Subsubsection 5.4.2.

Table 8: Rankings of the nodes for each SSAM filter setting

NODE	**Crashes**	**PM crashes**	**AM crashes**	**AM_0.01_Default**	**PM_0.01_Default**	**AM_0.01_1.5**	**PM_0.01_1.5**	**AM_0.01_1.0**	**PM_0.01_1.0**	**AM_0.01_0.5**	**PM_0.01_0.5**
1	3	3	3	11	11	10	7	19	19	20	14
2	17	9	13	7	12	7	12	10	10	9	15
3	14	7	12	9	13	11	15	11	12	15	20
4	7	6	4	10	14	8	13	7	9	8	9
5	12	11	14	19	19	19	19	14	11	10	8
6	16	18	18	15	18	18	17	12	20	14	17
7	9	19	19	16	15	17	14	15	17	13	13
8	4	17	10	14	8	14	9	9	7	5	7
9	10	5	11	8	17	9	18	13	16	12	16
10	18	12	8	5	4	6	5	5	8	7	4
11	5	2	5	6	10	5	8	6	14	11	10
12	13	14	9	3	3	4	4	3	2	3	5
13	15	8	6	18	9	15	10	16	15	16	18
14	1	1	2	2	1	2	1	1	1	2	2
15	8	10	7	1	2	1	2	2	5	1	3
16	19	20	20	20	20	20	20	20	18	19	19
17	20	16	17	17	6	16	6	18	6	17	11
18	6	13	15	4	5	3	3	8	4	4	6
19	11	15	16	13	16	13	16	17	13	18	12
20	2	4	1	12	7	12	11	4	3	6	1

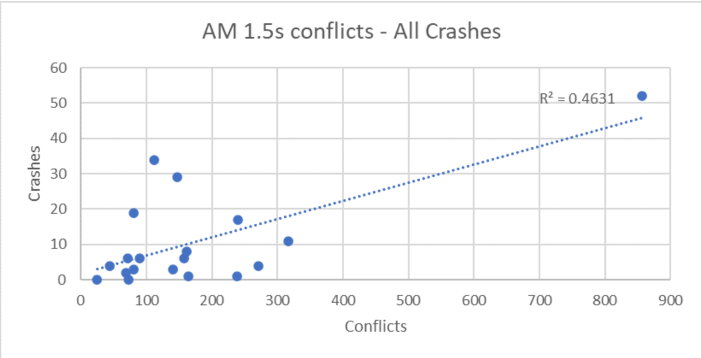
When using the ranks found in Table 8 and the Spearman rank correlation the values within Table 9 are found. Multiple comparisons were made for this validation in order to identify the most promising relationships, but also to see the differences when using certain combinations. For the conflict count three data sets are available: the "PM peak" which contains all the conflicts from the PM peak simulation, the "AM peak" which contains all the conflicts from the AM peak simulation and the "Peak sum" data set, which contains the combined conflicts from the AM and PM peak simulations. These three conflict data sets are compared to four different crash data sets: the "PM peak" which contains all the crashes that occurred during the PM peak in the last five years, the "AM peak" which contains all the crashes that occurred during the AM peak in the last five years, the "Peak sum" which contains all the crashes that occurred during the AM and PM peaks combined in the last five years and lastly, the "All" which contains all the crashes that occurred on the network during the last five years. For all these aforementioned crash data sets only multi vehicle crashes were taken into account. All the rankings of these different formats were compared and are found in Table 9 below. The Spearman coefficient has an outcome between -1 and 1, where -1 indicates a perfect negative relationship and 1 indicates a perfect positive relationship. Together with the Spearman coefficient, the P-value is also displayed. The P-value indicates a level of statistical significance, taking into account the degrees of freedom and the size of the data set.

Table 9: Results of the validation

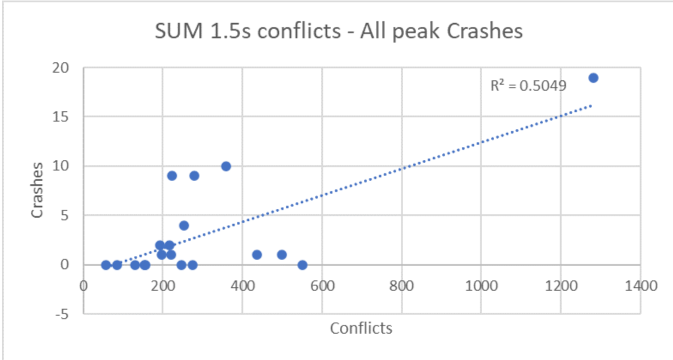
		TTC		***PET***						
Conflicts	**Crashes**	**low**	**high**	**low**	**high**	**Conflicts**	**Crashes**	**Spearman coefficient**	**P-value**	**Significance within:**
PM peak	*PM peak*	0.01	1.5	0.01	4.5	4722	35	0.274	0.243	Not significant
AM peak	*AM peak*	0.01	1.5	0.01	4.5	9161	25	0.481	0.031	95% confidence interval
Peak sum	*Peak sum*	0.01	1.5	0.01	4.5	13883	60	0.310	0.184	Not significant
Peak sum	*All*	0.01	1.5	0.01	4.5	13883	216	0.284	0.225	Not significant
PM peak	*PM peak*	0.01	1.5	0.01	1.5	2775	35	0.275	0.240	85% confidence interval
AM peak	*AM peak*	0.01	1.5	0.01	1.5	5089	25	0.570	0.009	95% confidence interval
Peak sum	*Peak sum*	0.01	1.5	0.01	1.5	7864	60	0.360	0.120	85% confidence interval
Peak sum	*All*	0.01	1.5	0.01	1.5	7864	216	0.362	0.116	85% confidence interval
PM peak	*PM peak*	0.01	1.0	0.01	1.0	287	35	0.182	0.443	Not significant
AM peak	*AM peak*	0.01	1.0	0.01	1.0	374	25	0.576	0.008	95% confidence interval
Peak sum	*Peak sum*	0.01	1.0	0.01	1.0	661	60	0.259	0.271	Not significant
Peak sum	*All*	0.01	1.0	0.01	1.0	661	216	0.406	0.076	90% confidence interval
PM peak	*PM peak*	0.01	0.5	0.01	0.5	78	35	0.208	0.380	Not significant
AM peak	*AM peak*	0.01	0.5	0.01	0.5	90	25	0.411	0.072	90% confidence interval
Peak sum	*Peak sum*	0.01	0.5	0.01	0.5	168	60	0.176	0.458	Not significant
Peak sum	*All*	0.01	0.5	0.01	0.5	168	216	0.498	0.0255	95% conficence interval

From table 9 it can be concluded that the lower threshold values better explain the crashes happening at the network for the AM scenario. Where the 1.0 second threshold value results in the highest correlation. The PM peak conflicts have a very weak correlation to the PM peak crashes. The highest correlation is found when comparing the AM peak conflicts to the AM peak crashes. The comparison of the peak sum crashes with the complete crash data set has a steadily increasing correlation when lowering the TTC and PET threshold settings. This is to be expected, because the severity of the conflicts would increase with lowering TTC and PET thresholds and would therefore be more related to crashes due to the proximity of the conflicts. A comment that cannot be missed when looking at Table 9 is that the number of crashes that have occurred during both the AM and PM peak are low. A strong correlation when taking 200+ crashes into account is more reliable than a correlation that is based on +/- 30 crashes.

Another point of interest is the inability of the Spearman coefficient to showcase which factors altered the value of the coefficient. It could be one intersection with a large difference in ranking or multiple intersections with small differences in ranking. This can be further investigated by looking at the relationship of the conflicts and crashes by the use of scatter plots with a linear regression. The scatter plots were created for every settings. When looking at the residuals by calculating the R-squared value the fit seems to correspond to the Spearman rank correlation. Two examples of these scatter plots are found in Figure 36. An overview of all the R^2 is found in Table 10.



(a) AM conflicts with 1.5 s threshold setting compared to all crashes



(b) All peak conflicts with 1.5 s threshold setting compared to all peak crashes

Figure 36: Scatter plots with linear regression of crash vs. conflict relationship

Within table 10, the R^2 values for the all the filter scenarios are displayed. In this table the conflicts of the morning and evening peak are also related to the total crash counts. The total crash count consists of the crashes during the whole day, not just during the peak hours. The SUM indicates that the conflicts during the morning and evening peak were summed and related to the total crash count.

Table 10: R-squared value for each combination of conflicts and crashes

	Crashes			
Conflicts	**All**	**All peak**	**AM peak**	**PM peak**
AM_0.01_Default	0.463	x	0.227	x
PM_0.01_Default	0.278	x	x	0.282
SUM_default	0.278	0.283	x	x
AM_0.01_1.5	0.463	x	0.227	x
PM_0.01_1.5	0.388	x	x	0.357
SUM_1.5	0.444	0.505	x	x
AM_0.01_1.0	0.430	x	0.254	x
PM_0.01_1.0	0.300	x	x	0.160
SUM_1.0	0.416	0.400	x	x
AM_0.01_0.5	0.404	x	0.200	x
PM_0.01_0.5	0.434	x	x	0.171
SUM_0.5	0.489	0.297	x	x

From table 10 it can be concluded that the conflicts within the default settings do not explain the crashes well. Overall, it can be concluded that the conflicts from the AM peak scenario are better at explaining the AM crashes than the conflicts from the PM scenario. The SUM of the conflicts from both scenario's seems to have the strongest correlation to the total crash count.

6.4 Safety performance function

Within this section the results of the SPF will be displayed. SPF was not applied to intersection 1, 14 and 20 since their geometry is very different from the other intersections on the network. They cannot be seen as three- or four-legged intersections. Intersections 1 and 14 are part of a diamond intersection which connect to highway A58 and distributor road N261 respectively. Intersection 20 is part of a cloverleaf crossing. The first step for preparing the SPF was to retrieve the volume on each major and minor road for every intersection. These volumes can be seen in Table 11.

