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Forecasting door-to-door travel time variability caused by incidents

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Final report

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Preface

This report forms the final thesis for attaining the grade Master of Science on Delft University of technology at the faculty of Civil Engineering, in the master Transport & Planning. This master thesis is the result of research carried out in an internship at research institute TNO. This report is the result of a research carried out in 2012 in 8 to 9 months' time.

I want to thank my supervisors for giving me feedback en new ideas for my research. I want to thank TNO for the facilities they gave to carry out my research, also I want to thank the KU Leuven for providing the marginal traffic models MIC and MaC and LTM executable for my research. In person I want to thank Ruben Corthout, Chris Tampere, Roderic Frederix from the KU Leuven for their advice and help during my master thesis.

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Samenvatting

De analyse van het verkeersysteem geschied in de huidige praktijk op basis van gemiddelde congestiepatronen. Deze gemiddelde congestiepatronen zijn de normale output van de meeste transportmodellen. Voor investeringsbeslissingen in de infrastructuur worden voertuigverliesuren berekend met transportmodellen, deze voertuigverliesuren worden vervolgens gemonetariseerd. Dit bedrag is een belangrijke invoer voor sociale kosten-batenanalyses voor investeringsbeslissingen in de infrastructuur. Het gemiddelde congestie patroon is niet de enige belangrijke indicator voor het functioneren van een verkeerssysteem. De betrouwbaarheid van reistijden voor de gehele reis, dus vanaf de herkomstplaats tot aan de bestemming, is ook een belangrijke indicator voor het functioneren van het verkeerssysteem. De huidige methodieken om reistijdbetrouwbaarheid te voorspellen kunnen worden verbeterd want in de huidige praktijk worden ruwe benadering methodes met een vuistregel gebruikt. De congestie die wordt veroorzaakt door incidenten is een belangrijke oorzaak van de onbetrouwbaarheid van reistijden, omdat waar en wanneer een incident zal plaatsvinden niet voorspeld kan worden. In dit onderzoek wordt de onbetrouwbaarheid van de reistijden veroorzaakt door incidenten, reistijd variabiliteit genoemd, omdat slechts één oorzaak van de onbetrouwbaarheid van reistijden is gemodelleerd.

Reistijdbetrouwbaarheid zou in sociale kosten- batenanalyses moeten worden meegenomen. Met een goede ex-ante voorspelling van de reistijdbetrouwbaarheid, kan een goed onderbouwde beslissing worden genomen over de gevolgen van een infrastructurele investering op de reistijdbetrouwbaarheid.

Het doel van dit onderzoek is om een model te ontwikkelen dat de reistijdvariabiliteit van deur-tot-deur ten gevolge van incidenten kan voorspellen. Om dit doel te bereiken zijn er meerdere onderzoeksvragen en sub onderzoeksvragen gesteld:

1. **Hoe kan deur-tot-deur reistijd variabiliteit door incidenten in een netwerk worden voorspeld?**

- *Welke indicator kan het best gebruikt worden om de reistijd betrouwbaarheid en de sociale kosten van reistijd betrouwbaarheid uit te drukken?*
- *Wat zijn de huidige problemen in het voorspellen van deur-tot-deur reistijdbetrouwbaarheid in een netwerk?*
- *Welke methodes/modellen zijn veelbelovende modellen/methodes om deur-tot-deur reistijd variabiliteit veroorzaakt door incidenten, in een netwerk te voorspellen, en kunnen verder worden onderzocht?*

2. **Hoe nauwkeurig kan deur-tot-deur reistijd variabiliteit door incidenten op een netwerk worden voorspeld?**

- *Welk onderzocht model is het meest bruikbaar om deur-tot-deur reistijd variabiliteit veroorzaakt door incidenten te voorspellen?*

In een literatuuronderzoek zijn verschillende indicatoren om reistijdbetrouwbaarheid uit te drukken geïdentificeerd. De meest gebruikte indicatoren zijn op een drietal groepen van criteria beoordeeld:

- Alle relevante aspecten van de reistijddistributie worden meegenomen;
- De indicator geeft stabiele resultaten en heeft een duidelijke definitie;

- De waarde die wordt gevonden voor de indicator kan worden gemonetariseerd.

De beste indicator om reistijdbetrouwbaarheid uit te drukken is de standaard deviatie omdat, zowel te vroeg arriveren als te laat arriveren wordt meegenomen, het een bekende statistische waarde is die een duidelijke definitie heeft en kan gemakkelijk worden vertaald tot een geld waarde. Nadelen van het gebruik van de standaarddeviatie is dat de scheefheid van de reistijddistributie niet expliciet wordt meegenomen en het gemiddelde wordt gebruikt in de berekening van de standaard deviatie. Het gemiddelde is namelijk gevoelig voor extreme waarden in de reistijddistributie. Alle onderzochte indicatoren hebben duidelijke nadelen, de standaard deviatie heeft er de minste.

De beste indicator om reistijdbetrouwbaarheid en de sociale kosten van de reistijdbetrouwbaarheid uit te drukken is de standaarddeviatie.

Verschillende methodes om reistijdbetrouwbaarheid te voorspellen zijn onderzocht. De meeste methodes maken gebruik van één of ander verkeersmodel, andere methodes zijn het gebruik van een vuistregel of een regressie analyse. Er kunnen drie methodes worden aangewezen waarin de rekentijd relatief klein is:

- Vuistregels, een vast gedeelte van de reistijdbaten wordt als reistijdbetrouwbaarheid baten toegevoegd.
- Regressie analyse, een vaste relatie tussen reistijd en reistijdbetrouwbaarheid wordt geschat met een regressie analyse op basis van verkeersdata.
- Analytische verkeersmodellen, de variabiliteit van de reistijd op een link wordt met een bepaalde kansverdeling gemodelleerd.

Het grote voordeel van deze methodes is de beperkte rekentijd. Grote nadelen van deze methodes zijn dat de tijd afhankelijke- en ruimtelijke patronen in congestie niet worden meegenomen. De terugslag van congestie naar andere links wordt niet meegenomen. De oorzaken van de reistijd onbetrouwbaarheid worden als onbekend beschouwd. In verschillende andere methodes worden juist deze oorzaken van reistijdbetrouwbaarheid, in een verkeermodel, gemodelleerd om de reistijdbetrouwbaarheid te voorspellen. Met het expliciet simuleren van oorzaken van variabiliteit zijn een aantal problemen geassocieerd.

- Rekentijd
- Aantal en kwaliteit van de variabele input
- Nauwkeurigheid van de modellering van de oorzaken van variabilitet.

Deze drie problemen zijn allemaal met elkaar geassocieerd. Als één van de zaken wordt verbeterd kan dat de andere twee problemen groter maken.

Er zijn snelle methodes om reistijdbetrouwbaarheid te voorspellen, die niet de terugslag van congestie meenemen en niet expliciet de oorzaken van variabiliteit achterhalen. Andere methodes zijn het expliciet simuleren van oorzaken van variabiliteit in een verkeersmodel. Deze verkeersmodellen hebben problemen met welke oorzaken van variabiliteit gemodelleerd moeten worden, en op welke manier, binnen een aanvaardbare rekentijd.

Er is gekozen om reistijd variabilteit veroorzaakt door incidenten te voorspellen met marginale verkeersmodellen MIC (marginale incident berekeningen) en MaC (marginale berekenignen). Deze modellen gebruiken de uitkomsten van een dynamisch verkeersmodel met een nauwkeurige en goede beschrijving van de verkeersstromen. De terugslag van file volgt eerste-orde verkeersstroom therorie. MIC en MaC kunnen tijdelijke capaciteits reducties uitrekenen, MaC is ook in staat om verschillen in de verkeersvraag op een route of HB (herkomst – bestemming) paar te modelleren. Van de onderzochte modellen, die reistijdbetrouwbaarheid modelleren, hebben MIC en MaC een veelbelovende combinatie van kleine rekentijd en nauwkeurige beschrijving van verkeersstromen.

Marginale verkeersmodellen MIC (marginale incident berekeningen) en MaC (marginale berekeningen) zijn veelbelovende modellen om deur-tot-deur reistijdbetrouwbaarheid veroorzaakt door incidenten, in een netwerk, te voorspellen.

Het concept van marginale simulatie is een relatief nieuw concept in verkeersstroom modellering, daarom zal het concept kort worden toegelicht. Marginale verkeersmodellen gebruiken de uitkomsten van een basis model als beginpunt voor de berekeningen. Het basismodel van de marginale modellen MIC en MaC is een dynamische verkeerstoedeling met een link transmissie model. Het basis model en de margianle modellen zijn gebaseerd op eerste orde verkeersstroomtheorie. Het voordeel van het gebruik van marginale verkeersmodellen is dat voor kleine variaties in de verkeersstromen slechts een deel van het netwerk herberekend hoeft te worden, dit in tegenstelling tot het doorrekenen van hetzelfde scenario in het basis model. In het marginale model moeten alleen die verkeersstromen worden uitgerekend in het deel van het netwerk waar het gesimuleerde incident een verandering in de verkeersstromen teweeg brengt. De rekentijd voor het doorrekenen van de gevolgen van een incident in een marginaal model kunnen significant worden gereduceerd in vergelijking met een volledig dynamisch verkeersmodel.

Ondanks dat MIC en MaC beide marginale modellen zijn met hetzelfde basis model, zijn er toch een aantal verschillen. Het MIC model berekend alleen de bovenstroomse verschillen vanwege een incident, terwijl MaC bovenstroomse en benedenstroomse gevolgen van een incident berekent. MIC is een grover model met theoretisch meer fouten in de berekeningen dan het MaC model.

Een model is ontwikkeld om incidenten in MIC en MaC te simuleren. Een incident in MIC en MaC wordt gemodelleerd met vier parameters:

- De locatie van het ongeluk,
- De start tijd van het ongeluk
- De eind tijd van het ongeluk
- De factor van de originele capaciteit die tijdens een incident nog beschikbaar is.

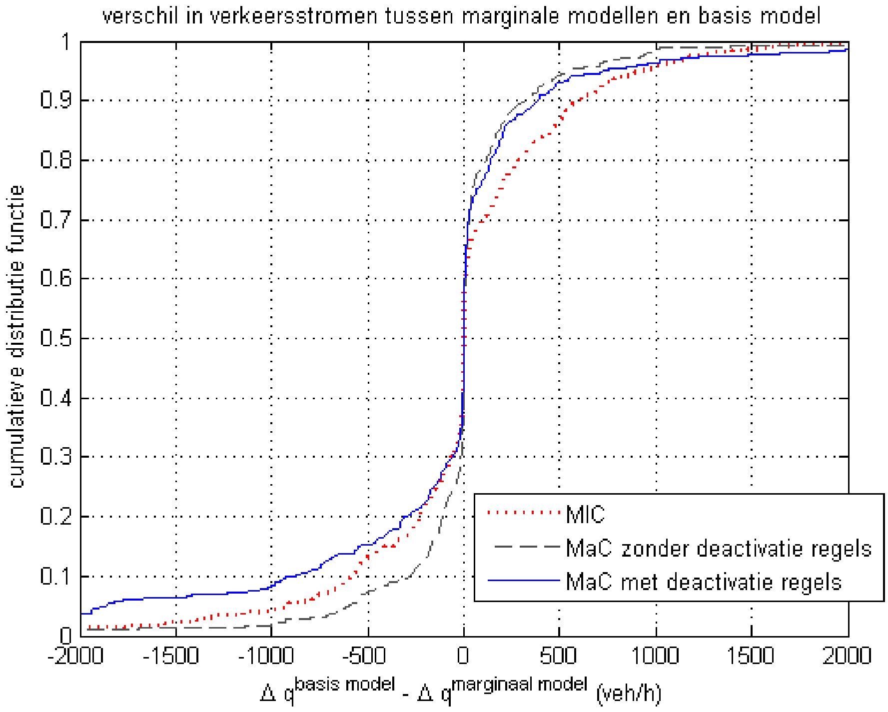
Er zijn twee verschillende versies van het model ontwikkeld, één gebruikmakend van MIC en de ander gebruikmakend van MaC. De berekende reistijden in deze modellen worden gebruikt om reistijddistributies te maken. De reistijddistributie voor één of meerdere routes, of herkomst bestemmings paren of het gehele netwerk kan worden uitgerekend. Twaalf verschillende incident types worden gesimuleerd op het netwerk. Deze incidenten verschillen in waarschijnlijkheid van optreden, de capaciteits reductie en de duur daarvan. Factoren worden gebruikt om de incident waarschijnlijkheid voor verschillende wegtypes te berekenen. Een factor wordt gebruikt voor het minder effectieve gebruik van de nog beschikbare capaciteit tijdens een incident.

Deur-tot-deur reistijd variabiliteit kan door het simuleren van 12 verschillende incident types met verschillende waarschijnlijkheid, duur en capaciteit reductie worden voorspeld. Deze incidenten worden met behulp van Monte Carlo techniek gesimuleerd in marginale verkeersmodellen MIC en MaC.

Het ontwikkelde model wordt getest op een netwerk van Amsterdam-Zuid. Het Amsterdam-Zuid netwerk bestaat uit 965 links en 3034 routes, een ochtend spits periode van vijf uur wordt gemodelleerd. Na een start-up periode van twee uur, wordt er ieder kwartier een reistijddistributie berekend. Dit kan gedaan worden voor één, meerdere of alle routes, HB paren, of voor het gehele netwerk. Als indicator voor de reistijd variabiliteit wordt ook de standaarddeviatie van de reistijddistributie uitgerekend. Om singifcante resultaten (standaard deviatie met betrouwbaarheids interval van 95%) uit het model te krijgen moeten minstens 1000 waarnemingen worden gedaan. De kans dat door een ongeluk de reistijd veranderd is verschillend bij beide versies van het ontwikkelde model. Voor het krijgen van significante resultaten zijn in MIC 14.000 incidenten gesimulleert en in MaC 5000. De rekentijd van het model gebruikmakend van MIC is 5,5 uur en 96 uur gebruikmakend van MaC.

Uit een analyse van de resultaten van het model gebruikmakend van MaC kwamen een aantal problemen naar voren: de rekentijd van de procedure is lang (96 uur) op nog een relatief klein netwerk, de deactivatie regels (deactivatie regels zouden er voor moeten zorgen dat verkeersstromen niet meer worden uitgerekend als de gevolgen van het incident zijn afgelopen) werken niet naar behoren en de benedenstroomse veranderingen in de verkeersstroom zijn niet hetzelfde als de verkeersstromen in het modelleren van het hetzelfde incident in het basis model, omdat de fracties afslaand verkeer niet worden gewijzigd als een incident wordt gesimuleerd in MaC.

De gevolgen van een incident in MIC en MaC zijn vergeleken met de resultaten van het basis model. MIC en MaC hebben hetzelfde vertrekpunt voor de berekeningen als het basis model en de algoritmes van beide marginale modellen lijken erg op het algoritme van het basis model, alleen de marginale modellen hebben een aantal simplificaties, daarom kunnen de verschillen tussen het basis model en het marginale model als benaderings fouten in de marginale modellen worden gezien. In een visuele vergelijking van de berekende verkeersstromen lijken de resultaten van de marginale modellen het basis model goed te benaderen. Er is ook een numerieke vergelijking uitgevoerd, hierbij is de uitsstroom van iedere link ieder kwartier vergeleken.



Vergelijking benadering fouten in MIC en MaC, bovenstrooms van incident

In het bovenstaande figuur worden de benaderings fouten bovenstrooms van het incident, voor een 7 tal incidenten, weergegeven. De benaderings fouten in de marginale modellen zijn soms groot, tot wel 2000 voertuigen per uur. De benaderings fouten in MIC en MaC zijn in dezelfde orde van grote. Ook is te zien dat MaC zonder deactivaite regels beter minder benaderings fouten maakt dan MaC met deactivatie regels

De gemodelleerde reistijddistributies zijn vergeleken met een gemeten reistijddistributie. In de gemeten reistijddistributie zijn minder zeer lange reistijden als in de gemodelleerde reistijddistributie. Het ontwikkelde model doet het nog slecht op het gebied van voorspellende validiteit. Het wordt aanbevolen om het ontwikkelde model uit te breiden met een vorm van omrijgedrag als er een incident plaats vindt. Het valideren van de gebruikte invoer variabelen op basis van verkeersdata wordt ook aanbevolen. Hopelijk kan dit de voorspellende validiteit van het model verbeteren.

De marginale verkeersmodellen MIC en MaC zijn vergeleken met het basis model, visueel lijken verkeersstromen in de marginale modellen goed op het basis model. In een numerieke vergelijking komen er benaderingsfouten voor tot wel 2000 voertuigen per uur. Het model heeft een lage voorspellende validiteit. Het verwaarlozen van om rijgedrag is hier en belangrijke oorzaak van de lage voorspellende validiteit.

Dit onderzoek laat zien dat het mogelijk is om deur-tot-deur reistijdvariabiltieit ten gevolge van incidenten te voorspellen door het expliciet simuleren van incidenten in een dynamisch verkeersmodel binnen aanvaardbare rekentijd. Dit kon bereikt worden door gebruik te maken van marginale verkeersmodellen, MIC en MaC, waarbij het aantal berekeningen noodzakelijk om de gevolgen van een incident te kunnen achterhalen wordt gereduceerd.

Als de kwaliteit en rekentijd van de MIC en MaC worden vergeleken, is MIC een veel geschikter model, omdat de winst in rekentijd groot is en het verlies in nauwkeurigheid gering. Daarom wordt het gebruik van het onwikkelde model gebruikmakend van MIC aanbevolen.

MIC is meer geschikt voor het voorspellen van deur-tot-deur variabiliteit veroorzaakt door incidenten dan MaC.

Summary

The traffic system performance is ex-ante, currently mainly analyzed based on average congestion patterns. This average congestion pattern is used because it is a basic output of most transport models. For infrastructure investment decisions the vehicle hours lost resulting from the transport model are monetized and form an important input for a social cost benefit analyses. The average congestion pattern is not the only important characteristic of the traffic system. How reliable the travel time between origin and destination is another important characteristic of the traffic system. Existing methodologies to forecast travel time reliability can be improved because in practice rough estimations with a rule of thumb are used. The congestion caused by incidents is an important cause of the unreliability of travel times, because where and when incidents occur cannot accurately be predicted. In this master thesis the unreliability of travel times caused by incidents will be named travel time variability, because only one source of unreliability is taken into account.

Travel time reliability should be incorporated in social cost benefit analyses for infrastructure investments. With an accurate ex-ante forecast of travel time reliability a well-educated decision of the consequences of infrastructure investments on travel time reliability, can be made.

The objective of this research is to develop a model to forecast travel time variability from door to door in case of incidents. To achieve this objective two research question and multiple sub questions are posed.

1 How can door-to-door travel time variability be forecasted due to incidents on a network?

- *Which indicator could best be used to describe travel time reliability and the societal costs of reliability?*
- *What are the current problems in forecasting door-to-door travel time reliability on a network?*
- *Which methods/models are promising methods/models to forecast door-to-door travel time variability due to incidents on a network, and can be further investigated?*

2 How accurately can door-to-door travel time variability due to incidents on a network be forecasted?

- *Which of the researched models is the most suitable model to forecast travel time variability from door-to-door due to incidents on a network?*

A literature research is carried out to find indicators that describe travel time variability. The most frequently mentioned indicators are assessed on three groups of criteria:

- All relevant aspects of the travel time distribution are valued;
- Stable results and stable formulation of the indicator;
- The ability to transform the indicator in a monetary value.

The best indicator to describe travel time reliability and the societal cost of reliability is the standard deviation because it values early and late arrivals, is known-statistical value with a clear definition and can easily be translated in a monetary value. Disadvantages of using the standard deviation is that it does not explicitly

take the skew of the travel time distribution into account and in the calculation of the standard deviation the mean is used. The mean is more sensitive to outliers in the distribution. Of all the investigated indicators the standard deviation has the fewest disadvantages and will be used to express travel time reliability.

The best indicator to describe travel time reliability and the societal cost of travel time reliability is the standard deviation.

Several methods described in literature to forecast travel time reliability are investigated. Most of these methods involve some kind of traffic model, others are a rule of thumb or results of a regression analyses. There are three categories of methods/models where simulation time is very small:

- Rules of thumb, adding a fixed proportion of travel time gains as travel time reliability gains;
- Regression analyses, where a fixed relationship between travel time and travel time reliability based on traffic data is fitted.
- Analytical traffic models, describing the variability in link travel time with some kind of probability distribution.

The big advantage of these methods is that they are fast, big disadvantages of these methods/models is that the spatial and temporary characteristics of the traffic system are not incorporated. Spillback of congestion to other links is not incorporated and the sources of variability are modelled in a simplified manner. Opposite of the approaches in which the sources of variability are not explicitly taken into account is the explicit simulation of the sources of variability in a traffic model. There are several problems with explicit simulation of sources of variability:

- Calculation time
- Number and quality of the variable input
- Accurate modelling of the sources of variability

Those three problems in forecasting travel time variability with a traffic model are all related to each other. Improving one of the three will make the other two problems bigger.

There are fast methods to forecast travel time reliability that do not take the spillback of congestion into account and approaches the sources of variability as a black box. Traffic models can take the sources of variability explicitly into account, but these models have problems which sources of variability have to be modelled, how these have to be modelled within a reasonable calculation time.

It is chosen to forecast travel time variability in case of an incident with a marginal traffic model MIC (marginal incident computation) and MaC (marginal computation). These models use the outcome of dynamic traffic model with an accurate description of traffic flows. The propagation of congestion in time and space are according to first order traffic flow theory. With MIC and MaC small disturbances to the equilibrium situation can be modeled with a small calculation time. MIC and MaC are able to model temporary capacity reductions; MaC is also able to simulate route or OD pair, demand differences. Of the investigated models that forecast travel time variability MIC and MaC have an attractive combination of relative small calculation time, an accurate description of traffic flows and are able to model the consequences of an incident.

Marginal traffic models MIC (marginal incident computation) and MaC (marginal computation) are promising models to forecast door-to-door travel time variability due to incidents on a network.

The concept of marginal simulation is relative new in traffic flow simulation; this concept will now be explained. Marginal traffic models use the outcomes of a base model as starting point of the calculation. The base model of MIC and MaC is a dynamic traffic assignment in a Link Transmission Model. This base model and the marginal traffic models are based on first order traffic flow theory. The big advantage of the marginal traffic models is that for small variations in the traffic system only a limited amount of the calculation has to be carried out in comparison with the base model. Traffic flows only have to be calculated in that part of the network where the simulated incident results in a flow different from the base simulation. The calculation time in a marginal traffic model of the consequences of an incident in a dynamic traffic assignment can significantly be reduced.

Although MIC and MaC are both marginal models with the same base model, there are some differences in the calculation of a temporary capacity reduction. The MIC model only identifies the upstream congestion of an incident while MaC calculates the upstream and downstream flow differences. The MIC model has theoretically a lot more estimation errors then the MaC model.

A model is developed to simulate incidents in MIC and MaC. An incident in these models is modeled with four parameters:

- The location of the incident,
- The start time of the incident,
- The end time of the incident,
- The factor of the original capacity that during the incident can still be used.

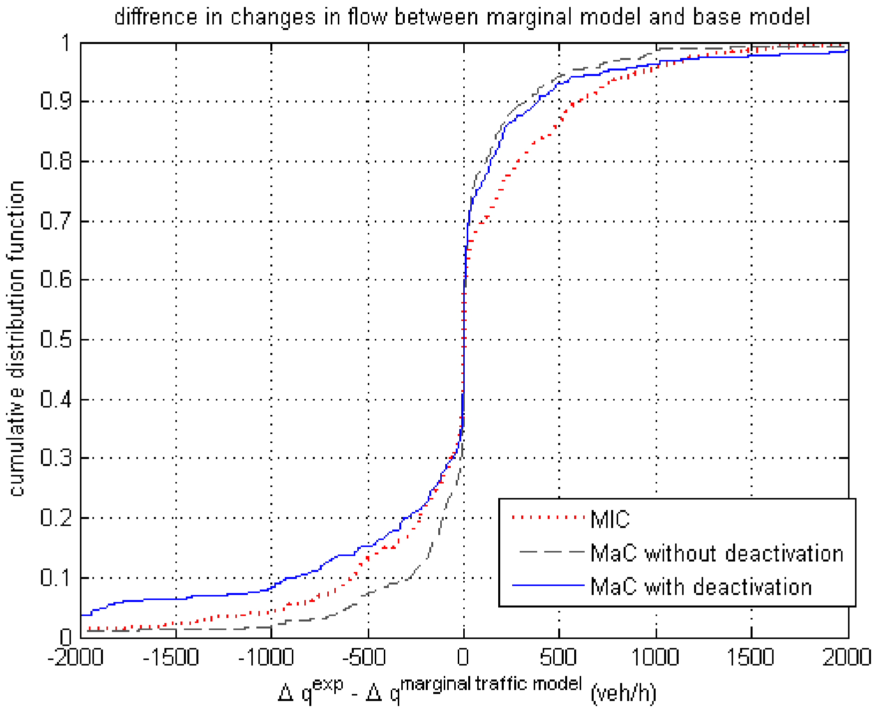
Two versions of the model are developed, one using marginal traffic model MIC and one using marginal traffic model MaC. The calculated travel times in these models are used to calculate travel time distributions. The travel time distribution for a route, OD-pair and a whole network can be calculated with this model. Twelve incident types are simulated in the network. The incidents differ in probability, duration and capacity reduction. Factors are used to calculate the incident probability on different road types. The less effective use of the capacity of the still opened lanes in case of an incident is incorporated in the model.

Door-to-door travel time variability can be forecasted by simulating twelve different incident types with different probability duration and capacity reduction in a marginal dynamic traffic model with the help of a Monte Carlo sampling technique.

The developed model is tested in a case-study on a network of Amsterdam-South. The Amsterdam-South network has 965 links and 3034 routes; a morning peak of 5 hours is simulated. After a start-up period of two hours, every quarter of an hour a travel time distributions can be calculated. This can be done for every route, or for every OD pair or for the whole network. As an indicator for the variability of travel times the standard deviation of the travel time distributions are calculated. For significant results (95%) of the standard deviation one needs at leads 1000 observations. The probability that an incident has an influence on the travel time is different for MIC and MaC the amount of sampled incidents in MIC and MaC is different; 14000 in MIC 5000 in MaC. The calculation time of the procedure using MIC is 5.5 hours and the procedure using MaC is more than 96 hours.

The results using the model MaC showed a few problems, the calculation time of the procedure is long (96 hour) on a relative small network, the deactivation rules (to deactivate a link after the flow changes due to an incident) do not work properly and the flow differences downstream of the incident location do not resemble to flow differences if the same incident is modeled in the base model because the turning fractions in MaC are not changed in case of an incident.

The consequences of an incident in MIC and MaC are compared with the results of the base model. Because MIC and MaC use the base model and there algorithms are closely related to the base model, only the marginal models have certain simplifications, the differences between the base model and the marginal model can be seen as estimation errors. In the visual comparison the modeled traffic flows seem correct, MaC simulating upstream and downstream differences and MIC only upstream differences. A numerical comparison is carried out in which the outflow of every link is compared every quarter of an hour:



Comparison errors in MIC and MaC in the upstream traffic direction

In the above figure the estimation errors in the upstream traffic direction of seven incidents are shown. The estimation errors in the marginal traffic models are up to 2000 vehicles an hour. The estimation errors in MIC and MaC are in the same order of magnitude. The MaC model without deactivation rules has less estimation errors as the MaC model with deactivation rules.