Table 11: Volumes on major and minor roads of each intersection for AM(veh/hour, PM(veh/hour) and AADT (veh/day)

		AM		**PM**		**AADT**	
Intersection	**legged**	*Major*	*Minor*	*Major*	*Minor*	*Major*	*Minor*
2	4	2041	31	1995	50	20180	406
3	4	1720	14	1712	470	17161	2418
4	4	1122	902	1022	1001	10720	9515
5	3	1639	595	1596	528	16174	5617
6	3	1598	566	1535	507	15666	5363
7	3	1509	768	1415	717	14621	7425
8	3	1390	1330	1370	1346	13800	13379
9	3	1801	583	1918	524	18596	5534
10	4	1920	2	2034	2	19769	20
11	3	2033	872	2164	923	20986	8973
12	3	1983	1663	2025	1750	20041	17066
13	3	2915	422	3170	406	30426	4138
15	4	1530	92	2611	533	20703	3126
16	4	1672	95	2754	115	22129	1052
17	3	1581	696	2462	892	20215	7939
18	4	1884	23	2472	29	21778	261
19	3	2241	102	2772	255	25065	1786

When using the volumes from Table 11 and applying them to the formula explained in Subsection 5.5, the predicted crashes are obtained as seen in Table 12

Table 12: Predicted crashes using the safety performance function

Intersection	**legged**	**AADT Major**	**AADT Minor**	**SPF**	**Crashes**
2	4	20180	406	8	1
3	4	17161	2418	9	3
4	4	10720	9515	8	8
5	3	16174	5617	10	4
6	3	15666	5363	9	2
7	3	14621	7425	9	6
8	3	13800	13379	10	19
9	3	18596	5534	11	6
10	4	19769	20	5	1
11	3	20986	8973	12	17
12	3	20041	17066	13	4
13	3	30426	4138	15	3
15	4	20703	3126	11	9
16	4	22129	1052	10	0
17	3	20215	7939	12	0
18	4	21778	261	8	11
19	3	25065	1786	11	6

The crashes predicted by the SPF do not correspond well to the historical crashes on the network when looking at Table 12. The safety performance function is only dependent on volume and assumes an exponential relationship with the volume to predict the crashes. When correlating the predicted crashes with the historical crashes no significant relation was found. The fact that the safety performance function was not calibrated has led to results that do not correlate well. This does give the insight that micro simulation was able to predict the conflict crash relationship better than just the volume.

6.5 Scaling of indicators with linear model

Within this section, the results of the translation are found. For this, the analysis is also performed without intersections 1, 14 and 20. A new SSAM run was performed with the preliminary PET and TTC threshold value set at 5 seconds, as explained in subsection 5.6. When using the threshold settings explained in Subsection 5.6 and filling in Equation 6.1, Table 13 is obtained.

$$\begin{bmatrix} SPF_1 & TTC_1 & PET_1 & MaxS_1 & DeltaS_1 & DR_1 & MaxD_1 & MaxDeltaV_1 \\ SPF_2 & TTC_2 & PET_2 & MaxS_2 & DeltaS_1 & DR_2 & MaxD_2 & MaxDeltvaV_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ SPF_m & TTC_m & PET_m & MaxS_m & DeltaS_m & DR_m & MaxD_m & MaxDeltaV_m \end{bmatrix} * \begin{bmatrix} C_{TTC} \\ C_{PET} \\ C_{MaxS} \\ C_{Deltas} \\ C_{DR} \\ C_{MaxD} \\ C_{MaxDeltaV} \end{bmatrix} = \begin{bmatrix} Crashcount_1 \\ Crashcount_2 \\ \vdots \\ Crashcount_m \end{bmatrix} \quad (6.1)$$

Within Table 13 the conflicts per intersection are showcased for each surrogate safety indicator used within the SSAM. This means that the conflicts are only filtered on that conflict indicator and the upper threshold values of the other conflict indicators are set to the maximum value (5 seconds for TTC and PET). This would be the A matrix within the linear system. Within this stage of the study the results of the safety performance function are left out of this translation since no significant correlation could be found between the predicted crashes from the safety performance function and the historical crashes on the network.

Table 13: Conflicts per indicator per intersection

Intersection	TTC	PET	MaxS	DeltaS	DR	MaxD	MaxDeltaV	Crashes
2	76	219	28	41	44	135	99	1
3	26	266	24	36	33	112	66	3
4	43	104	32	26	27	81	74	8
5	9	143	27	72	18	40	102	4
6	23	190	17	51	18	69	122	2
7	22	207	26	80	26	74	128	6
8	47	191	40	105	34	124	157	19
9	42	183	32	35	34	121	92	6
10	92	409	71	84	68	269	144	1
11	90	357	78	102	84	311	181	17
12	162	412	77	85	124	427	182	4
13	18	169	30	63	28	99	106	3
15	388	1065	52	42	484	1595	120	9
16	6	73	17	25	9	28	44	0
17	22	96	22	45	34	84	65	0
18	111	274	32	39	39	209	123	11
19	24	215	25	40	26	108	99	6

When searching for the least squares estimate for the linear system Table 14 was obtained.

Table 14: Estimated coefficients from linear least square estimation

	Coefficient estimate			
Indicator	*all 3 legged*	*Random 3 -legged*	all 4-legged	*All*
N	10	5	7	17
C_{TTC}	0.0204	0.001	0.2222	0.014
C_{PET}	0.000	0.000	0.0140	0.000
C_{MaxS}	0.000	0.000	0.000	0.000
C_{Delta_S}	0.000	0.000	0.000	0.087
C_{DR}	0.000	0.000	0.000	0.000
C_{MaxD}	0.000	0.000	0.000	0.000
$C_{MaxDeltaV}$	0.0662	0.072	0.0146	0.000
Residuals	30.9	28.6	9.34	19.1

Four different estimations were performed to be able to check the consistency of the method. From these three estimations the TTC, $Delta_S$ and $MaxDelta_V$ turn out to be the best predictors of the crashes on the network. The PET only has a share in the prediction of the 4-legged intersections. All the other conflict indicators are estimated to have no share in the prediction of the least square estimate. Since no conflict indicator coefficient can be below zero, these values turn to zero. The TTC is the only indicator that has a share in predicting the crashes for all of the four estimations. Within table 14 it can be seen that the estimations are different for the four different estimation types. Whereas the TTC and $MaxDelta_V$ combination is within three of the four estimations, the TTC and Max_S is in only one. When looking at the residuals, the third estimate performs the best, with the residuals under 10. These residuals can be seen as the difference between an observed value, and the fitted value provided by the model. So, the residuals should be looked at in perspective to both the number of intersections used within the estimation and the number of crashes within that estimation.

It could be argued that the inconsistencies in the four estimations are a result of the relatively low number of data points used for the estimation. This is a first attempt to look at the usability of this framework. If more networks will be investigated the performance of this framework and its consistency could be tested.

7 Discussion and Conclusions

7.1 Discussion

Within this study the use of surrogate safety measures to evaluate safety at a network level was investigated. The primary focus was on methods that used microsimulation as a base, this focus was shifted to also include the crash rates and safety performance function. This was done to create a complete view of the methods to assess safety. From the literature review it has become clear that there were no established methods for evaluating safety at a network level using micro simulation. The most promising method or tool is the surrogate safety assessment module. This software developed by the Federal highway administration in the united states offers a tool for analysing the conflicts that occur within a micro simulation. Though, this tool on itself is not a method for evaluating traffic safety. It provides multiple surrogate indicators but does not propose a framework which can be used to measure absolute safety, let alone relative safety. The Surrogate safety assessment model was used to validate the microscopic model of the use case of Tilburg. The conflicts from the microscopic simulation proved to have significant relationships with the crash count at this network. When looking at the number of conflict in the use case, it became apparent that it is possible to identify crash prone locations, but some false positives do arise. These false positives regard intersections at which a high conflict was predicted, whereas in reality, little crashes occur on these intersections. Especially the morning peak simulation showed to be quite consistent in its performance. In order to investigate the validation procedure, the conflicts were compared with the crashes during the same time frame, but also with the total crash count at the network. It can be concluded that for this use case, the conflicts do not show a better correlation with the crashes during the same time period compared to the total crash count. The crashes predicted by the SPF do not correspond well to the historical crashes on the network. The safety performance function is only dependent on volume, which does give the insight that micro simulation was able to predict the conflict crash relationship better than just the volume. When correlating the predicted crashes with the historical crashes no significant relation is found. Four estimations of the least square estimate method were performed using the newly proposed framework. One including all intersections, one including only 3-legged intersections, one including all 4-legged intersections and one including five random 3-legged intersections. This was done to to be able to check the consistency of the method. From these three estimations the TTC, $Deltas_S$ and $MaxDelta_V$ turn out to be the best predictors of the crashes on the network. All the other conflict indicators are estimated to have no share in the prediction of the least square estimate. Since no coefficient can be negative, these values turn to zero. The TTC is the only indicator that has a share in predicting the crashes for all of the four estimations. This makes sense since the majority of the conflicts from the simulation are rear-end conflicts which can be easier identified by TTC compared to the other indicators. The framework proposed in the translation section can be a very useful tool when wanting to combine different indicators of safety. The addition of the results of the safety performance function was not feasible within this study since the results from the safety performance function showed no correlation with the historical crashes. But if the results from a calibrated safety performance function are at hand, these could be included in the framework. This is also applicable to other indicators of safety. The volume for example could be introduced within the framework.

7.2 Conclusions

Within this subsection the research questions will be answered starting with the sub research questions, followed by the main research questions.

Which indicators exist to quantify safety at vehicle level and at a network level, and how do these relate?