The modeled travel time distribution is compared with a measured travel time distribution. In the measured travel time distribution less really long travel times are present then in the modeled travel time distribution. Thus the developed model still performs weak on the predictive validity. It is recommended to improve the developed model with a kind of rerouting behavior in case of an incident. Justification of the used capacity reduction is also recommended. Hopefully this can increase the predictive validity of the model.

The marginal traffic models MIC and MaC are compared with the base model, visually the flow differences in MIC and MaC resemble the flow differences in the base model closely. In a numerical comparison estimation errors up to 2000 vehicles per hour are measured. The output of the model does not resemble measured travel time distributions.

The research shows that it is possible to forecast travel time variability from door to door in case of an incident, with explicit simulation of incidents in a dynamic traffic model within reasonable calculation time. This could be done because of the usage of marginal traffic models, MIC and MaC, reducing the number of calculations needed and therefor the calculation time.

If the procedure using MIC and MaC are compared, the loss of accuracy in MIC is relatively small compared to the gain in calculation time. The developed model using MIC is recommended.

MIC is better suitable then MaC to forecast door-to-door travel time variability caused by incidents.

Notation

List of abbreviations

CVN	cumulative vehicle numbers
DTA	dynamic traffic assignment
DUE	deterministic user equilibrium
INDY	name dynamic traffic model of TNO (model)
LTM	link transmission model
MaC	marginal computation (model)
MIC	marginal incident computation (model)
MC	multi commodity
OD	origin destination matrix (most of the times also dynamic in time).
TSTT	total system travel time
SC	single commodity
SUE	stochastic user equilibrium

List of symbols

a	factor in the second probability indicator [minutes]
a_1, a_2, a_3	parameters for the value of reliability [€/h]
a_4	parameters for the value of reliability [€]
AE	time of arriving early [h]
AL	time of arriving late [h]
AL_d	dummy variable for arriving late
b_{ja}	formula describing the travel time of a link [hour^2 veh^{-1}]
C_a	capacity of link a [veh/h]
$CVN^{model\ xx}$	cumulative vehicle numbers of link a in model xx at time t [veh]
Δq^{exp}	change in flow in base model [veh/h]
Δq^{MC}	change in flow in marginal traffic model MIC or MaC [veh/h]
Δq^{MaC}	change in flow in marginal traffic model MaC [veh/h]
ΔS_p	change in the standard deviation of the travel time distribution of route p [hour]
ΔS_{od}	change in the standard deviation of the travel time distribution between origin o and destination d [hour]
ΔT	duration of an incident [hour]
D	demand [veh/h]
D^{od}	demand between origin o and destination d [veh/h]
Φ	the cumulative distribution function of the standard normal distribution
f(x)	function expressing travel time reliability indicator
f_p	route fraction, part of demand of between origin and destination that takes route p
θ	location parameter of the log-normal distribution [hour]
σ	shape parameter of the log-normal distribution / the standard deviation of a normal distribution
i	iteration i
I	total amount of iterations
k	time slice k
l_a	length of link a [km]
L_p	route length [km]
μ	average of the travel time observations [hour], or scale parameter of the logit formula [hour^{-1}]
m	scale parameter
n	number of incidents in a simulation
n_{acc}	number of standard deviation, accuracy threshold for planning a trip,

N	number of observations
$N(0, \sigma)$	normal distribution
ψ	turning fraction
p'	route set between origin o and destination d
P_{act}	probability that the influence area of two incidents intersect
P_n	probability of occurrence of n number of incidents
q_a	traffic flow on link a [veh/h]
r	capacity reduction
RM_E	reliability multiplier arriving early
RM_L	reliability multiplier arriving late
RR	reliability ratio
S	standard deviation of a sample [hour]
t	time [hour]
T_{cost}	travel cost [€]
tt_a	travel time of link a [hour]
TT	expected travel time [hour]
TT_i	travel time observation i [hour]
TT_p	route travel time [hour]
TT_{xx}	the xx percentile of the travel time distribution [hour]
$TTST$	total system travel time [vehicle hours]
U	utility [€]
v_{ff}	free flow travel time [km/h]
VoT	value of time [€/hour]
ζ_{max}	dispersion factor

1 Introduction

1.1 Motivation

Recurrent congestion patterns are a daily phenomenon in many areas of the world. The time and severity of the congestion is to some extent predictable. The travel times can usually be forecasted and the delays caused by congestion can be scheduled in the activity patterns of people. However, problems with predicting travel time arise when unforeseen incidents occur. Due to possible unexpected incidents, time between activities has to be increased in order to deal with the unexpected delay. This extra time is called buffer time and is a hidden cost in the transport network as this time would normally not be taken into account.

The current tools to analyse the traffic system ex-ante only explain the average traffic system. The differences in the traffic system in day-to-day traffic pattern are not modelled with these models. The quality of the forecasts of travel time reliability needs to be improved. With a better forecast of travel time reliability, travel time reliability could more systematically be used for policy purposes. Hoogendoorn-Lanser et al. (2011) also recognize that defining and operationalizing reliability is not trivial, looking at the amount of studies carried out on this subject the recent years.

Policy makers recognize that travel time reliability is an important characteristic of the traffic system. In the Netherlands, the Ministry of Infrastructure and Environment focuses on travel time reliability as an important indicator for accessibility and the quality of the traffic system. Reliability was introduced by the former Ministries "Verkeer en Waterstaat" (traffic and public works) and "VROM" (housing, spatial planning and environment) in 2004 as an important indicator in the mobility policy document (Ministerie van Verkeer en Waterstaat, Ministerie van VROM, 2004) for the coming years. The importance of reliability can also be seen in the subtitle of this policy document: "towards a reliable and predictable accessibility." In recent studies a new indicator of accessibility, the generalized travel cost, is proposed by Hoogendoorn-Lanser et al. (2011) and Groot et al. (2011). Both studies recommend incorporating travel time reliability as a factor in the generalized travel cost function. In the generalized travel cost function all kinds of (social) costs associated with making a trip could be incorporated. Travel time reliability is not only relevant in indicators measuring accessibility but also in cost benefit analyses for investment decisions in the infrastructure. Groot et al. (2011) claim that for this goal also generalized travel cost can be used. For accessibility and cost benefit analyses for infrastructure investments a good forecast of travel time reliability is wanted.

The importance of incorporating reliability in the assessment of new infrastructure can be very useful if a mix of alternatives is studied. If two different solution directions are compared with each other, the first direction is expanding the capacity by building more asphalt. The second solution direction incorporates existing capacity utilisation, such as smart traffic regulation, ITS, better use of the current infrastructure (Dutch: beter benutten). When selecting the second option, reliability and average travel time will contradict each other. With better use of the current capacity the traffic system will probably become less reliable.

In this master thesis the focus lies on the influence of incidents on the travel time distribution from door to door. The idea is that a good forecast of the variability due to incidents can be extended in such a way that it eventually can forecast travel time reliability (incorporating more sources of variability). This is however out of the scope of this research.

Studying the influence of incidents on the traffic system is relevant research area. Recent studies from Snelder et al. (2010b, 2011), Kraaienveld (2008), Knoop (2009) all focus on those consequences and Snelder et al. (2012) is focused in a broader sense on robustness of a transport network. Studying the impact of incidents is relevant because traffic accidents and car breakdowns add up to 20-25% of the total delay on the Dutch main roads (Snelder et al., 2011).

1.2 Goal

The goal of this research is to develop a door-to-door travel time variability forecast model in case of incidents.

The output of the model can be used in a social cost benefit analyses for infrastructure investment decision. Travel time reliability is one of the elements that should be incorporated in the cost benefit analyses. The output of the model is then used to account for (a part of) the changes in reliability in travel times due to the infrastructure investments. For an infrastructure investment plan a social cost benefit analysis should be performed, to determine which of the alternatives is rated the best, and whether the project has to be carried out at all (mostly doing nothing is called alternative zero and is one of the alternatives considered). The cost of building new infrastructure for the different alternatives has to be determined. Also the benefits of a better functioning traffic system have to be determined. The benefits are now mostly calculated by the reduction of the travel times for all users (reduction in vehicle hours lost). These benefits are calculated based on the average traffic flows for a working day. It is argued that also the changes in reliability of travel times should be accounted for. The benefits of the infrastructure investment should exist of the travel times gains and reliability gains.

To be able to reach the set goal of this research, first the current possibilities to forecast travel time variability are investigated.

The first research question is formulated as:

1. **How can door-to-door travel time variability be forecasted due to incidents on a network?**

For this research question some sub questions are formulated.

- *Which indicator could best be used to describe travel time reliability and the societal costs of reliability?*
- *What are the current problems in forecasting door-to-door travel time reliability on a network?*
- *Which methods/models are promising methods/models to forecast door-to-door travel time variability due to incidents on a network, and can be further investigated?*

The promising methods/models are those that can tackle the problems mentioned in the second sub question. For the selected methods/models in the third sub question a model setup will be proposed to make a forecast. This results in a forecast of travel time variability due to incidents. Next the quality of the output of the model is assessed. The forecast of travel time variability is compared with the reality and the accurateness of the forecast is determined.

The second research question is:

2 How accurately can door-to-door travel time variability due to incidents on a network be forecasted?

For this research question a sub questions is formulated.

- *Which of the researched models is the most suitable model to forecast travel time variability from door-to-door due to incidents on a network?*

In this master thesis the words variability of travel times and reliability of travel times will be used a lot. In literature it seems that every author has his own preferences for using the term variability or reliability. In policy documents often the term reliability is used. Corthout (2012) claims that reliability is related to the information and expectations of road users and variability is not. In this thesis reliability will be used when the results are a forecast of the whole travel time distribution (in the literature survey the term reliability will be used constantly). When only a part of the variations in travel time is explained, the term variability will be used. For instance if only the variation due to incidents is modelled, variability will be used. The term variability can be used for more things than reliability. If the term variability of travel time is used, what you actually compare is not known in advance. Is that the variability within a day, or the averages of travel time between days or the travel time between days for a specific moment? For reliability it is clear that it is the variability as mentioned in policy documents and studies focussing on how people observe travel time variability. Reliability in these studies are always day to day differences in travel times, the frequency of observing the travel variability within a day changes between 4 an hour and two a day (peak/off-peak). When using reliability it is always tried to explain travel time variance as how people observe it. This is not the case for travel time variability.

This master thesis explores the possibilities to forecast travel time variability. A limitation of this thesis is that it is restricted to only one source of unreliability, namely incidents (accidents and car breakdowns). Other sources like weather and demand differences for instance due to events are omitted. The decision for incidents is made because it is has a significant influence on the variability of travel times and it is clear that incidents lead to unreliability, where for weather conditions or extra demand due to events it is argued that this is to some extend not the case.

1.3 Structure of the report

Chapter 2 gives an overview of indicators mentioned in literature that are used for travel time reliability. The indicators are assessed whether they are suitable for the developed model. The exciting possibilities to forecast travel time variability are also described in chapter 2. The most promising method is chosen and used in the developed model.

In chapter 3 the developed model is described. The input variables for the sampled incidents are described. The functioning of the traffic models used is explained. And the functioning and the assumptions in the developed model are presented.

The developed model is used on a network of Amsterdam-South. The results of the model are presented in chapter 4. Two versions of the model are developed and the outcomes of both models are compared with each other.

The validity of the developed model is investigated in chapter 5. It is investigated if the simulated results are in line with the theory behind the models. The results of model are also compared with real traffic data.

In the end of this thesis the main findings and conclusions are presented in chapter 6, and recommendations are made in chapter 7.

2 Selecting Indicator and model

In this chapter an indicator to express travel time reliability is chosen and a model to forecast travel time variability is chosen.

Which indicator is suitable for explaining differences in travel time reliability is investigated in paragraph 2.1. The first step is to determine on which criteria the indicator will be assessed. Secondly the list of reliability indicators is presented in 2.1.2. In paragraphs 2.1.3, 2.1.4 and 2.1.5 the applicability of the indicators is discussed. In 2.1.6 a choice for a specific indicator is made.

There are different possibilities to forecast reliability differences due to road network improvements. These possibilities can be classified in three categories, as mentioned by Snelder et al. (2010a):

- Rules of thumb: Rules of thumb are used in Dutch social cost-benefit analyses. These rules assume a fixed percentage of the total travel time gains can be added to the benefits as reliability gains.
- Regression analysis: In regression analyses, based on empirical data, a relationship between travel time gains and reliability gains is fitted with the help of traffic data.
- Traffic models that use a flexible travel time distribution: With the use of Monte Carlo (first proposed by Metropolis et al., 1949) simulation and traffic assignment the effects of variation in demand and supply are identified. This category will later be subdivided in different subcategories.

In paragraph 2.2 rules of thumb are discussed, in paragraph 2.3 regression analyses, and in paragraph 2.4 traffic models are discussed. In these paragraphs first the methodology is described, there after the quality of the forecast is evaluated.

2.1 Indicator

In this paragraph different reliability indicators are discussed. The goal of this paragraph is to find an indicator that is most suitable for evaluating the results of the model.

2.1.1 Criteria

The criteria for the indicator are first assessed whether the indicator values all relevant aspects of travel time distribution. Secondly, the indicator should wildly be accepted as indicator for travel time reliability. The precise form of the indicator should be known. Thirdly, the indicator should be able to translate the outcome to a monetary value. In the introduction the relevance of this research in respect to social cost benefit analyses for infrastructure investment decision is explained. For that reason it is important to be able to monetize the indicator.

Criteria: relevant aspects of travel time distribution

The travel time distribution does not always have the same shape. In literature many different distributions are mentioned to characterize the travel time distribution (Pu, 2011). In the frame on page 7 the relationship between skewness (see figure 2.1) of the travel time distribution and the traffic situation is discussed.

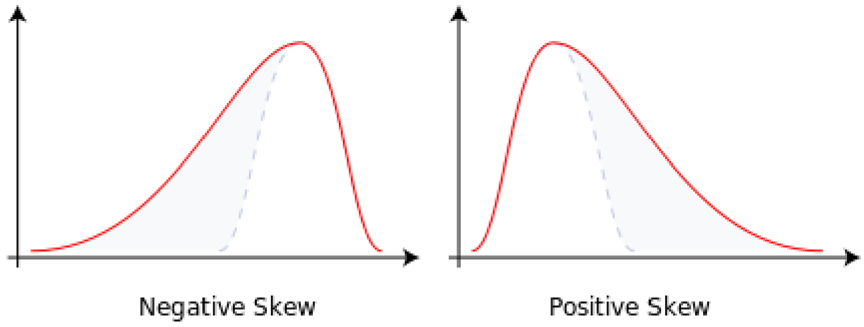


Figure 2.1 Definitions of positive and negative skewed (Hermans, 2008).

People value late arrivals higher than early arrivals (Fosgerau et al., 2008). Especially longer delays are valued higher because a long delay will not only result in being late for an appointment but totally missing that appointment (Van Lint et al., 2008). An indicator for travel time reliability should value early arrivals lower than late arrivals, especially larger delays.

What is the shape of the travel time distribution in different traffic states?
Van Lint et al. (2008) states that in onset and dissolving of congestion the travel time distribution is heavily positive-skewed (large right tale of the distribution) and that in free-flow the travel time distribution is symmetrical and narrow. In heavy congestion the travel time distribution is symmetrical or a bit negative skewed and wide. Eliasson (2006) also found that there are more positive-skewed distributions then negative-skewed distributions. Eliasson (2006) found more positive-skewed distributions with high congestion and high standard deviation. The correlations found by Eliasson (2006) are not strong. At least it can be said that the findings of Van Lint et al. (2008) and Eliasson (2006) are not in contradiction with each other.

Pu (2011) assumes that the travel time distribution is log-normal distributed, see formula 2.1.

$$f(x)=\frac{1}{(x-\theta)*\sigma*\sqrt{2\pi}}*e^{-\frac{\left(\ln\frac{x-\theta}{m}\right)^2}{2\sigma^2}} \qquad (2.1)$$

With this assumption, the different indicators can analytically be compared. In the derivation of the formulas for indicators as a function of the shape parameter the scale parameter (*m*) is assumed to be constant and location parameter (θ) to be zero. The shape parameter (σ) in the log normal distribution is expressed as a function of the different variables. With m=1 and $\theta=0$ formula 2.1 becomes:

$$f(x)=\frac{1}{x\sigma\sqrt{2\pi}}*e^{-\frac{(\ln x)^2}{2\sigma^2}} \qquad (2.2)$$

Most of the characteristics described by Van Lint et al. (2008) (see appendix A) can be modeled with the log-normal distribution. The only difference between the log normal distribution and the characteristics described by Van Lint et al. (2008) is that the travel time distribution in congestion is assumed positive-skewed (large right

tale of the distribution) where Van Lint et al. (2008) found a negative-skewed distribution..
The analytical expressions can be used to assess the quality of the output of the different indicators. Increasing shape parameter (σ) results in a more positive-skewed and wider travel time distribution. An indicator of reliability should have an increasing convex function with the shape parameter (σ), because both with and skew increase with increasing shape parameter.

Criteria: accepted indicator with stable results
The mean is sensitive to outliers and therefore the indicators using the mean and/or variance can lead to biased estimations. This problem can be solved by using the median instead of the mean (Van Lint et al., 2008).

The indicator should be a well-known statically tests where no arbitrarily chosen parameters are used. The parameters used in the indicator should always be the same. Also in literature the problem of parameterized indicators is mentioned (Van Lint et al., 2008). The problem with parameters in an indicator is that the outcome of the indicator is highly depended on setting of the parameter.

Criterion: monetizing indicator
Most monetizing possibilities rely on economic and financial utility theory. For a specific form of the utility function the value of reliability is investigated with revealed and stated preference research. This research is carried out for a limited number of all indicators.

Selected criteria
The six criteria for an indicator expressing travel time variability are summarized as:

- Value early arrivals and late arrivals;
- Value longer delays more than relative small delays;
- Use an indicator that has an increasing convex function with the shape parameter with an log normal distribution;
- Use variables in the indicator that are not sensitive to outliers;
- Use a well-known statistical test that utilizes no arbitrary chosen parameters;
- Know the value of reliability with respect to the indicator.

2.1.2 Indicators

To explain reliability from the travelers perspective day-to-day travel time distributions are commonly used. There are a number of indicators that describe the variation in the travel time distribution. The indicators can be divided in categories of indicators. In this thesis the same categories are presented as in Van Lint et al. (2008):

- Statistical
- Buffer time
- Tardy-trip
- Probabilistic
- Skew-width

The categories and the travel time reliability indicators that belong to these categories are explained below.

Statistical

In Van Lint et al. (2008) and Lomax et al. (2003) the statistical range is described as one of the possible indicators of travel time reliability. The reliability is then mostly described with the standard deviation.

$$S = \sqrt{\frac{1}{N-1}\sum_{N}(TT_i - \mu)^2} \tag{2.3}$$

The reliability can also be explained with the coefficient of the standard deviation. The advantage of using a coefficient is that is unit less and independent of the travel time.

$$CoV = \frac{S}{\mu} \tag{2.4}$$

The standard deviation can be described in a travel time window. The expression has generally this form:

$$TT_{window} = \mu \pm n_{acc} * S \tag{2.5}$$

In which n_{acc}, is the selected number of standard deviations. With *n*=1, 68% of the travel times are with in the travel time window.

Buffer time

The buffer time indicator calculates the extra time someone required to account for arriving on time in *x* [%] times of the cases. The indicator is made unit less by dividing it with the average travel time. The exact number of *x* that should be used is not known. In Van Lint et al. (2008) and Lomax et al. (2003) values of 90% and 95% are used, respectively. In the formula below the threshold of arriving on time in 90% of the cases is used.

$$BI = \frac{TT_{90} - \mu}{\mu} \tag{2.6}$$

Tardy-trip

An indicator that is quite similar to the buffer time is the group of tardy-trip indicators. The difference is the ratio behind the indicator. Tardy trip aims at calculating the amount of late arrivals and buffer index at calculating how much buffer time must be scheduled. The reasoning behind these two indicators is different; the resulting indicator could be the same. In Lomax et al. (2003) and Van Lint et al. (2008) the misery index is proposed as an indicator in the group of tardy-trip indicators. In this indicator the average travel time of the 20% longest routes is used instead of the 90th percentile, as in the buffer index.

$$MI = \frac{TT_{\text{avarage } (TT80 \text{ up to } TT100)} - \mu}{\mu} \tag{2.7}$$

Probabilistic

Van Lint et al. (2008) identify an extra category of robustness indicators, namely the probabilistic measures. These indicators are used in the Dutch mobility policies

(Minsterie van Verkeer en Waterstaat, Ministerie VROM, 2004). For trips longer than 50 km, the probability of travel time is 1.2 times the median travel time is calculated.

$$\boldsymbol{PR_1 = P(TT_i \geq 1,2 * TT_{50})} \tag{2.8}$$

For trips shorter than 50 km the probability that a trip is more than 10 minutes longer than the median travel time is calculated.

$$\boldsymbol{PR_2 = P(TT_i \geq 10 + TT_{50})} \tag{2.9}$$

The travel times are called reliable if the outcomes of these indicators are lower than 5%. In other words, if 95% per cent of the trips are within 10 minutes longer than the median travel time, or within 1.2 times of the median travel time for trips longer than 50 km.

Skew-width
Van Lint et al. (2008) proposed a new indicator that takes the skew and the width of the distribution into account. The reasoning behind this indicator is that not only the width of the distribution is important but also the skewness of the distribution. A heavily positive skewed distribution (long right-tale) leads travelers to not only be late at their arrival but completely miss an appointment. A heavily positive skewed distribution leads to less reliable travel times and therefore needs to be incorporated in the reliability indicator. Van Lint et al. (2008) determines the width of the distribution with the distance between the 90th and the 10th percentile divided by the median.

$$\boldsymbol{\lambda^{var} = \frac{TT_{90} - TT_{10}}{TT_{50}}} \tag{2.10}$$

The skewness of the distribution is calculated by the ratio of the distance between the 90th percentile and the median and the distance between the median and the 10th percentile, values larger than 1 are for positive skewed distributions.

$$\boldsymbol{\lambda^{skew} = \frac{TT_{90} - TT_{50}}{TT_{50} - TT_{10}}} \tag{2.11}$$

These two indicators can be combined to one indicator. Van Lint et al. (2008) claims that the indicator for width of the travel time distribution is route length depended. To get rid of this location specificity he divides by the route length, resulting in a reliability indicator per unit length.

$$\boldsymbol{SW = \begin{cases} \dfrac{\lambda^{var}\ln(\lambda^{skew})}{L_p} & \lambda^{skew} > 1 \\ \dfrac{\lambda^{var}}{L_p} & \text{otherwise} \end{cases}} \tag{2.12}$$

2.1.3 Evaluating relevant aspects of the travel time distribution

In this paragraph the indicators are assessed on three criteria:

- value early arrivals and late arrivals;

- value longer delays more than relative small delays;
- increasing convex function with the shape parameter, with an assumed log normal distribution.

The standard deviation (*S*), the coefficient of variance (*CoV*) and the width indicator (λ^{var}) account for late arrivals with the same weight as early arrivals. The skew width indicator (*SW*) proposed by Van Lint et al. (2008) incorporates late arrivals and early arrivals, but late arrivals are considered more important. The other indicators only utilize late arrivals.

With an assumed log normal distribution the indicator is expressed in relation to the shape variable of the log normal distribution. The width, the skew-width, the second probabilistic indicator are not investigated by Pu (2011), Pu (2011) was not able to come up with an analytical expression for the misery index because of the specific form of this indicator. Most of the resulting functions are increasing convex functions. The buffer index is decreasing after a certain value of the scale variable. This is not in line with the expectations of a reliability indicator because an increasing shape parameter results in a more positive-skewed and wider travel time distribution. This problem can be solved using the median instead of the mean (Pu, 2011). The first probability function (PR_1) is increasing concave instead of convex. In appendix B the second probability indicator (PR_2), the width indicator $\boldsymbol{\lambda^{var}}$ and the skew-width indicator (*SW*) are investigated in the same way as the other indicators in Pu (2011). A log-normal distribution is assumed, and for the three indicators an analytical expression is found. The second probability indicator (PR_2) turns out to have an increasing concave function with the shape parameter (σ)**.** This is the same results as found for the first probability indicator (PR_1). The probability indicators approach the probability of a 0.5 with increasing shape parameter. The width indicator and the skew-width indicator turn out to be increasing, convex functions.

In figure 2.2 the analytical expressions for all the indicators are presented. The indicators are presented for shape parameters between 0 and 2.5. Pu (2011) claims that shape parameters above 2 are rarely found for travel time distributions. The results of the first probability indicator (*PR1*) is multiplied with 10 and the second probability indicator (*PR2*) is multiplied with 100, this is multiplication is carried out to visualize all formulas in one figure. The travel time is expressed in minutes in the second probability indicator (*PR2*)

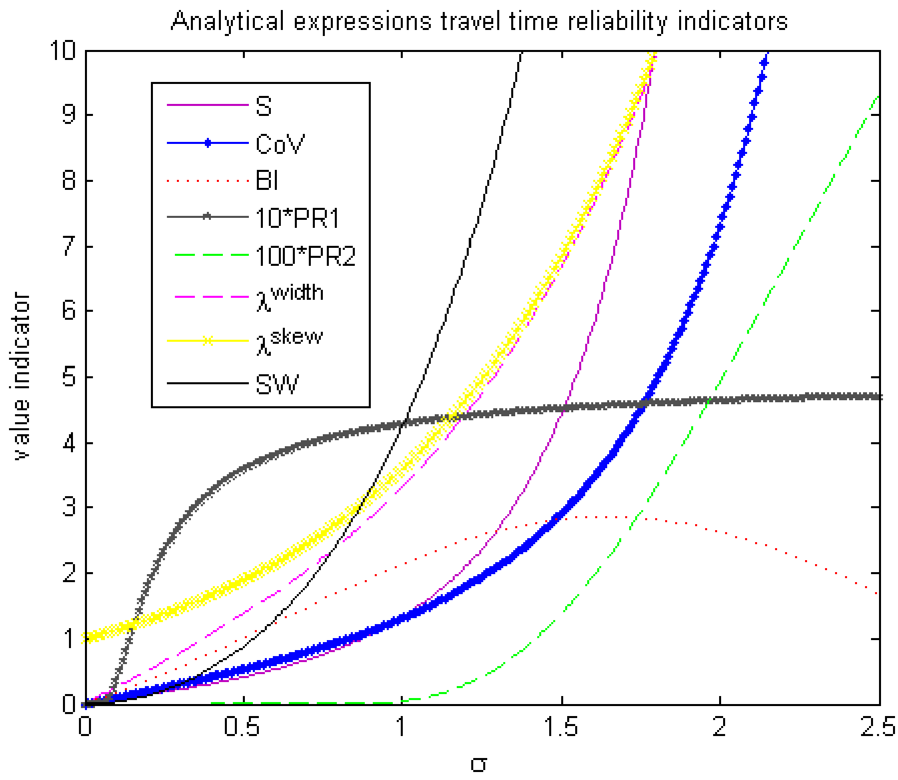


Figure 2.2: Value of indicator with increasing shape parameter of log-normal distribution

The second probability indicator looks increasing convex in this domain. For bigger values of the shape parameter this is not the case.