Many surrogate safety indicators exist to quantify safety at vehicle level. The advantages of these indicators vary widely, depending on the conflict type that is being investigated, whether the conflict severity is taken into account and which type of infrastructure is being investigated. From the literature review it became clear that the surrogate safety indicator called the unsafe density is the only surrogate safety indicator derived from micro simulation that can easily be scaled to a higher level. This indicator does only look at longitudinal conflicts and could therefore not capture all the conflicts within a complete network. Many surrogate and non-surrogate safety indicators exist to quantify traffic safety at network level. The non-surrogate safety indicators are all subject to needing empirically gathered historical traffic data. The problem with this data is that it will always be available after the investigated network is already in use, and therefore finished. The surrogate safety measures or methods that provide a level of safety at a network level are found in the form of safety performance indicators or safety performance functions. The safety performance indicators could not be properly investigated within this research due to unavailability of data. The safety performance function could be very promising, but it is not very applicable to network safety study's like the one in Tilburg. Safety performance function need a certain level of homogeneity in the network's infrastructure to be useful. Within the Netherlands this lack of homogeneity in infrastructure has led to the fact that no Safety performance functions were developed for rural intersections or road sections. In other words, the consistency in infrastructure in the Netherlands is too low to be able to develop models that are able to predict the crashes on that type of infrastructure using the traffic volume. The wide variety of safety performance functions developed by the federal highway administration in the united states do provide a solid base, but these safety performance functions are not yet calibrated for use in the Netherlands and the results in this study are therefore not much more than a relationship with the traffic volume.

How can the used network in combination with the surrogate safety assessment module be validated?
The use of the SSAM to analyse the conflicts can be validated using the Spearman rank correlation coefficient. For this, all the intersection of the network are ranked in descending order with respect to the indicator of safety (in this case, crashes and conflicts) the rankings are then compared. This validation offers a simple to use coefficient. A linear regression method was also used to check the relation between conflicts and crashes in the use case. By looking at the R^2 value of these linear regression the Spearman correlation could be substantiated.

What is the result of different threshold values on the performance of the surrogate safety assessment module?
This question should by answered by looking at the performance of the SSAM. When varying the TTC and the PET threshold value a clear change in correlation could be seen, both when looking at the Spearman coefficient and at the R^2 values. The highest correlations out of the values tested, and therefore the best performance, were seen at 1.0 seconds threshold values for both the PET and the TTC when looking at the spearman correlation. When looking at the R^2 as a performance measure the differences are smaller, but the 1.5 second threshold value performed the best out of the tested values.

Can the methods be combined to increase their individual performance?
A framework consisting of a linear matrix equation was proposed to combine the results of the SSAM and the safety performance function. The results of the Safety performance function were not good enough to be used in this framework. The framework was used to estimate the influence of different surrogate safety indicators that are used within the SSAM. This provided useful results. If reliable results are available for the safety performance function, this framework could be promising in finding the weights to combine predicted crashes from an SPF with conflicts from SSAM.

Which methods are available to scale traffic safety indicators from microsimulation from vehicle to network level and how do these methods perform when applied in a use case consisting of a large-scale network?
So, to answer the main research question is not that simple. There exist multiple methods that use conflict indicators from microsimulation to assess safety of a network of intersections and road sections. The most straight forward methods are the SSAM and the Zombie driver software. These two methods are able to give a lot of detailed insights in the conflict indicators that are used. But both of these methods are not a standalone method, they need an extra step to be useful for evaluation of a network. The macroscopic fundamental diagram proposed by Alsalhi and Dixit [2015] offers a framework that includes the conflicts from SSAM but does not offer a safety benchmark. The transferability of this method to (sub)urban networks still needs to be investigated. The biggest challenge within evaluation of network traffic safety was found to be the use of a uni formal parameter to evaluate safety, or a safety benchmark. This has not been established within previous research. Within subsection 3.2 the traditional safety indicators are found, which still seem to be the basis of evaluation of safety. When looking for methods to scale traffic safety indicators from microsimulation the focus might have been too much on these historical indicators, which led to looking for relationships between them. The result of this strategy is that one would still need to validate and therefore evaluate with historical crash data, while the goal is to be able to evaluate traffic safety without the need of historical crash data. That might also be the paradox of using surrogate safety indicators from microsimulation. The use of SSAM in combination with the proposed assessment framework is quite straightforward and gives good insight into what contributes to the level of safety, but it cannot be concluded that this can be used as a standalone tool.

8 Limitations and future research

8.1 Limitations

As is every research project, this study was subject to a number of limitations. These will be discussed in the same order as the report's structure. First of all, the location of the crashes within the historical data set could have been more detailed. The level of detail was low, it was only possible to trace back the crashes to the level of road sections. Normally, the crashes can be traced back to hectometre level. This would have led to more information on the specific location of the crashes and therefore a less course aggregation of the crashes. A less course aggregation on its turn leads to better comparisons which could results in better correlations. Another limitation was the unavailable raw volume data over the day/week/season/year. The network was previously calibrated for volume, which saved time, but this led to not being able to draw strong conclusions on the influence of traffic volume, which supposedly does play a role in traffic conflicts. Having the raw volume data would have also made it possible to create more simulation scenarios, weekend scenarios for example. Now, the weekend crashes were removed from the data set. Another data related limitation is that the conflict type was not validated using the crash type because of the limited information within the crash data set. This would not have resulted in reliable conclusions, but if the information was available, this could have been an addition to the level of detail of the validation.

The Netherlands is known to have a relatively low crash density, which is a good thing because it means that this country is safe. For this research however it meant that a low number of crashes was available to draw conclusions from. One would expect five years of crash data to be enough to discover a trend within that data, but it is unknown to what extend the historical crashes on this network are subject to stochasticity. By removing the single vehicle and weekend crashes part of this stochasticity will have been filtered out. For this network the crash data base was only consistent from 2015 onwards, partly due to an added section of the N260 in the year 2012, partly because of an increase in crashes from 2015 onwards of which the reason is unkown. This led to five years of crash data being useful for analysis, whereas ten years of crash data might have led to a lot more insights regarding the relationships found is this study.

The network was not created to be used for traffic safety analysis. If one would be building the network from scratch, it would be wise to match the road sections that indicate the crash location to the links within vissim, for easier data handling. Within the model a change should be made in the accepted gap distribution, as of now, around 30% of the conflicts that were analysed were 0.0 second conflicts. These 0.0 second conflict indicate that two individual trajectories crossed which means in reality a crash would have occurred. Within this model, no crashes should occur, since the driver behaviour models were not deliberately programmed in such a way. The fact that these 0.0 second conflicts did appear in the analysis could also have resulted in corrupted results, or strange patterns in vehicle interaction. Simply said, the current settings led to 0.0 second conflicts that should not have happened, but could have also lead to 0.1 second conflicts, that should not have happened. Both as a result of the accepted gap settings. Nevertheless if one were to increase the minimum accepted gaps or change the gap acceptance model, the capacities and hence realized flows will not be realistic. So it is not ideal for safety analysis, but changing the models to be more suitable for safety analysis might lead to corrupted results.

A safety performance function should be calibrated for this specific situation but the data to perform this calibration was not available. This led to the use of a pre-calibrated model that did not show credible results. For this reason the SPF results were not taken into account in the translation framework which led to not being able to apply the complete proposed methodology.

Conflicts from micro simulation can mostly address alignment issues, they won't show special driver behaviour problems. A drunk or exhausted driver could cause a crash but this will never be showed within micro simulation. The nature of the crashes should be further investigated to get to an even better correlation. Within the SSAM a conflict angle has to be specified for each conflict type, as seen in subsection 5.3. The clock angles for lane change and rear-end conflict could overlap in real life, but it is not possible to specify this in SSAM. For example, if a car would make a lane change and hit the side of a vehicle next to it, the driving directions are almost equal but the conflict would be marked as a rear-end conflict due to the angle of the two vehicles. This is a limitation of the SSAM and could lead to more conflicts being indicated as rear-end while in reality they are lane change conflicts.

The spear man rank coefficient is a very straight forward tool for comparing two rankings. But explaining the data through this indicator is hard. It shows a clear correlation for each filter setting which is a nice way to determine the next validation steps. But as a validation on its own it might not be the best choice. Comparing with peak hour crashes does provide the highest correlation but it can be argued what would be more valuable, a lower correlation on the entire crash data set or a higher correlation on a small share of the crash data set. This also has to do with the low crash density in the Netherlands. Of course, this is a good thing on its own, but correlating something with few data points will always be questionable in reliability. Nevertheless, without validation a new method could never be substantiated, so either way the crash data would be needed to make steps forward.

8.2 Future research directions

One should always look at the future value of a study. From TNO side it would be valuable to have a tool that can be sold. Saying you have a network of a city and TNO would be able to simulate this network and show the locations which offer the most improvement or just show the most accident prone locations. On the other hand it would scientifically be very interesting to have a clearly defined relative safety formulation for networks. If one could compare all the networks of big cities in the Netherlands and could analyse whether one city is relatively unsafe compared to the mean safety of the Netherlands, it would be possible to showcase room for improvement on a much larger scale. This would be possible if one were to incorporate micro simulation indicators within macroscopic simulations.

8.2.1 Practical recommendations

- For future study's it would be recommended to use the total crash count and not differentiate between morning and evening peak crashes. Especially if the crash data is limited.
- Use more sophisticated driver behaviour models. Implementing these driver behaviour models in the simulation could lead to more realistic behaviour of drivers in the simulation which could lead to a better representation of reality.
- Apply the proposed framework to multiple networks with more available data on historical crashes and information on volume, speed distributions and other useful indicators. This could lead to stronger conclusions on discovered relationships when using the proposed framework.