2.1.4 *Accepted indictor with stable results*

In the statistical indicators (standard deviation and coefficient of variance), the buffer index and the misery index, the mean is used. In all other indicators the median of the travel time distribution is used. The mean is sensitive to outliers and the results out of this indicator will be less stable. Pu (2011) also showed that the buffer index would have more realistic results if the median was used instead of the mean.

The probability indicators rely on setting the right parameter values. The usefulness of these indicators is highly dependent on the right parameters (Van Lint et al., 2008). As earlier mentioned the exact form of the buffer time index is not known. This same problem is present in the width and skew indicator. The skew-width indicator is not a well-known statistical test. In international literature this indicator is not used much. Also the variance, skew and misery index are not the most used indicators for reliability. These three indicators make use of percentiles, and it is not clear why exactly these percentiles should be used and not a higher or lower percentile. For instance why using the 90th percentile and not the 80th percentile or 95th percentile.

2.1.5 *Monetizing reliability*

Which indicator for reliability can be translated to a monetary value? Most possibilities to monetizing travel time reliability rely on economic and financial utility theory. Two different possibilities of a utility function with travel time reliability is given by Fosgurau (2008):

Mean-variance approach

$$U = T_{cost} + VoT * TT + a_1 * S \tag{2.13}$$

Scheduling approach

$$U = T_{cost} + VoT * TT + a_2 * AE + a_3 c * AL + a_4 * AL_d \tag{2.14}$$

The last term in the mean-variance approach and the last three terms in the scheduling approach are the parts of the utility function describing the dis-utility of travel time unreliability.

The last term of the scheduling approach is omitted from the utility function in a number of studies. Only the costs of arriving early and arriving late are determined. The possibilities given by Fosgerau et al. (2008) are explicit utility functions where in other studies marginal values of reliability are used, expressing the value of reliability as a relative indicator. The indicator is relative with respect to the value of time. The marginal values of reliability are called the reliability ratio (RR) and the reliability multiplier (RM). The reliability ratio gives the marginal value of one minute standard deviation and the reliability multiplier the value of being one minute early or late. The value of reliability (VoR) can be calculated with formulas described below, with the use of the reliability ratio or the reliability multiplier and the value of time.

$$VoR = RR * S * VoT \tag{2.15}$$

$$VoR = \begin{cases} RM_E * AE * VoT \\ RM_L * AL * VoT \end{cases} \tag{2.16}$$

The way of expressing reliability in the reliability ratio is the same as the mean-variance approach. The reliability ratio is the same as dividing a_1 by VoT.

$$RR = \frac{a_1}{VoT} \tag{2.17}$$

The same sort of relationship can be found for the scheduling approach, the reliability multiplier can be calculated if the values of reliability (a_2,a_3,a_4) and the value of time are known.

The values for a_1,a_2,a_3,a_4,RR,RM_E, and RM_L are investigated in a large number of stated preference and/or revealed preference studies. In Fosgerau et al. (2008), Zheng et al. (2010) and Carrion et al. (2012) overviews are given of the different values found in different studies.

A major problem of the scheduling approach is to determine the expected travel time. Is the expected travel time the mean travel time, the median travel time, the free flow travel time, or something else. The median and free flow travel times will result in a large part of travelers arriving too late which is not likely because it is known that people value late arrivals higher than early arrivals (Fosgerau et al., 2008). With the assumption that people choose their departure time such that they minimalizes the total costs the expected travel time can be calculated if the travel time distribution is known. In Carrion (2012) it is stated that reliability is linked with unpredictable variation and that the perceived travel time (distribution) is different as the real travel time (distribution). Basically this means that people are not capable of choosing their optimal departure time. Li (2009) claims that for every travel time distribution the mean-variance approach and scheduling approach is the same. Li (2009) provides analytic proof of this statement.

Another problem in monetizing is that variables can be country-specific. In the Netherlands only a limited amount of studies for the value of reliability have been carried out. The ratios used by the Dutch government are from Hamer et al. (2005) and Kouwenhoven et al. (2005a). They use a reliability ratio to express reliability. Kouwenhoven et al. (2005a) found a reliability value for freight traffic on the road of 1.2. Hamer et al. (2005) found a reliability ratio of 0.8 for passenger traffic for all purposes of travelling. Carrion et al. (2012) did a regression analysis on the results of a lot of studies. The meta-analysis from, Carrion et al. (2012) found for the a.m. period for the Netherlands for the case only route choice and not mode choice is considered a reliability ratio of 0.9. This result is approximately the same as the ratio Hamer et al. (2005) proposed.

The possibility to monetize the different indicators for travel time reliability is limited. Only the standard deviation can be easily translated into a monetary value. With knowledge about the mean travel time the coefficient of variance could also be translated to a monetary value. In that situation, different indicators for determining the monetary value and the reliability of travel times are used.

2.1.6 Conclusion

In this subparagraph a decision for a specific indicator is made. Van Lint et al. (2008) and Palsdottir (2011) show that the decision for a specific indicator has significant influence on the results. They both applied the different indicators on Dutch traffic data.

The criteria introduced in 2.1.1 are used to make a decision for a specific indicator: The different indicators are ranked on these six criteria in table 2.1

Table 2.1: Ranking of indicators on criteria

		Statistical		Buffer time	Tardy trip	Probabilistic		Skew-width indicator		
Indicators		S	COV	BI	MI	PR1	PR2	λvar	λskew	SW
Travel time distribution	Value early arrival	+	+	-	-	-	-	+	-	+
	Incorporating skew	-	-	+/-	+/-	+/-	+/-	+/-	+	+
	Increasing convex	+	+	-	N/A	-	+/-	+	+	+
Stable results	Use median instead of mean	-	-	-	-	+	+	+	+	+
	No parameters well-known indicator	+	+	+/-	+/-	-	-	+/-	+/-	-
Monetizing	Monetizing reliability	+	+/-	-	-	-	-	-	-	-

From table 2.1 it can be seen that none of the found indicators meets all the requirements. The overall score of the standard deviation is the highest. Also the skew-width indicator has a relative high overall score. Although used in practice the misery index and the buffer index overall score is low.

The criterion that an indicator can be monetized is important. If the indicator could be translated to social costs, the outcome of the model could not be used in social cost-benefit analyses. Because the overall score of the standard deviation is the highest and it can easily be translated to a monetary value the standard deviation is chosen as indicator.

2.2 Rules of thumb

In this paragraph the quality of the forecast of the travel time reliability with a rule of thumb is investigated. First is explained how the reliability can be forecasted with a rule of thumb and what a used value for the rule of thumb is, subparagraph 2.2.1 In 2.2.2 the quality of the forecast is discussed.

2.2.1 Forecasting travel time reliability with a rule of thumb

As a rule of thumb, a linear relationship between mean delay and variation in delay is assumed together with a linear relationship between variation in delay and the valuation of travel time reliability as discussed by Besseling et al., 2004. They come up with the rule of thumb of 25% of the travel time savings can be additional added as reliability benefits. This value is used in the Netherlands in social-cost benefit analyses. In social cost benefit analyses for an infrastructure investment the travel time savings can be forecasted with a traffic model. The traffic model calculates the differences in the average traffic situation due to the chance in the infrastructure. The benefits of the infrastructure investment, the travel time savings can then be multiplied with 0.25 (25%). The calculated value is the forecast of the travel time reliability benefits.[1]

2.2.2 *Quality of the forecast with a rule of thumb*

The quality of the forecast with a rule of thumb is highly depended on a correct value for the rule of thumb. The value of the rule of thumb is not exactly known; different authors find totally different values. In 2.3.1, (Peer et al., 2012 and Eliasson, 2006) other values that could be used as rule of thumb are found, also Snelder et al. (2010a) and Palsdottir (2011) conclude that the rule of thumb does not accurately calculate the travel time reliability changes. Van der Loop (2012) investigated the ex-post relationship between the changes in vehicle loss hours and the changes in hours unreliability, for infrastructure investments in the period 2002 to 2010. For the investment in new road lanes 84% and for traffic management measures 86% of the travel time gains are reliability gains. This is a lot more than the rule of thumb found by Besseling et al. (2004).

The assumption of both the linear relationships is rather arbitrary. The first one, which assumes a linear relationship between mean delay and the variation in delay, is the most arbitrary. The traffic system has all kinds of spatial and time depended interdependence that cannot be explained by a linear relationship between the average travel time and travel time reliability. The underlying assumptions of the rule of thumb are arbitrary and several empirical studies found totally different relationships between mean delay and variation in delay (Peer et al., 2012, Eliasson, 2006 and Van der Loop, 2012). Because of these reasons the results calculated with a rule of thumb are sensitive to errors. The predictive validity of the results is low.

2.3 Regression analyses

In this paragraph forecasting travel time reliability with a regression analysis is explained. The outcomes of three regression analyses are summarized in 2.3.1. In 2.3.2 the quality of the forecast of the travel time reliability is discussed.

2.3.1 *Forecasting travel time reliability with a regression analyses*

The results of three regression analyses from Peer et al. (2012), Eliasson (2006) and Kouwenhoven et al. (2005b), respectively, are discussed. The most important characteristics of the regression analyses are depicted in table 2.2.

Table 2.2 Differences between regression analyses

Author	Data	Route/ link	Explanatory variable	Explained variable
Peer	NL motorways	Link	Mean delay	Standard deviation
Eliasson	Sweden, Urban roads	Link	TT/ free-flow TT	Coefficient of variance
Kouwenhoven	NL motorways	Route	speed	Probabilistic indicators

These three regressions are one by one discussed, in more detail.

Result regression analyses Peer et al. (2012)

Peer et al. (2012) fitted a relationship between the standard deviation of the travel time distribution and the mean delay of these travel times. In the paper two models

[1] The calculated benefits could theoretically be negative leading to cost instead of benefits.

are fitted: one that assumes that the expected travel times for all working days are the same. The second model assumes that the expected travel time is workday, weather class and season specific. It is argued that these factors are a priori known to drivers and do therefore not relate to unexpected variability. It is not surprising that model 2 leads two lower estimates of travel time variability, because a part of variability is assumed to be known.

Peer et al. (2012) state that for cost-benefit analyses only little or nothing is known about the relative shares of different traffic regimes. Traffic regimes are classes with different congestion levels. Shares of different traffic regimes can be known. Many dynamic traffic models, like INDY (Bliemer, 2004 and Yperman, 2007), use a fundamental diagram to calculate traffic flows. The relative share of different traffic states could be calculated. For more information about the relation between traffic states and travel time reliability, see appendix A. Peer et al. (2012) advise to use the outcomes of a model that has link length, number of lanes, free-flow speed and speed-at-capacity as explanatory variables. They show that for an average link of 10 km the model leads to a reliability benefit of 0.32 times the travel time under the assumption that the expected travel time is the same for all working days. The reliability benefit is 0.19 of the travel time gains under the assumption that the expected travel times are dependent on day of the week, weather conditions and the season. The outcome of the model of Peer et al. (2012) is close to the rule of thumb of Besseling et al. (2004) of 0.25. The reliability increases less than proportional to the length of a link and the mean delay. The link length is defined as the distance between motorway junctions.

The outcomes of the regression analysis are not linear for shorter delays and for longer delays approximate linear to the reliability. This phenomenon can be explained with the definition of delay. Delay is calculated by subtracting the free flow travel time from the measured travel time. The definition allows negative values for mean delay while the standard deviation is strictly above zero. This results in a function with relative high standard deviations (because of a lot of negative values that are in the dataset for relative low mean delays) for low mean delays.

The variables used in the analyses are not all logically related to travel timer reliability. There can be several reasons for a lower free-flow speed or lower speed at capacity. In The Netherlands speed reductions are used more on busy links around cities, i.e. the links where a higher unreliability would be expected. But this is not necessarily a general rule.

Another problem addressed by Peer et al. (2012) is that traffic management measures can have different impacts on the relationship between travel time and reliability, which makes the obtained results useless for cost benefit analysis. This is indicated as a direction for future research.

The results obtained by Peer et al. (2012) could be used to estimate travel time reliability. There are however a few important drawbacks of his approach. The definitions of the explained and explanatory value lead to in linearity’s in the results. The extra explanatory variables are not all logically related to travel time reliability and the results cannot be used for traffic management measures.

Results regression analyses Eliasson (2006)

Eliasson (2006) also performed a regression analyses on urban roads in Stockholm, Sweden. A strange outcome of his paper is that the variability is higher during night hours and lower during mid-day. Eliasson (2006) added a number of variables to his regression: number of lanes, number of intersections, speed limit, link length, volume-delay function and “type” of road. These variables did not make the model fit better. The outcomes of the regression analyses are used in a cost benefit analyses of the comparison of two alternatives. The reliability benefits are 15% of the total travel time savings. This result is lower than the rule of thumb found by Besseling et al. (2004).

Results regression analyses Kouwenhoven et al. (2005b)

Kouwenhoven et al. (2005b) preformed a regression analysis on the Dutch motorways. In difference to Eliasson (2006) and Peer et al. (2012), routes were considered instead of road links. Reliability was expressed in four different indicators: the probability indicators (2.1.2), the probabilistic indicators also valuing earlier arrivals, the 10^{th} percentile and the 90^{th} percentile. The regression analyses explain the reliability as a function of speed. In Peer et al. (2012) and Eliasson (2006) the reliability is explained as delay and relative increase in travel time (travel time divided by free-flow travel time) respectively. Kouwenhoven et al. (2005b) investigated the influence of accidents, road works and rain on the travel time reliability. His conclusion is that improvements in incident management and better road works planning have only a limited influence on the reliability. But he acknowledges that his dataset might be biased. The results of Kouwenhoven et al. (2005b) with the reliability ratio found by Hamer et al. (2005), see 2.1.5, were used for developing the tool LMS-BT, which is able to calculate the reliability benefits out of the results from Dutch national and regional models (LMS and NRM).