8.2.2 Scientific recommendations

For building upon this study a few concrete future research directions are:

- Develop a similar network and investigate the relative safety. Within this study it was not possible to compare but if another similar VISSIM network is available the results can be even further validated by comparing the two networks.
- Safety performance functions have been developed that take observed real life conflicts into account. A promising direction could be to investigate the development of a safety performance function that takes conflicts from micro simulation into account.
- It could be interesting to look at the Unsafe density and its scale ability. That study would have to focus only on rear end conflicts, since those can be captured by the unsafe density indicator.
- A focus could be put on mesoscopic data, like platoon distribution, headway distribution and lane changes, and see if this can be used to connect microscopic data to macroscopic data.
- Single-vehicle crashes were deleted from the historical data set but are however also of interest when considering different road designs. It could be interesting how single vehicle crashes could be analysed or compared using microsimulation

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Appendices

A Overview tables

Table 15: Summarising table of indicators

Notation	*Name*	*Equation*	*Threshold*	*Used for*
Time based				
TTC	Time to collision	$\frac{\Delta X_{i,j}(t)}{\Delta V_{i,j}(t)}$	0.9 - 3.5 (s)	Rear end, turning/weaving, hit objects/parked vehicle, crossing
TET	Time exposed time to collision	$\sum_{t=t_0}^{t_n} \delta_i(t) \cdot \tau_{sc}$	"	Same as TTC
TIT	Time integrated time to collision	$\sum_{t=t_0}^{t_n} ([TTC^* - TTC_i(t)] \cdot \delta_i(t) \cdot \tau_{sc})$	"	Same as TTC
MTTC	Modified TTC	$\frac{-\Delta V_{i,j}(t) - \sqrt{\Delta V_{i,j}^2(t) + 2 \cdot \Delta a_{i,j}(t) \cdot \Delta X_{i,j}(t)}}{\Delta a_{i,j}(t)}$	"	vehicle-vehicle crash, same as TTC
CI	Crash Index	$\frac{(V_i(t)+a_i(t) \cdot \mathrm{MTTC}_i(t))^2 - \left(V_j(t)+a_j(t) \cdot \mathrm{MTTC}_i(t)\right)^2}{2 \cdot \mathrm{MTTC}_i(t)}$	"	Same as MTTC
TA	Time to accident	$TTC_i(t_a)$	1.5 s	Same as TTC
H	Time headway	$\frac{\Delta X_{i,j}}{V_j}$	1.8 - 3 (s)	Rear-end
PET	Post encroachment time	$t_{cp,2} - t_{cp,1}$	t <1.5 (s)	mainly right angle or crossing, merging/diverging, head on
Distance based				
PICUD	Potential index for collision with urgent deceleration	$\frac{\mathrm{V}_j^2 - \mathrm{V}_i^2}{2\alpha} + \Delta X_{i,j}(0) - \mathrm{V}_i \Delta \mathrm{t}$	ratio < 1	Same as TTC
PSD	Proportion of stopping distance	$\frac{RD}{MSD} = \frac{X_{i,c}(t)}{MSD_i(t)}$		Hit object, overturning
DSS	Difference of space distance and stopping distance	$\left(\frac{\mathrm{v}_j^2}{2*d_{j,max}} + \Delta X_{i,j}(t)\right) - \left(\mathrm{v_i(t)} * \mathrm{t_r} + \frac{\mathrm{v}_i^2}{2*d_i,max}\right)$		rear-end, hit object and turning
TIDSS	Time integrated DSS	$\int_0^{\mathrm{t}} \{\mathrm{TH} - (\mathrm{DSS})\} \tau_{sc}$		same as DSS
U	Unsafety	$\Delta V_{i,j}(t_c) * V_i(t) * R_{d,j}(t)$		
UD	Unsafe density	$\frac{\sum_{\mathrm{s=1}}^{S_{\mathrm{t}}} \sum_{\mathrm{V=1}}^{V_{\mathrm{t}}} *\mathrm{unsafety}_{V,S} * \mathrm{dT}}{\mathrm{T \cdot L}}$		rear-end
Deceleration based				
DRAC	Deceleration rate to avoid a crash	$\frac{\Delta V_{i,j}^2(t)}{2 * \Delta X_{i,j}(t)}$	3.35 $\frac{m}{s^2}$	Rear-end, hit object, merging, diverging
CPI	Crash potential index	$\frac{\sum_{t_0}^{t_n} P\left(d_{i,\mathrm{max}} < DRAC_i(t)\right) \cdot \tau_{sc} b_i(t)}{\Delta t_i}$		Same as DRAC
CIF	Critically index function	$\frac{V_i^2(t)}{TTC_i(t)}$		Turning accident, right angle
Other indicators				
\Delta V	Delta V	Delta $\mathrm{V}_i = \frac{m_j}{m_i+m_j} * (V_j(t_c) + V_i(t_c) * cos(\alpha))$		
CS	Conflict severity	DeltaV$_i - \frac{m_j}{m_i+m_j} (TA_i \cdot d_{i,\mathrm{max}})$		
E\Delta V	Extended delta V	$\frac{m_i}{m_j+m_i} * \sqrt{V_j^2(t_c) + V_i^2(t_c) - 2 * V_j * V_i * cos(\alpha)}$		

B Python scripts

```
In [1]: import pandas as pd
        import numpy as np
```

```
In [3]: wegvakken_netwerk = pd.read_csv('wegvakken_netwerk.txt')
        Kruispunten_netwerk = pd.read_csv('kruispunten_netwerk.txt')
        Ongevallen = pd.read_csv('ongevallen_2010_2019.txt',encoding='latin1')
```

```
In [9]: wegvakken = wegvakken_netwerk.to_dict("list")
        wegvakken = wegvakken['wegvakken']
        kruispunten = Kruispunten_netwerk.to_dict("list")
        kruispunten = kruispunten['kruispunten']

        # locaties = kruispunten.dict.update(wegvakken)

        ongevallen_wegvakken_netwerk = Ongevallen[Ongevallen['FK_VELD5'].isin(wegvakken)]
        ongevallen_kruispunten_netwerk = Ongevallen[Ongevallen['FK_VELD5'].isin(kruispunten)]

        # print(ongevallen_kruispunten_netwerk)
        # print (ongevallen_netwerk)

        ###################creates new excel file
        ongevallen_wegvakken_netwerk.to_csv('ongevallen_op_wegvakken_op_netwerk_2010_2019.csv')
        ongevallen_kruispunten_netwerk.to_csv('ongevallen_op_kruispunten_op_netwerk_2010_2019.csv')
```

Figure 37: Python code for exporting the accidents from the national database

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [28]:
```
df = pd.read_csv('gps_per_ongeval.txt', delimiter = "\t")
df_am = pd.read_csv('gps_per_ongeval_AM_peak.txt', delimiter = "\t")
df_pm = pd.read_csv('gps_per_ongeval_PM_peak.txt', delimiter = "\t")
df_mv = pd.read_csv('gps_per_ongeval_excluded_single_vehicle.txt', delimiter = "\t")

# encoding='latin1')
# Ongevallen_2010_2019 = pd.read_csv('ongevallen_2010_2019.txt')
df.columns = ['longitude', 'latitude']
df_am.columns = ['longitude', 'latitude']
df_pm.columns = ['longitude', 'latitude']
df_mv.columns = ['longitude', 'latitude']

df.head()
```

Out[28]:

	longitude	latitude
0	51.56272	5.13419
1	51.59782	5.07156
2	51.60294	5.01525
3	51.59782	5.07156
4	51.60294	5.01525

In [26]:
```
# BBox =((df.longitude.min(), df.longitude.max(),
#         df.latitude.min(, df.latitude.max())
BBox = (4.9495, 5.1394, 51.5492, 51.6102)
```

In [27]:
```
ruh_m = plt.imread('network_for_python.JPG')
```

In [22]:
```
fig, ax = plt.subplots(figsize = (20,40))

ax.scatter(df.latitude,df.longitude, zorder=10, alpha= 1, c='b', s=35)
ax.set_title('Historical crashes on Tilburg network')
ax.set_xlim(BBox[0],BBox[1])
ax.set_ylim(BBox[2],BBox[3])
ax.imshow(ruh_m, zorder=0, extent = BBox)
```