2.3.2 *Quality of the forecast with a regression analyses*

First the quality of the forecast is discussed on theoretical arguments. Secondly a comparison between observed traffic data and the results of the regression analyses is made.

The regression analyses from Peer et al. (2012), Eliasson (2006) and to some extend also the results from Kouwenhoven et al. (2005b) do not take spatial correlation of travel times between links into account, a drawback that is acknowledged by Peer et al. (2012). This is an important factor because road users observe reliability from their origin to their destination, which is not incorporated in the analyses. Many different kinds of correlations and interdependences are not taken into account:

- Rerouting of traffic because of certain local capacity reductions or local demand increase. For instance an event or car incident.
- The spillback of congestion of one link to another link has influence on the reliability of travel times of road users that travel over both links (Engelson et al., 2011)
- Events as weather conditions, public transport disturbances can influence the whole study area. Leading to an above average travel time on that day for that period of the day on all links. (Engelson et al., 2011)

- Negative correlation can also exist when upstream an incident reduces the inflow into a downstream link resulting in a lower than average travel time on the downstream link. (Engelson et al., 2011)

Since there is not a fixed relationship between travel time changes and reliability changes is shown by a series of empirical studies [Palsdottir (2011), Van der Loop (2012), van Lint et al.(2005), Higatani et al. (2009) and Fosgerau (2008)], because this relation does not exist approximations of the reliability changes with a regression analysis have a low predictive power. The empirical studies showing that there is no fixed relationship are discussed below in order of mention.

Palsdottir (2011) performed an ex-post evaluation of the consequences of opening of a rush hour lane, an extra lane, lower speed limit, dynamic route information panel and ramp metering on the travel time reliability. Palsdottir calculated the reliability impact for different indicators, next to travel time changes and vehicle loss hours. From these calculations it can be seen that the changes in the reliability (expressed in standard deviation, see 2.1.2) have no fixed relationship with the changes in travel times. In figure 2.3 and figure 2.4 the relationship between travel time and reliability found by Palsdottir is plotted. The reliability study of Palsdottir shows that there is no fixed relationship between travel time gains and reliability gains. The scatter of points in these graphs is so wide that regression analysis cannot accurately predict changes. The regression analysis always results in a positive relationship between travel time and standard deviation. The regression analysis would predict that all points are in the first quadrant (part of the chart where both axes are positive) and the third quadrant (part of the chart where both axes are negative). In figure 2.3 and figure 2.4 many data points are not in these quadrants.

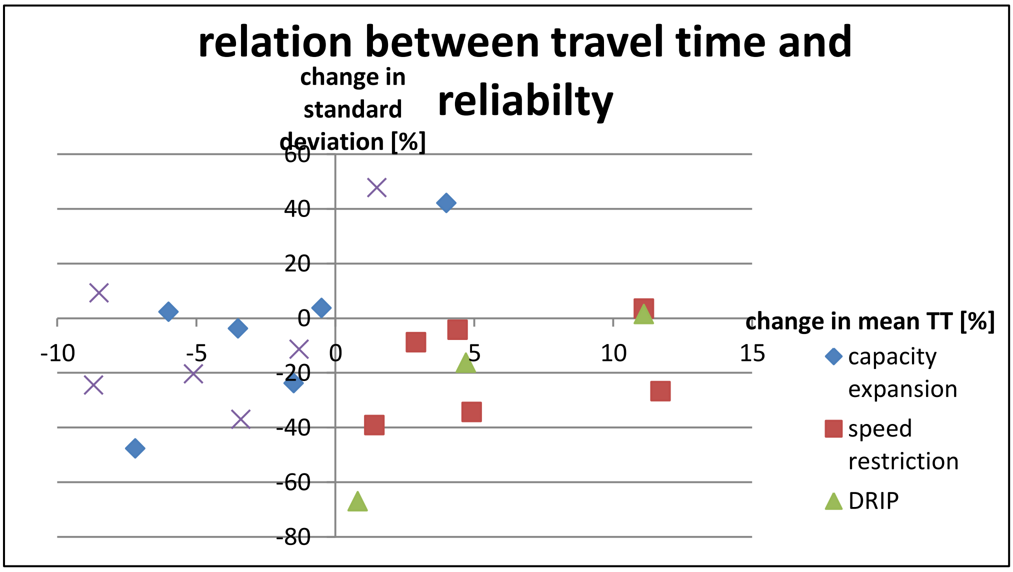


Figure 2.3 Relation between changes in mean travel time and standard deviation for different projects, data: derived from Palsdottir (2011)

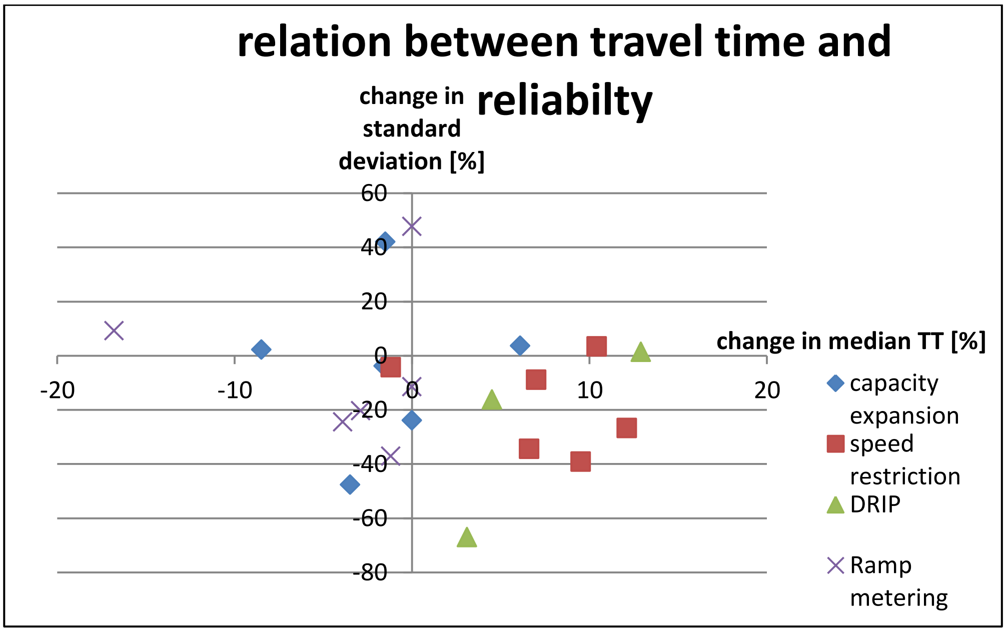


Figure 2.4 Relation between changes in median travel time and standard deviation for different projects, data: derived from Palsdottir (2011)

Van der Loop (2012) states that travel time changes differently than travel time reliability. Reliability changes in the same way as travel time losses, but the regression analysis described before explains reliability as changes in travel time and not in total travel time loses. This study of Van der Loop (2012) focuses on an aggregate relationship for the Netherlands.

Van Lint et al. (2005) showed that the reliability expressed in the width of the travel time distribution does not follow the curve of the mean travel time. The differences can be seen in figure 2.3. The differences between Friday mornings and Saturday are the most striking.

A Higatani et al. (2009) show for 5 motorway corridors in Japan that the average travel time is inconsistent with the uncertainty of travel times. Higatani et al. (2009) expressed travel time uncertainty in the buffer time index.

Fosgerau et al. (2008) showed that mean travel time and the standard

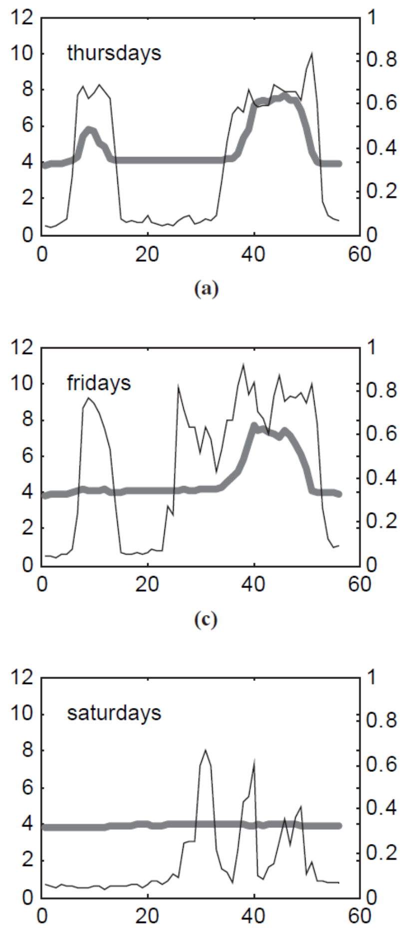


Figure 2.5: Relation between travel time (thick line) and reliability (thin line) indicated by the width indicator, Van Lint et al. (2005).

deviation are different curves with a different shape. If the travel time is plotted against the standard deviation there is a specific pattern recognizable. In the peak period with congestion these two variables make a counter clockwise round, for more information see appendix A. This means that during the dissipation of the congestion, high standard deviations are still measured but mean travel time is rapidly decreasing. Strangely enough, Fosgerau et al. (2008) does not come to the conclusion that using change in travel time as predictor of reliability is not accurate because of the not-linear behavior of these variables during different traffic states.

2.4 Traffic models forecasting reliability

In this paragraph different models that can forecast travel time reliability are described. The models will be investigated on eight aspects, which are discussed in 2.4.1. The traffic models that will be discussed are divided in three categories:

- Analytical approaches with momentum analysis
- Marginal traffic models
- Uncategorized traffic models

This categorization is chosen because the analytical models and the marginal traffic models have a lot of common characteristics within their category. The three categories of models are discussed in 2.4.2, 2.4.3 and 2.4.4 respectively. Finally, in 2.4.5, the applicability of traffic models to forecast reliability and the quality of the different models is assessed. A decision for a specific (group of) traffic model (s) is made.

2.4.1 Relevant aspects for modelling of traffic reliability:

The nine aspects on which the traffic models will be assessed are:

- Input
- Modeling of congestion
- Capacity drop
- Size of network
- Time step
- Route choice
- Intersection delays
- Output
- Calculation time

Input

The models are investigated by the kind of input they need or are able to handle. The input can be divided into two categories, general input that is also necessary for a traffic model that only calculates one value and input describing the variability in the traffic system. The spatial and temporal characteristics of the traffic system are better incorporated if the modeled incidents are modeled in a representative way. The result of the model will reassemble reality better when more sources of variation are incorporated.

Modeling of congestion

For all models the following questions are answered: How is the spillback of congestion modeled? Is the queue modeled vertically or horizontally? How is the dissipation of congestion modeled? The modeling of congestion must be as representative as possible, so with horizontal queuing and a representative way of congestion spillback.

Capacity drop

The central question is whether the capacity drop phenomenon is incorporated in the model? The capacity drop phenomenon means that the capacity in congestion drops (approximately between 10% and 15%, Goemans 2011) in comparison with the situation in free-flow traffic operation.

Size of network

The size of the networks that can be modeled with the model is relevant. The area that is influenced by large-scale infrastructure investments can be large. To be able to perform a reliability analyses for these large projects large networks must be modeled. Large scale networks, of at least a large city have to be modeled in reasonable amount of time (typically over a night).

Time step

Is the model dynamic and what is the time step of the model? Travel time reliability and various sources of variability are time depended. To model these various sources of variability in an accurate way, a dynamic model is needed. Travel time reliability can be described as a value for a peak period but within this period the reliability can change as well. It is the question to what accuracy people observe travel time reliability. People plan their departure time within a certain window, although this window will be different for everybody and all destination purposes. Generally differences of 5 minutes will not be noticed while differences of one hour or more will be noticed by the driver. The optimal time step of the model is not easy to determine because too small time steps will result in a too high computation time while a too large time step results in an inaccurate representation of traffic flows. Event based models in which time step is determined within the calculation can optimize the time step, and therefor calculate more efficiently.

Route choice

How is the route choice determined, and how can the model cope with en-route route choice in case of an incident? On which assumptions does the assignment technique rely? Which route choice is assumed in the average situation and what is done with the route choice with variable input?

Intersection delays

Are intersection delays modeled in an accurate way? The desired results from the model are from door-to-door. To be able to get a good forecast of the travel time from door-to-door, an accurate modeling of intersection delays on the underlying road network is needed. The delays on intersection can be modeled with point queues or spatial queues. Specific node models exist for different types of nodes: signalized intersections, roundabouts, un-signalized intersection with priority to the right.

Output

In this aspect the usefulness of the output is discussed. The following questions are answered: What is the output of the model? Can the output be used to monetize the reliability of the modeled disturbances? To be able to monetize the reliability a travel time distribution or a standard deviation has to be known.

Calculation time
The time necessary to obtain the results is an important factor. Although the aim is not to create a real-time model, the calculation time of the model must be within reasonable proportion, within a few hours.

2.4.2 Analytical approaches with moment analyses

This category forms a separate group of models that try to forecast travel time reliability with another strategy then the other discussed models that forecast travel time variability. The amount of repetitive calculation in traffic models is avoided as much as possible. The amount of input variables necessary for the model is also reduced to a minimum, because most input variables are not (accurately) known. Instead of repetitive simulations statistical moment analyses are used. All models aim at calculating the total system travel time. These models are discussed in Clark et al. (2005), Ng et al. (2010, 2011), and Ma et al. (2012). The models of Clark et al. (2005) and Ng et al. (2011) will be discussed in more detail. This subparagraph ends with a discussion about the quality of the forecast of reliability of this category.

Model of Clark and Watling:
The model proposed by Clark et al. (2005) aims at deriving a probability function of the total network travel time. The authors state that the results need to be obtained without making use of extensive Monte Carlo simulations, but using a more analytical approach. The O-D demand is modeled as a stationary Poisson random variable with constant mean above zero. The route choice fractions are modeled with constant probabilities. These probabilities are determined with a probit based, stochastic user equilibrium (SUE). Here Clark et al. (2005) needed to use Monte-Carlo simulations, for bigger networks the authors recommend to use Taylor series approximation of the SUE.

The probability function of the total network travel time is obtained by assuming that the function of the travel time on a link has a polynomial form.

$$\boldsymbol{tt_a(q_a) = \sum_{j=0}^{m} b_{ja} q_a^j} \tag{2.18}$$

The total link travel time is then the sum of the link travel time and the link flow. The total network travel time is given as the summation of all total link travel times. The first four moments of the total network travel times are computed. This is done with an analytical approach. These moments are fitted on a flexible set of probability functions.

Table 2.3: characteristics model Clark and Watling

Criteria	Assessment
Input	OD demand modeled with a stationary Poisson random variables
Modeling of congestion	Spillback of congestion is not modeled only delay on the link itself, link travel times expressed as a polynomial form, in example use of BPR function
Capacity drop	Not modeled, link travel times of polynomial form cannot deal with capacity drop
Size of network	Used in a small test network, can be extended to bigger networks within fast computation times
Time step	Independent realizations of OD fluctuations
Route choice	Constant route choice probabilities, (with varying OD demand no equilibrium assignment)
Intersection delays	Not incorporated
Output	Probability function of the total travel time distribution
Calculation time	Fast; the model exists of analytical expressions.

Model of Ng, Szeto and Waller[2]

The model of Ng et al. (2011) is also based on an analytical derivation, with the use of moments of the travel time distribution. It is different from the approach of Clark and Watling in the use of the Input variables. In Ng et al. (2011) paper the first N moments of the travel time has to be known. With this input it calculates upper boundaries of the probability function of the total network travel time. Surprisingly the input of the model is a set of travel times. These are necessary to calculate the first N moments. The output of the model is less valuable information as the input of the model. This model cannot be applied for ex-ante studies simply because the measurements of future travel times haven't been acquired.

The model assumes that all sources of variability are accounted for as long as they are statistically independent. The authors claim that in their framework demand/link flow variations cannot be modeled because they are not statistically independent; they claim that their model is valid for small capacity variations because of minor traffic accidents. Total link travel times are assumed to be independent random variables. This is an assumption that is used in a lot of the other analytical models with the use of statistical moments. The assumption of independent link travel times makes all these models not able to model demand differences or spillback due to a source of variability.

[2] Source of all information is Ng et al. (2011)

Table 2.4: characteristics model Ng, Szeto and Waller

Criteria	Assessment
Input	Moments of the link travel time and upper and lower boundaries for the link travel times
Modeling of congestion	Not incorporated, the sources of uncertainty are assumed to be spatial independent
Capacity drop	Not modeled
Size of network	The hole procedure is based on analytical derives upper bounds of the total system travel time. A big network can rapidly be calculated
Time step	Independent realizations, de dependency in time is not taken into account
Route choice	Not considered
Intersection delays	Not incorporated
Output	Upper boundary of the probability function of the total system travel time
Calculation time	Fast: the model exists of analytical expressions.

Conclusion analytical approaches with moment analyses

The positive side of analytical models is that these procedures can be applied to large networks with a fast computational time. Negative aspects of these models are that they have stringent assumptions. All these papers calculate the probability function of the total network travel time, where in this thesis the aim is to calculate the probability function of specific OD pair or route. There is mostly a limited amount of input variables, for instance in the model of Clark et al. (2005) the OD demand is a stationary Poisson random variable with a constant mean. All sources of variability have to be modeled by changing this input variable. Relations between the traffic system and sources of variability cannot be modeled, or only in a very limited way.

Another stringent assumption in a few of these papers is that the link travel time is assumed to be an independent random variable. This means that the sources of variability must be independent of time and space. This assumption for instance does not allow for differences in demand or spillback of congestion to other links. Most sources of variability will result in changes in demand or spillback of congestion.

2.4.3 *Marginal computation*

Two marginal models are described by Corthout (2012). The idea of a marginal model is that the consequences of a variation are calculated by calculating the differences with a base simulation. In this way only a small part of the network is computed, i.e. the part of the network (in time and space) that is affected by an imposed change to the base situation. A marginal model needs the output of a base model that first simulates the average or normal traffic situation. The output of the base model is then used as input for the marginal model. The benefit of this procedure is that it can calculate small differences in the traffic situation fast. The two marginal models described by Corthout (2012) are using the LTM assignment technique as base model (see 3.2.1 for more information about LTM assignment). The two marginal models developed by Corthout are called MIC (marginal incident computation) and MaC (marginal computation). MIC and MaC are discussed in more detail below.

MIC model (Corthout, 2012):
The results from the base simulation are loaded in the form of cumulative vehicle numbers (CVN) at all links, at the beginning and the end of the link. Also the CVN to all direct downstream links have to be known. These results can be obtained from a dynamic network loading model such as the LTM-assignment model. The network of the dynamic traffic assignment model has to be loaded into MIC and the incident characteristics: the duration of the capacity reduction, the location and the capacity reduction due to the incident.

The model can calculate large networks within a reasonable amount of time. The MIC module calculates the output 100 times faster than a full LTM-assignment. The simulation of 76 incident scenarios in a small network of Sioux Fall (24 origin and destinations, 76 links and 1752 routes) takes 11 seconds. Snelder (2010) used MIC on a larger network for her optimal redesign of the Dutch main roads.

A set of affected links per incident are calculated; at these links there is another flow as in the base simulation. For these affected links this following output can be generated:

- For the affected links new cumulative vehicle numbers are printed;(It is possible to calculate the CVN outgoing link specific, then there are several cumulative vehicle numbers per link.);
- Vehicle hours lost for each affected link are calculated;
- Travel time of each affected link is calculated;
- Route travel times of all affected routes are calculated.

Table 2.5: Characteristics of the MIC model

Criteria	Assessment
Input	Local capacity reduction and duration
Modeling of congestion	First order traffic flow theory
Capacity drop	Not modeled
Size of network	Large number of incidents can be modeled in large networks
Time step	Event based, depended on speed of congestion spillback
Route choice	Base run with an equilibrium assignment, with imposing the local capacity reductions the same route choice as the base run is assumed
Intersection delays	In MIC not incorporated, in the base model it can be incorporated
Output	The links and routes with different values then the base run will be reported
Calculation time	Fast: consequences of 76 incidents in 11 seconds

MaC model (Corthout, 2012):
As input for the MaC model the network characteristics (links and nodes) routes (choice) and dynamic OD matrix are used. This information is also necessary for the base run in LTM. Out of the base run the following things have to be known: CVN at upstream and downstream links, turning fractions on downstream end of a link, dependency of the base turning fraction to traffic demand (this is a numerical approximation). The characteristics of the variation: changes in O/D demand or changes in route demand, or changes in local capacity variation. For all these characteristics also the duration of the change have to be known.

The model can handle large networks. The modeling of 2032 OD demand variations in a network with 32 origin destination pairs, 992 links and 2032 routes costs 62 minutes. The computational gain in comparison with repetitive simulation with the LTM model is a factor 25.

The time step of the assignment is the same as in the LTM model. The changes in the turning fraction on demand changes are calculated less often. The recalculations of changes in the turning fractions are out of computational efficiency in the order of several minutes.

Because the MaC module works with turning fractions the whole route travel time equilibrium point is destroyed and cannot be guaranteed. For small demand changes the differences between the equilibrium output of LTM and MaC are reasonably small.

Table 2.6: characteristics MaC model

Criteria	Assessment
Input	Local capacity reductions and duration of the reduction, changes in O-D demand changes and route demand changes
Modeling of congestion	First order traffic flow theory
Capacity drop	Not incorporated
Size of network	Big network can be modeled fast
Time step	Event based: smaller than the smallest free flow travel time of a specific node
Route choice	Base run with an equilibrium assignment, with imposing the sources of variability the same route choice as the base run is assumed
Intersection delays	Can be incorporated
Output	Time depended flows an all links that are enough changed from the base simulation. And secondary link travel time, route travel time and vehicle loss hours can be calculated.
Calculation time	Fast: 2032 demand differences take 62 minutes.

Conclusion

A Positive thing about marginal simulation is that the base model has a realistic representation of the traffic system. The variations can be calculated with relative small errors to the base simulation and with significant reduction of the calculation time. Negative about these models is that they are not able to deal with en-route rerouting in a straightforward way. The implementation of an en-route rerouting model in MaC is investigated (Corthout, 2012 appendix G). In small test networks the functionality of the en-route rerouting algorithm proposed by Pel et al. (2009) is demonstrated. For larger networks the en-route rerouting model in MIC and MaC will be computational demanding, and difficult to implement.

2.4.4 Uncategorized traffic models forecasting travel time reliability

In this subparagraph models are discussed that are not a marginal traffic model or an analytical model and can forecast travel time reliability. The models discussed in the papers of Mehran et al. (2009), Dong et al. (2011), KAPASIM, MacroSim, Miete (2011) and SMARA. These models will be separately discussed below; KAPASIM and MacroSim will be discussed together.

Model of Mehran and Nakamura:

The model of Mehran et al. (2011) uses specific input variables to model travel time reliability. This model was applied to an expressway in Japan of 9 kilometer length. This expressway does not have on- or off-ramps. On this corridor the

consequences of opening the hard shoulder for traffic is investigated. The same demand input variables between the two scenarios are assumed. Extra demand because of the extra supply of infrastructure is not incorporated in the assessment.
The input variables used in this model are: demand variations over the months and over the days (Monday to Saturday, Sunday and holidays, consecutive holidays, special days) random demand fluctuation between two time steps and demand factors for rain fall. Capacity variations are modeled with a Weibull distribution and reduction factors for rain fall were applied. Sampling of accidents as a function of the traffic density, the accident duration is modeled with Weibull function, the capacity reduction is modeled with fixed factors.

The modeling of the congestion is done in great detail by applying shockwave theory to an empirical fitted flow density curve and incorporating the capacity drop. With 5 minutes, this is huge time step for a dynamic model, but with one link of 9 kilometer with no on or off ramp this is approximately the travel time of one vehicle. Shockwave theory can still produce a good approximation with this time step. Only such a detailed horizontal description of the congestion becomes really interesting if blocking back occurs. In this paper only a road stretch is considered so no spillback to other roads is considered.

The output of the model is the buffer time index (see 2.1.2 Indicators) that is a function of the time of the day. The 95th percentile is used instead of the 90th percentile. To be able to calculate the buffer index a travel time distribution is calculated.

Table 2.7: Characteristics of the model by Mehran and Nakamura

Criteria	Assessment
Input	Demand variations, capacity variations, capacity and demand variations because of weather, speed and capacity reductions because of accidents.
Modeling of congestion	First an speed-flow curve is fitted to empirical data, this fitted relationship is used in the application of shockwave theory
Capacity drop	10% capacity reduction
Size of network	A road stretch is considered, not a whole network
Time step	Every 5 minutes interval a new calculation is carried out and new input variables are determined
Route choice	Not incorporated, only one road stretch considered
Intersection delays	Not incorporated
Output	Buffer time index, intermediate also a travel time distribution is calculated so all kind of other outputs can be derived from this
Calculation time	Not mentioned

Model of Dong and Mahmassani
In the paper of Dong et al. (2011) a bottleneck is investigated. The stochastic behavior of the traffic brake-down phenomenon is modeled with macroscopic probability function in microscopic model. The macroscopic input variables are a probability function of traffic breakdown with a given inflow and a probability function of the speed during breakdown. The congestion wave speed is determined with a probability function of the time and space displacement of individual drivers.

Spillback is not considered explicitly in this paper because the traffic breakdown phenomenon of one potential bottleneck is considered. But the model is based on the stochastic version of Newell's car following model. The LTM assignment (3.2.1) relies on the deterministic variant of the car following model by Newell. From the results spillback could be constructed. Measurements downstream a bottleneck or in recovering traffic situation are not modeled. So the capacity drop does not have to be incorporated. The car following model of Newell is also not capable of dealing with the capacity drop. The time till recovery is only a function of the sampled speed at traffic breakdown. This is a big simplification of the world, when microscopic traffic model is used. A properly calibrated model is able to model that by its own not of the result of some aggregated relationship.

The output of the model is a flow-density relation. The free flow measurement (all with the same speed) and congestion measurements with flow, speed and density and specific congestion duration. The congestion measurements are a function of a stochastic determined congestion wave speed and a pre-breakdown flow rate and a stochastic determined speed at traffic breakdown. The notion of differing conditions in congestion and the interdependence with the measurements of 15 minutes intervals (of the observed data) is not incorporated. It is not clear what exactly they claim is the outcome of the proposed model.

Table 2.8 characteristics model Dong and Mahmassani

Criteria	Assessment
Input	Probability functions of: a traffic breakdown, speed during breakdown, time displacement and space displacement of individual drivers
Modeling of congestion	Not explicitly modeled, can however be derived from input variables
Capacity drop	Not incorporated
Size of network	One bottleneck
Time step	Independent realizations
Route choice	Not modeled
Intersection delays	Not modeled
Output	Flow-density relation
Calculation time	Not mentioned

KAPASIM, MacroSim

At the Ruhr University Bochum, Germany, the KAPASIM model was developed (Brilon et al., 2009). This model uses stochastic capacity and demand as input and is a model with a simple deterministic queue. MacroSim models congestion with a macroscopic traffic flow model.

The variability input is random generation of capacity and demand for every 5 minutes. The random capacity is a function of road geometry, weather conditions and incidents. Accidents and car breakdowns are randomly generated, with a typical accident and car breakdown rate. The effect of the accidents and car breakdowns are derived from the Highway Capacity Manual. The probability of rainfall is based on monthly coefficients.