Out[22]: <matplotlib.image.AxesImage at 0x1909f92ce10>

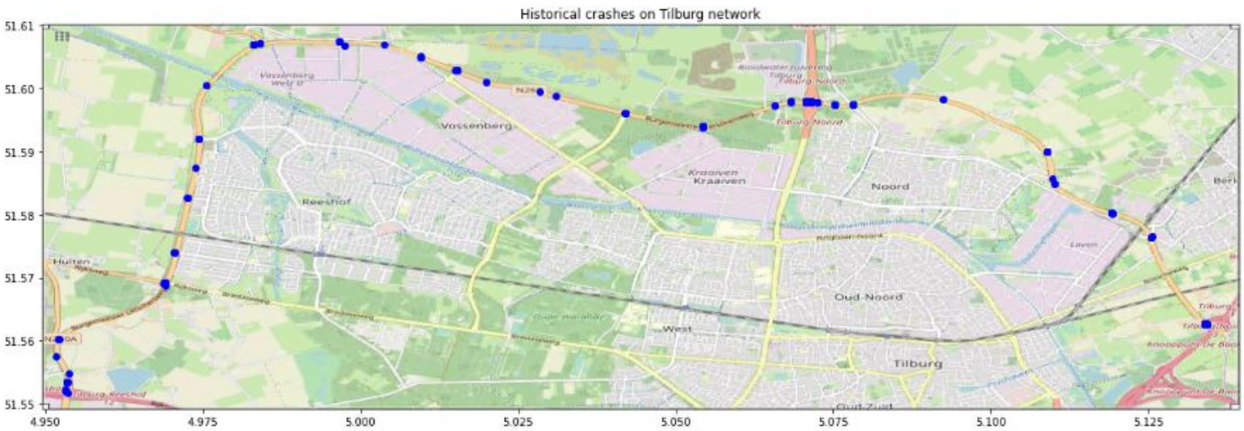


Figure 38: Python code for projecting the crashes on the map of Tilburg

```
In [1]: from numpy.random import rand
        from numpy.random import seed
        from scipy.stats import spearmanr
```

```
In [65]: Test_X = (10,9,8,7,6,5,4,3,2,1)
         Test_Y = (10,9,8,7,6,5,4,3,2,1)

         #With the ranking in the data set
         conflicts_am_peak = (5,1,3,2,8,6,15,16,17,11,12,10,14,7,4,20,19,9,18,13)
         conflicts_pm_peak = (3,1,5,2,9,7,19,16,18,13,15,8,14,6,4,20,11,10,17,12)
         conflicts_all     = (3,1,4,2,8,6,18,16,19,11,14,9,15,7,5,20,13,10,17,12)

         #with only taking into account 0s conflicts
         conflicts_am_peak_0 = (3,1,4,2,7,9,16,15,18,13,12,8,14,5,6,19,17,11,20,10)
         conflicts_pm_peak_0 = (3,1,6,2,9,8,17,15,19,13,16,7,14,4,5,20,11,10,18,12)

         #With PET<1.5
         conflicts_pm_peak_1_5 = (3,1,6,2,11,8,19,16,18,13,15,7,14,5,4,20,10,9,17,12)
         conflicts_am_peak_1_5 = (3,1,5,2,8,7,17,14,16,11,13,10,15,6,4,20,19,9,18,12)

         # crashes_am_peak_with_weekend = (3,11,12,4,13,14,15,5,16,7,6,8,9,1,10,17,18,19,20,2)
         crashes_am_peak = (3,13,12,4,14,15,17,10,11,9,5,8,6,2,7,19,18,16,20,1)
         crashes_pm_peak = (3,13,8,6,14,15,17,12,5,11,2,10,7,1,9,19,18,16,20,4)
         crashes_all     = (3,17,14,7,12,16,9,4,10,18,5,13,15,1,8,19,20,6,11,2)

         coef_test, p_test = spearmanr(Test_X, Test_Y)

         coef_pm, p_pm = spearmanr(conflicts_pm_peak, crashes_pm_peak)
         coef_am, p_am = spearmanr(conflicts_am_peak, crashes_am_peak)
         coef_all, p_all = spearmanr(conflicts_all, crashes_all)

         coef_pm_T_1_5, p_pm_T_1_5 = spearmanr(conflicts_pm_peak_1_5, crashes_pm_peak)
         coef_am_T_1_5, p_am_T_1_5 = spearmanr(conflicts_am_peak_1_5, crashes_am_peak)


         coef_am_T_0, p_am_T_0 = spearmanr(conflicts_am_peak_0, crashes_am_peak)
         coef_pm_T_0, p_pm_T_0 = spearmanr(conflicts_pm_peak_0, crashes_pm_peak)
```

```
In [66]: print("To test the function the test values are:", coef_test, p_test)
         print ()
         print ("PM peak is", coef_pm, "With a P-value of:", p_pm)
         print ("AM peak is",coef_am, "With a P-value of:", p_am)
         print()
         print ("PM peak with 1.5 for the PET threshold is", coef_pm_T_1_5, "With a p-value:", p_pm_T_1_5
         print ("AM peak with 1.5 for the PET threshold is", coef_am_T_1_5, "With a p-value:", p_am_T_1_5
         print()
         print ("AM peak with 0 seconds conflicts is",coef_am_T,"With a P-value of:",p_am_T)
         print ("PM peak with 0 seconds conflicts is",coef_pm_T,"With a P-value of:",p_pm_T)
         print()
         print ("The whole data set is",coef_all, "With a P-value of:",p_all)
```

```
To test the function the test values are: 0.9999999999999999 6.646897422032013e-64

PM peak is 0.33684210526315783 With a P-value of: 0.1464329432946607
AM peak is 0.41353383458646614 With a P-value of: 0.06992073829262123

PM peak with 1.5 for the PET threshold is 0.34586466165413526 With a p-value: 0.1352523431335
165
AM peak with 1.5 for the PET threshold is 0.4796992481203006 With a p-value: 0.03232606920021
4205

AM peak with 0 seconds conflicts is 0.5353383458646617 With a P-value of: 0.01499712964363260
3
PM peak with 0 seconds conflicts is 0.3383458646616541 With a P-value of: 0.1445260996635991

The whole data set is 0.10075187969924812 With a P-value of: 0.6725564354857818
```

Figure 39: Python code for validation using the spearman rank coefficient

Jupyter Translation Laatste checkpoint: 10-09-2021 (automatisch opgeslagen)

File Edit View Insert Cell Kernel Help   Vertrouwd   Python 3

```
In [1]: import numpy as np
        import scipy as scipy
```

```
In [54]: from scipy import optimize
```

```
In [55]: A_v5 = [
             [76,219,28,41,44,135,99],
             [26,266,24,36,33,112,66],
             [43,104,32,26,27,81,74],
             [9,143,27,74,18,40,102],
             [23,190,17,54,18,69,122],
             [22,207,26,81,26,74,128],
             [47,191,40,98,34,124,157],
             [42,183,32,32,34,121,92],
             [92,409,71,84,68,269,144],
             [90,357,78,104,84,311,181],
             [162,412,77,84,124,427,182],
             [18,169,30,65,28,99,1065],

             [388,1065,52,36,484,1595,120],
             [6,73,17,25,9,28,44],
             [22,96,22,43,34,84,65],
             [111,274,32,41,39,209,123],
             [24,215,25,37,26,108,99],
             ]

         #######All except 1, 14, &20########
         B_v5 = [1,3,8,4,2,6,19,6,1,17,4,3,9,0,0,11,6]

         X_v5 = np.linalg.lstsq(A_v5, B_v5, rcond = -1)

         print (X_v5[0])

         [-0.01330114 -0.033933   -0.06117937  0.19019191 -0.36125655  0.13892461
          -0.00447292]
```

```
In [56]: from scipy.optimize import nnls

         solution_v5 = nnls(A_v5, B_v5)

         print (solution_v5)

         (array([0.01424758, 0.        , 0.        , 0.08777986, 0.        ,
                 0.        , 0.        ]), 19.099033198793364)
```

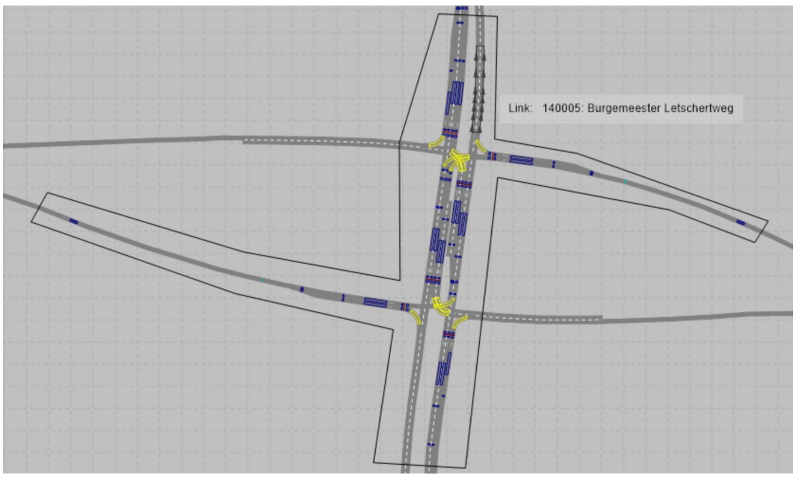
Figure 40: Python code for the translation using the least square estimation method

C Traffic volumes

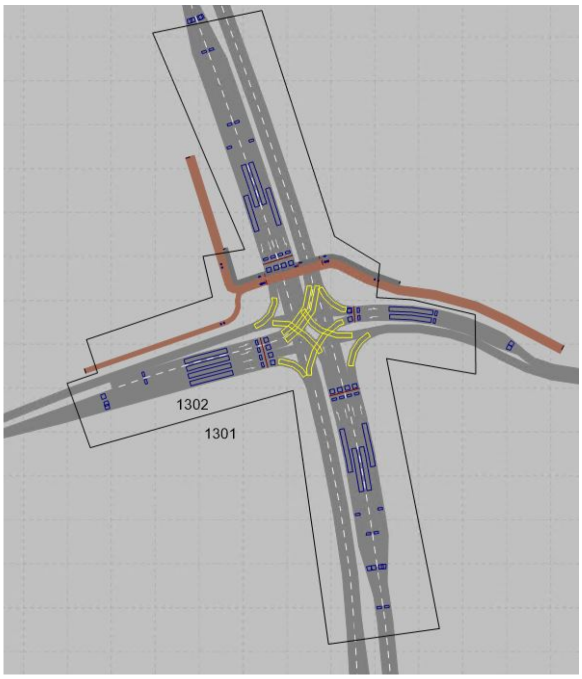
Table 16: Volumes during peak hours from simulation

		Volumes					
		AM			PM		
Node	**legged**	**W - E**	**E - W**	**SUM**	**W - E**	**E - W**	**SUM**
1	4	802	311	1113	807	383	1190
2	4	901	1140	2041	870	1125	1995
3	4	743	977	1720	747	965	1712
4	4	461	661	1122	437	584	1022
5	3	671	968	1639	713	883	1596
6	3	810	788	1598	579	957	1535
7	3	928	581	1509	429	986	1415
8	3	975	415	1390	290	1080	1370
9	3	1149	652	1801	566	1352	1918
10	4	1149	771	1920	675	1359	2034
11	3	1180	853	2033	735	1429	2164
12	3	863	1120	1983	791	1234	2025
13	3	1141	1774	2915	1295	1875	3170
14	4	1196	1215	2411	1557	1229	2786
15	4	87	1443	1530	1215	1396	2611
16	4	191	1481	1672	1241	1513	2754
17	3	176	1405	1581	1158	1304	2462
18	4	402	1482	1884	1188	1283	2472
19	3	483	1758	2241	1391	1381	2772
20	3	196	1192	1388	530	926	1457

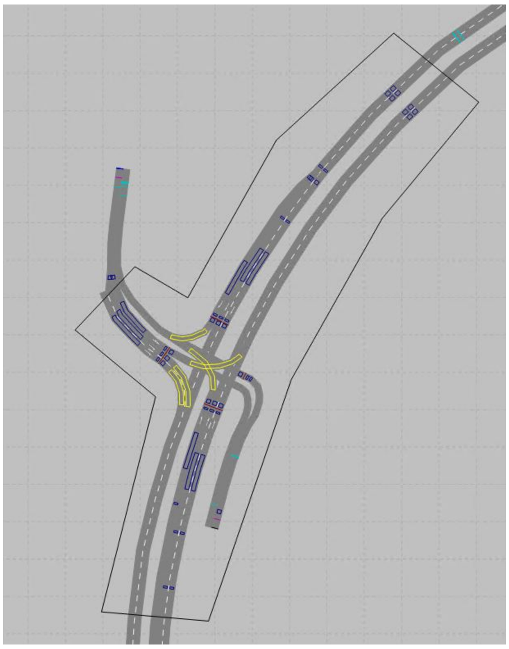
D Intersections of the network



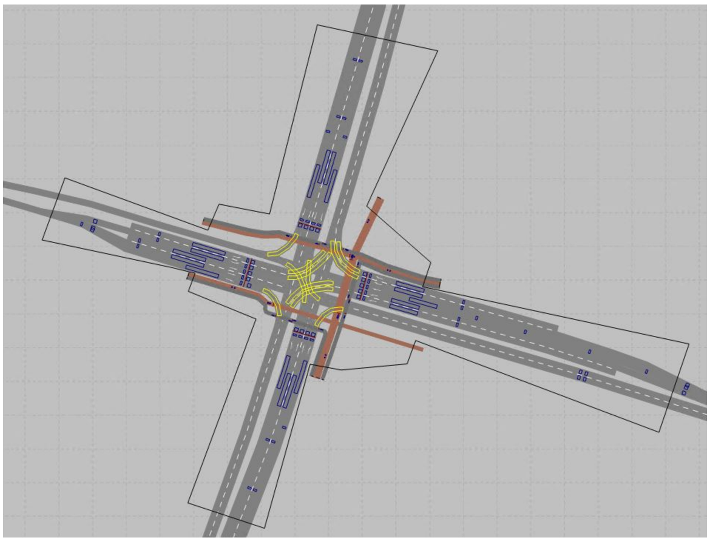
(a) Node 1



(b) Node 2

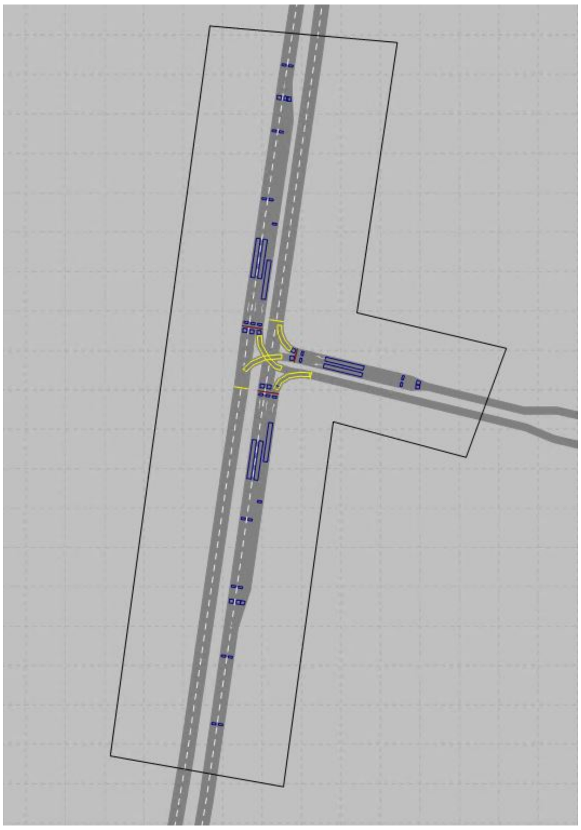


(a) Node 3

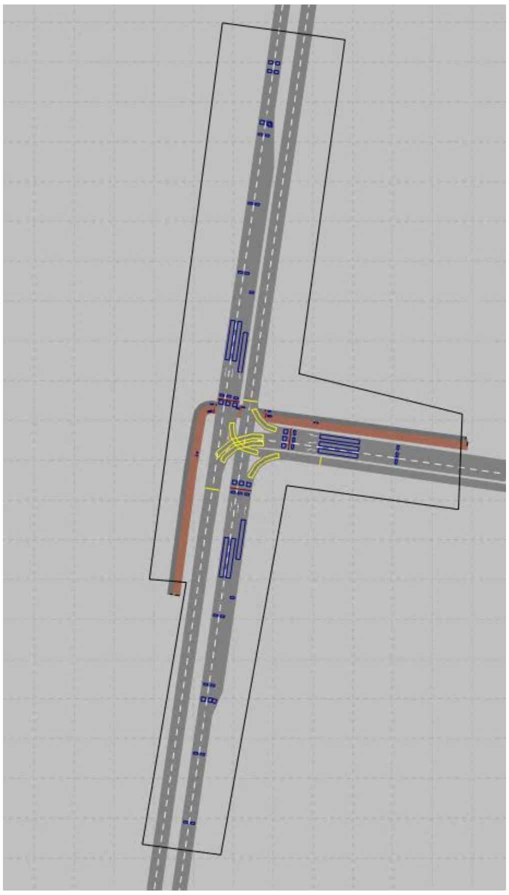


(b) Node 4

.

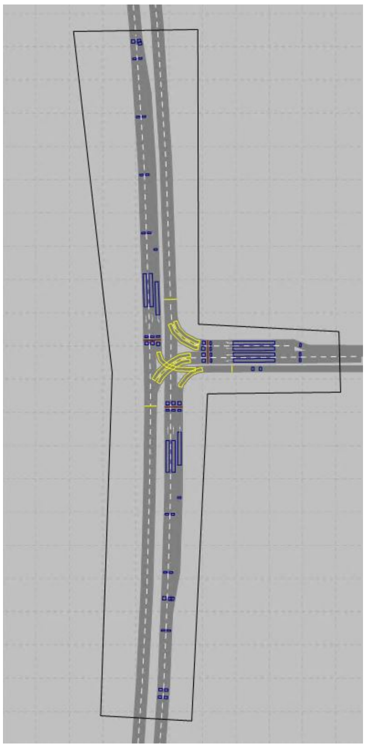


(a) Node 5

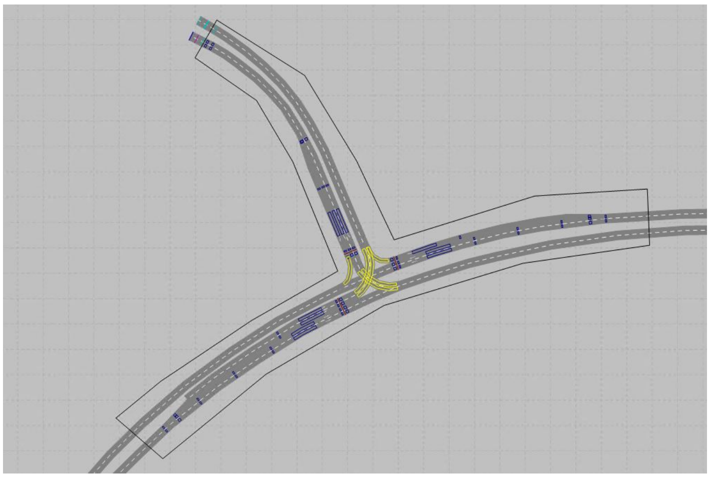


(b) Node 6

.

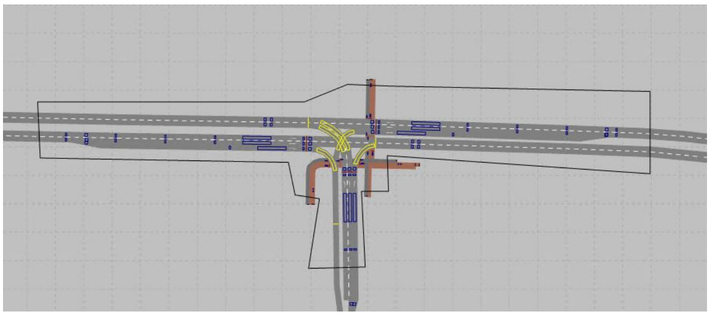


(a) Node 7

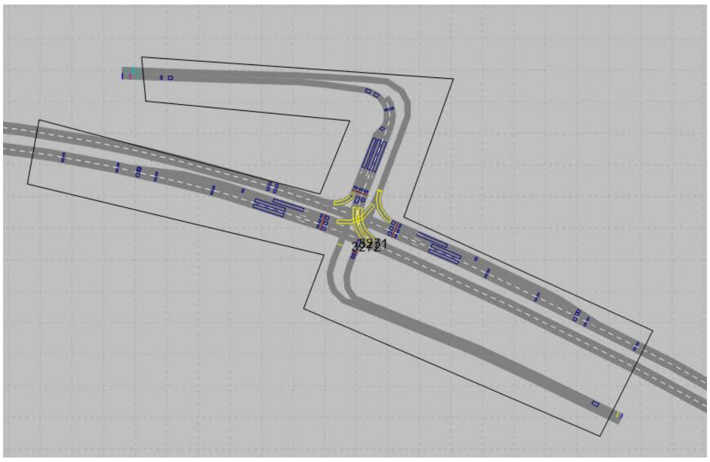


(b) Node 8

.

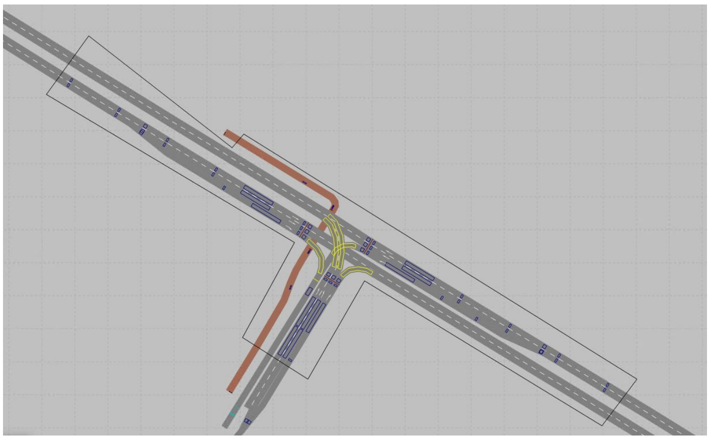


(a) Node 9

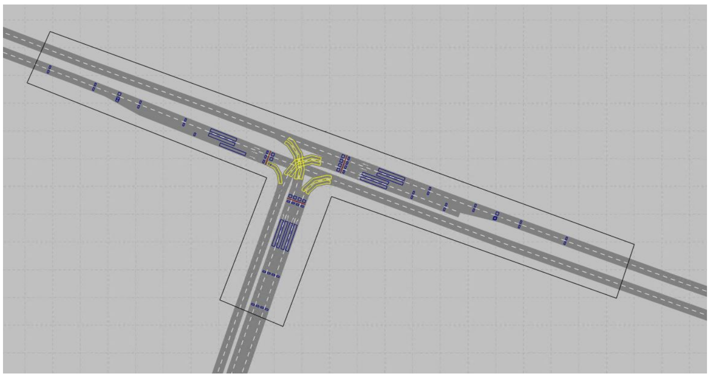


(b) Node 10

.

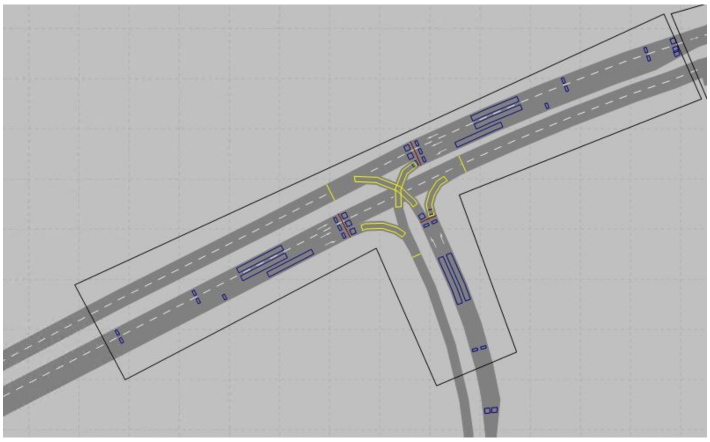


(a) Node 11



(b) Node 12

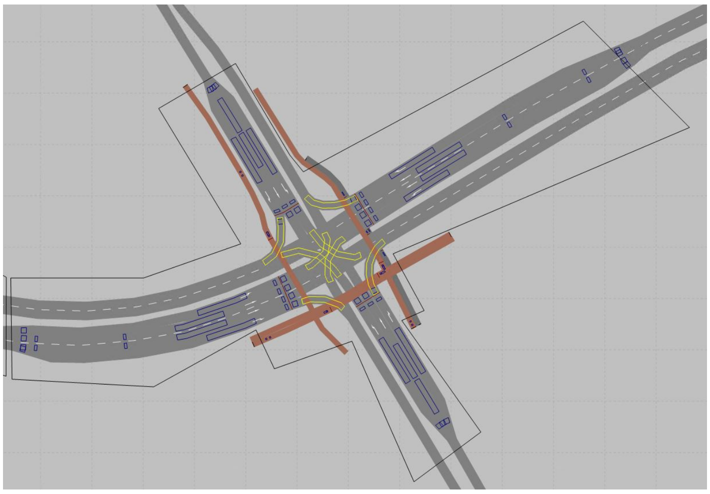
.



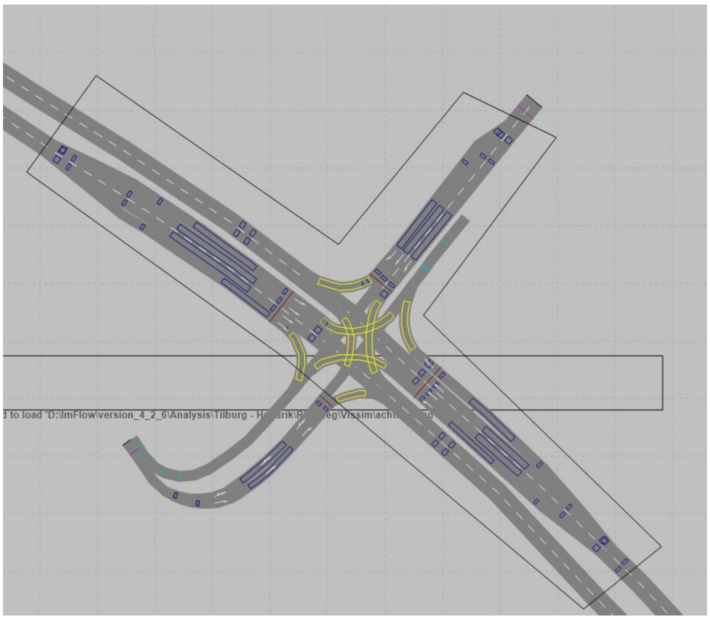
(a) Node 13

(b) Node 14

.

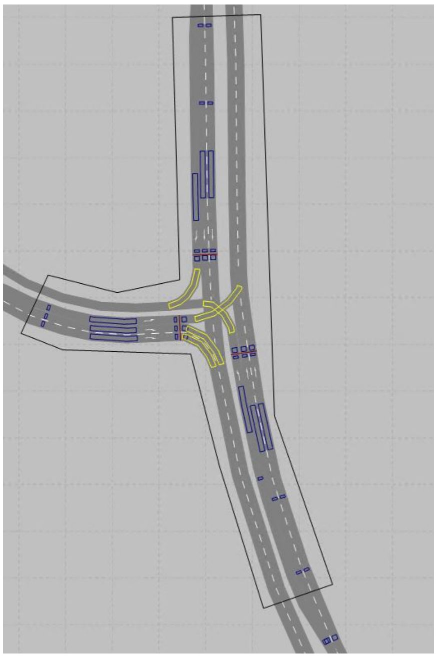


(a) Node 15

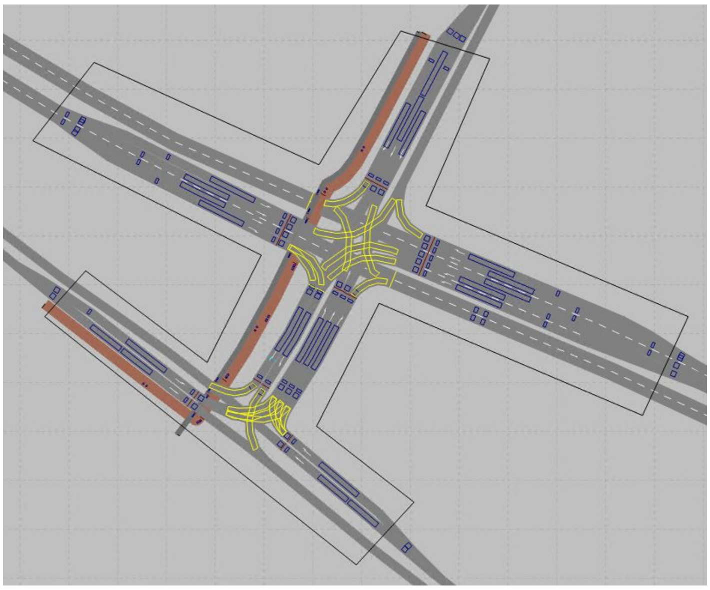


(b) Node 16

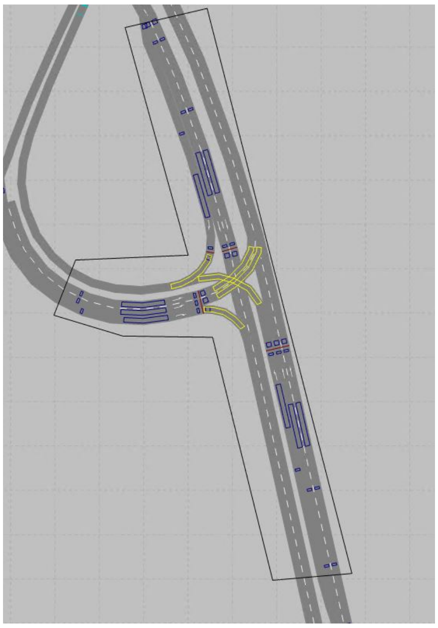
.



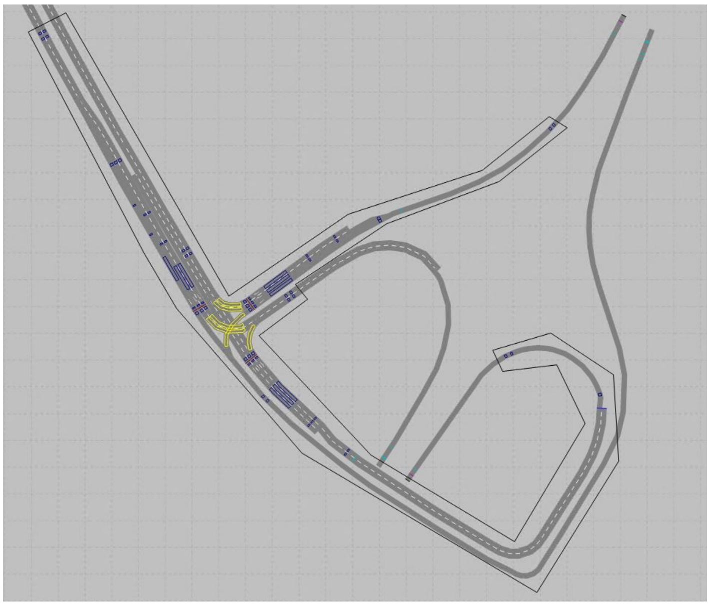
(a) Node 17



(b) Node 18



(a) Node 19



(b) Node 20

E VISSIM settings

Desired Speed Decisions / Desired Speed Distributions By Vehicle Class

Select layout... Desired spe

Count: 41	No	Name	Lane	Pos	TimeFrom	TimeTo	DesSpeedDistr(10)	DesSpeedDistr(20)	DesSpeedDistr(30)
1	1		12601 - 1	2,571	0	99999	60: 60 km/h	60: 60 km/h	
2	2		126005 - 1	2,000	0	99999	80: 80 km/h	80: 80 km/h	
3	3		126005 - 2	2,000	0	99999	80: 80 km/h	80: 80 km/h	
4	4		126011 - 2	2,000	0	99999	80: 80 km/h	80: 80 km/h	
5	5		126011 - 1	2,000	0	99999	80: 80 km/h	80: 80 km/h	
6	6		12701 - 1	2,500	0	99999	60: 60 km/h	60: 60 km/h	
7	7		127011 - 1	1,000	0	99999	80: 80 km/h	80: 80 km/h	
8	8		127011 - 2	1,000	0	99999	80: 80 km/h	80: 80 km/h	
9	9		127005 - 1	1,000	0	99999	80: 80 km/h	80: 80 km/h	
10	10		127005 - 2	1,000	0	99999	80: 80 km/h	80: 80 km/h	
11	11		126008 - 1	1,000	0	99999	60: 60 km/h	60: 60 km/h	
12	12		127008 - 1	18,500	0	99999	60: 60 km/h	60: 60 km/h	
13	13		8 - 1	2,500	0	99999	60: 60 km/h	60: 60 km/h	
14	14		133008 - 1	13,134	0	99999	60: 60 km/h	60: 60 km/h	
15	15		133005 - 1	1,000	0	99999	80: 80 km/h	80: 80 km/h	
16	16		133005 - 2	1,000	0	99999	80: 80 km/h	80: 80 km/h	
17	17		133011 - 2	1,000	0	99999	80: 80 km/h	80: 80 km/h	
18	18		133011 - 1	1,000	0	99999	80: 80 km/h	80: 80 km/h	
19	19		131011 - 1	37,731	0	99999	60: 60 km/h	60: 60 km/h	
20	20		131008 - 1	1,000	0	99999	80: 80 km/h	80: 80 km/h	
21	21		131008 - 2	1,000	0	99999	80: 80 km/h	80: 80 km/h	
22	22		131002 - 2	1,000	0	99999	80: 80 km/h	80: 80 km/h	
23	23		131002 - 1	1,000	0	99999	80: 80 km/h	80: 80 km/h	
24	24		14405 - 1	2,986	0	99999			60: 60 km/h
25	25		144005 - 1	1,000	0	99999			80: 80 km/h
26	26		144011 - 1	1,558	0	99999			60: 60 km/h
27	27		128010 - 1	3,727	0	99999	60: 60 km/h	60: 60 km/h	
28	28		12806 - 1	1,998	0	99999	60: 60 km/h	60: 60 km/h	
29	29		128002 - 2	1,000	0	99999	80: 80 km/h	80: 80 km/h	
30	30		128002 - 1	1,000	0	99999	80: 80 km/h	80: 80 km/h	
31	31		128008 - 2	1,000	0	99999	80: 80 km/h	80: 80 km/h	
32	32		128008 - 1	1,000	0	99999	80: 80 km/h	80: 80 km/h	
33	33		11322 - 1	2,295	0	99999	60: 60 km/h	60: 60 km/h	
34	34		11328 - 1	2,232	0	99999	60: 60 km/h	60: 60 km/h	
35	35		113002 - 1	6,000	0	99999	80: 80 km/h	80: 80 km/h	
36	36		113002 - 2	6,000	0	99999	80: 80 km/h	80: 80 km/h	
37	37		113008 - 1	2,000	0	99999	80: 80 km/h	80: 80 km/h	
38	38		113008 - 2	2,000	0	99999	80: 80 km/h	80: 80 km/h	
39	39		11332 - 1	1,000	0	99999	60: 60 km/h	60: 60 km/h	
40	40		11330 - 1	1,000	0	99999	60: 60 km/h	60: 60 km/h	
41	41		130011 - 1	4,071	0	99999	60: 60 km/h	60: 60 km/h	

Figure 51: The desired speed settings in the VISSIM model

Public Transport Lines / Public Transport Line Stops

Select layout... Line stops

Count: 10	No	Name	EntryLink	DestLink	DestPos	EntTmOffset	VehType	DesSpeedDistr	Color
1	1301	130 Noord	14004: Langenbergseweg	134002: Burgemeester Ballingsw...	89,473	0,0	300: Bus	80: 80 km/h	(255, 168, 0, 168)
2	1302	130 Zuid	13408: Burgemeester Ballingsw...	140011: Langenbergseweg	295,662	0,0	300: Bus	80: 80 km/h	(255, 168, 0, 168)
3	1311	131 Noord	13507: Nerhoven	134002: Burgemeester Ballingsw...	87,949	0,0	300: Bus	80: 80 km/h	(255, 127, 255, 212)
4	1312	131 Zuid	13408: Burgemeester Ballingsw...	135002: Nerhoven	247,971	0,0	300: Bus	80: 80 km/h	(255, 127, 255, 212)
5	3271	327 Noord	14405: Atlasstraat	144005: Eindsestraat	244,932	0,0	300: Bus	80: 80 km/h	(255, 190, 0, 0)
6	3272	327 Zuid	14411: Eindsestraat	144011: Atlasstraat	225,325	0,0	300: Bus	80: 80 km/h	(255, 190, 0, 0)
7	6291	629 Noord	11: Bredaseweg	132005: Uiterste Stuiver	226,389	0,0	300: Bus	80: 80 km/h	(255, 224, 224, 0)
8	6292	629 Zuid	13212: Uiterste Stuiver	125008: Bredaseweg	493,815	0,0	300: Bus	80: 80 km/h	(255, 224, 224, 0)

Figure 52: The PT lines in the VISSIM model

Vehicle Inputs / Vehicle Volumes By Time Interval

Select layout... Vehicle volumes by ti

Count: 72	No	Name	Link	Volume(0)	VehComp(0)
1	1	144	6: A65	924,0	1: Standaard
2	2	144	13612: A65	519,0	1: Standaard
3	3	146	14604: Koningsoordlaan	105,0	1: Standaard
4	4	113	11313: Schepersvenweg	153,0	1: Standaard
5	5	113	11322: Jules Verneweg	560,0	1: Standaard
6	6	113	11328: Zuiderkruisweg	263,0	1: Standaard
7	7	119	11906: De Baggerweg	513,0	1: Standaard
8	8	145	14512: Zwaluwenbunders	2,0	1: Standaard
9	9	117	11711: Stokbasseltlaan	233,0	1: Standaard
10	10	117	11705: Stokbasseltlaan	304,0	1: Standaard
11	11	123	12404: Midden-Brabantweg	392,0	1: Standaard
12	12	124	12310: Midden-Brabantweg	1340,0	1: Standaard
13	13	128	12806: Vloeiveldweg	360,0	1: Standaard
14	14	129	12904: Burgemeester Baron van Voorst tot Voorstw...	884,0	1: Standaard
15	15	130	13004: Gesworenhoekseweg	758,0	1: Standaard
16	16	144	14411: Eindsestraat	255,0	1: Standaard
17	17	131	13104: Athenastraat	446,0	1: Standaard
18	18	132	13212: Uiterste Stuiver	628,0	1: Standaard
19	19	133	8: Middeldijksdreef	239,0	1: Standaard
20	20	127	12701: Dalemdreef	173,0	1: Standaard
21	21	126	12601: Koolhovenlaan	174,0	1: Standaard
22	22	125	11: Bredaseweg	1134,0	1: Standaard
23	23	125	12: Rijksweg	761,0	1: Standaard
24	24	134	13402: Geen	1,0	1: Standaard
25	25	134	13408: Burgemeester Ballingsweg	487,0	1: Standaard
26	26	135	13502: Hultenseweg	35,0	1: Standaard
27	27	135	13507: Nerhoven	406,0	1: Standaard
28	28	140	14003: A58	422,0	1: Standaard
29	29	140	14009: A58	595,0	1: Standaard
30	30	140	14004: Langenbergseweg	756,0	1: Standaard
31	34	113	133	30,0	2: Fietsers
32	35	113	16	30,0	2: Fietsers
33	36	117	281	30,0	2: Fietsers
34	37	117	283	30,0	2: Fietsers
35	38	117	282	30,0	2: Fietsers
36	39	117	278	30,0	2: Fietsers
37	40	117	137	5,0	3: Voetgangers
38	41	117	136	5,0	3: Voetgangers
39	42	123	273	30,0	2: Fietsers
40	43	124	274	30,0	2: Fietsers
41	44	130	289	30,0	2: Fietsers

Figure 53: The vehicle input settings of the VISSIM model