Spillback is not incorporated in the KAPASIM model, because the congestion is modeled with a horizontal queue. In MacroSim vertical queuing is implemented. However, in the information provided it is not described how the algorithm for the vertical queuing looks like.

The motorway network of a whole province can be modeled in MacroSim, In KAPASIM only a freeway stretch is considered; in this model spillback is not modeled. Therefore network effects would be hard to model.

Table 2.9: Characterization of MacroSim and KAPASIM

Criteria	Assessment
Input	Random demand and capacity variations, weather and incident consequences modeled
Modeling of congestion	In MacroSim a kind of vertical queuing
Capacity drop	Incorporated
Size of network	MarcroSim a hole province in Germany can be modeled
Time step	5 minute interval (KAPASIM)
Route choice	No Information
Intersection delays	Not incorporated
Output	Different reliability indicators
Calculation time	Not mentioned

Model Miete (JDSMART)
This model was developed by Onno Miete during his graduation project at the Delft University of Technology (Miete, 2011). The proposed model is extensively documented in his Master Thesis. All aspect mentioned in 2.4.1 will be discussed.

Input: new demand and supply characteristics are determined for every 5 minutes. Mainly discrete choice probabilities to determine the variability of:

- Demand variations of the time of the day
- Demand coefficients of the day of the week
- Demand coefficients of the month of the year
- Demand coefficients for vacations
- Demand coefficients for special days
- Demand and supply coefficient for weather conditions (black ice, snow and fog)
- Supply coefficient for darkness
- Supply coefficient for different driver populations
- Variation in the percentage of truck drivers, during the day end between days
- Demand changes because of events
- Supply coefficient for incidents (depended on the amount of traffic on a link)
- Supply coefficients for small road works
- Supply changes due to intrinsic variability in human driving behavior
- Demand changes due to intrinsic variability in human travel behavior

Spillback: For modeling congestion the model JDSMART is used, which is a cell transmission model that is able to simulate congestion on the basis of first order traffic flow theory. This is a realistic way of modeling congestion.

Capacity drop: Capacity drop is included by lowering the potential outflow out of a cell with high densities. The capacity drop is not explicitly modeled due to the problems with discontinuity and potential high speeds of the congestion wave speed, these high speeds are unrealistic and not found in reality.

Network: For the results Miete (2011) uses the road network of the Rotterdam area. The runs with the model in this simple network take several minutes. For a reliability assessment one needs a travel time distribution with a lot of simulations. Now the results are in order of one day for one travel time distribution.

Time step: 5 seconds, for good functioning of the numerical solution of the cell transmission model the time step has to be chosen small enough. Only the computational time increases significantly with lowering the time step. Miete claims that a smaller time step would be desirable but is practically not feasible because of the higher computation time.

Route choice: route choice in the base run on the basis of free-flow travel time and not on an equilibrium assignment. The turning fraction are kept, destination specific, constant.

Intersection delays: Miete does not tell how intersection delays are modeled. But JDSMART is able to explicitly compute green times of signalized intersections and for not signalized intersections a linear decreasing turn capacity function is implemented in the model (Van Hinsbergen et al., 2008)

Table 2.10: characteristics model Miete

Criteria	Assessment
Input	Demand and capacity variations of a large number of sources of variability is incorporated
Modeling of congestion	First order traffic flow theory
Capacity drop	Implicitly the capacity drop is modeled. By lowering the potential outflow at higher density's
Size of network	A simple network of a big city is modeled
Time step	5 seconds
Route choice	Base run the route choice is determined with free-flow travel times, in determining the variability the destination specific turning fractions are kept constant
Intersection delays	Used model is able to model intersection delays
Output	Vehicle lost hours, travel time distribution
Calculation time	Slow: one day for a travel time distribution

SMARA

SMARA is a model developed at TNO and was described by Schrijver (2004), Schrijver et al. (2007), Meeuwissen et al. (2004) and Carlier et al. (2003). It calculates travel time reliability between zones and uses a static transport model. Discrete choice probabilities are imposed with the use of a Monte Carlo technique. The static transport model that SMARA uses is called SMART.

A network for the whole Netherlands can be modeled. The model has between 400-500 origin and destination zones. In 2004 a simulation with SMARA took about one night. Currently the same simulation can be done in a few minutes.

In SMARA, at least 400 simulations are needed to obtain a good image of the travel time (distribution). The claim is that with 400 simulations the approximation error due to the amount of simulations is less than 5%.

Out of social economic data and network characteristics of public transport and road network a mode specific OD matrix is constructed in SMART. In the assignment of the road transport specific OD matrix, a deterministic user equilibrium is performed. In SMARA two options are open, the first one is a totally new user equilibrium and the second one is the same route choice as in the base model.

The output of the model is the standard deviation (compared to the definition given in 2.1.2 the number of observations is used instead of number of observation minus 1) and frequencies tables of travel times in a certain category.

Table 2.11: Characterization of SMARA

Criteria	Assessment
Input	Seasonal effects, events, incidents, weather and road works are modeled
Modeling of congestion	Spillback of congestion is not incorporated, use of a fixed speed flow realization that look like the BPR function
Capacity drop	Not modeled
Size of network	The Netherlands, with 400-500 zones can be modeled
Time step	Static model. Two different models for peak and off-peak
Route choice	Base run is done with deterministic user equilibrium, the reliability can be modeled with a full new equilibrium assignment and with the same route choice as in the base run
Intersection delays	Not incorporated
Output	Standard deviation and frequency tables of travel time categories
Calculation time	Fast: standard deviation can be calculated in a few minutes.

2.4.5 *Conclusion*

Three possibilities of forecasting reliability are assessed. Rules of thumb (2.2) and relations between travel time and travel time reliability (2.3) are based on assumptions that are not valid. There is no linear or smooth relationship between travel time gains and reliability changes, since there are spatial and time depended interdependencies. With a traffic model these interdependencies could be taken into account. In the remainder of this thesis the focus will be on traffic models. The traffic models discussed before are compared on the aspects of section 2.4.1 in table 2.12. In table 2.13 the scale for giving a + or – is explained.

Table 2.12: comparison different traffic models

		Input	Modeling of congestion	Capacity drop	Size of network	Time step	Route choice	Intersection delays	output	Calculation time
Analytic	Clark et al.	-	-	-	-	-	0	-	-	+
	Ng et al.	-	-	-	-	-	-	-	-	+
Marginal models	MIC	0	+	-	+	+	+	-	+	+
	MAC	+	+	-	+	+	+	+	+	+
Uncategorized traffic models	Mehran et al.	+	+	+	-	+	-	-	+	?
	Dong et al.	0	0	-	-	-	-	-	0	?
	KAPASIM	+	0	+	-	+	-	-	+	?
	MacroSim	+	+	?	+	+	?	-	+	?
	Miete	+	+	0	-	0	0	+	+	-
	SMARA	+	0	-	+	-	+	-	+	+

Table 2.13: Scale for +, 0 and -

Criteria	+	0	-
Input	Multiple sources of variability could be modeled	One source of variability of too simplified modeling of sources of variability	Sources of variability are not modeled explicitly
Modelling of congestion	Horizontal, with spillback of congestion	Horizontal, with volume delay function	Vertical
Capacity drop	Incorporated	A rough estimation	Not incorporated
Size of network	The model is used on a network of more than 300 links	-	The model is not used on a network of more than 300 links
Time step	Dynamic models with time steps >5 sec.	Models that need small time steps ≤ 5 seconds	Static or independed realizations
Route choice	Incidents are modeled with a new equilibrium or the same route choice as in an equilibrium situation without an incident	Route choice based on free flow travel times	No route choice
Intersection dealays	Incorporated in the model	-	Not incorporated in the model
Output	Travel time distribution or standard deviation	Flow-density relationship	Total system travel time
Calculation time	Output could be obtained within 2 hours	Output could be obtained within a night	Longer then a night

The results in table 2.12 give a picture on the performance of the different models. The analytical models from Clark et al. (2005) and Ng et al. (2011) preform on most selected aspects worse. The line of reasoning used in these papers is different from our reasoning. In these papers the sources of variability are approached as a black box.[3] This is a problem because the relationship between sources of variability and the variability are not modeled explicitly. Changes in sources of variability can therefore not be modeled, and logical interdependencies between the traffic flows and sources of variability cannot be modeled. This group of models is not further investigated because of these drawbacks.

The models of Mehran et al. (2011), Dong et al. (2011) and KAPASIM only simulate one road stretch. It is possible to make a model for every road stretch in the studied area, but still the spatial interdependencies cannot be taken into account. The spatial correlation mentioned by the assessment of the regression analysis (page 17) cannot be taken into account with these models. Also these models are not further investigated in this thesis.

The nine aspects of traffic models (2.4.1) that forecast travel time reliability can be further reduced. With a further reduction of the aspects the current challenges in

[3] The group of analytical models have this black box approach of the sources of variability in common with the earlier discussed methods: regression analyse and rules of thumb, in which the sources of variability are not explicitly considered.

forecasting travel time reliability stands for, can be better explained. Three aspects that are interrelated are important, namely:

- Number and quality of the input used to simulate variability;
- The size of the network in relation to the calculation time of the model;
- An accurate discretion of the traffic system.

These aspects and their interrelation are graphically presented in figure 2.6. The aspects mentioned in (2.4.1) could be divided into the three aspects mentioned above. The time step, the network, and the calculation time are related to the calculation time, and the modeling of congestion, incorporating the capacity drop, the assumptions about route choice and intersection delays are a part of the accurateness of the modeling of the traffic flows.

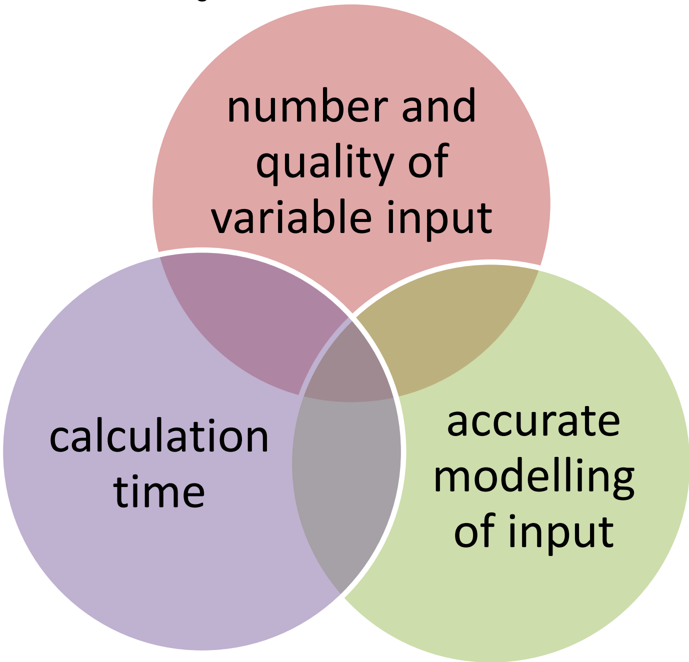


Figure 2.6: Problems in forecasting travel time reliability

Improving one of the aspects in figure 2.4 will increase the problems of the other aspects. For a good forecast of the travel time reliability a traffic model is needed that has a good tradeoff between these three aspects. The marginal models combine an accurate modeling of the traffic flows with a lot faster calculation time then explicit simulation of all sources of variability. This is done in the model developed by Miete (2011). To make a decision for a traffic model also not totally theoretical, arguments like the availability of the model play a role. Because of the overall strong performance of the marginal models in table 2.12, and the strong performance in terms of the calculation time and accurateness of the modelling of traffic flows and the availability of the models for this master thesis the marginal models are chosen.

3 Model formulation

In this chapter a model is proposed to forecast travel time variability due to incidents on routes.

First the input variables to simulate incidents are determined in 3.1.

The traffic models used are described in detail in paragraph 3.2. All models are based on first-order traffic flow theory. The estimation errors of the models in relation to this theory are described here.

How the different models are used to forecast travel time variability due to incidents is explained in 3.3.

The assumptions used in the model under consideration, forecast travel time variability, are described in paragraph 3.3.

3.1 Input variables

In this paragraph the input variables for the variation are determined. To model an incident, three input variables are needed viz:

- the incident probabilities;
- the duration of the capacity reduction;
- the capacity reduction because of the blockage.

To be able to model incidents input variables that describe the correlations between these three input variables are needed. Although the three input variables should be coupled they will be discussed separately in 3.1.1, 3.1.2, and 3.1.3.

3.1.1 Incident probabilities

The incident probabilities are linked in a number of studies to duration and capacity reduction. In these studies the incidents or accident probabilities are also linked to other variables. An overview of the used variables for the incident probability per vehicle kilometer is given in table 3.1.

Table 3.1: explanatory variables of the incident risk

Source	Explaining variables	Classes
Snelder et al. (2011)	Period of the day	morning peak/evening peak/rest day
	Amount of traffic on a link	<50.000 vehicles a day/>50.000 vehicles a day
	Flow capacity ratio	<0.5/0.5-0.6/0.6-0.7/0.7-0.8/0.8-0.9/0.9-1
	Number lanes	1/2/3/4
	Vehicle composition	car / truck
	Rain	<1mm hour^{-1}/> 1 mm hour^{-1}
	Type of incident	breakdown/accident
	Road geometry	onramp/off-ramp/merging/ normal
	Area	the regional traffic authorities
	Type of traffic measure	right lane/left lane/ two lanes/ complete blocking

Snelder et al. (2010b)	Type of incident	breakdown/ accident with injuries/ accident without injuries
	Road geometry	onramp/off-ramp/merging/ normal
	Number of lanes	1/2/3/4/5
Mehran et al. (2009)[4]	Congestion	free flow / congestion
	Density	continuous function
Higatani et al. (2009)	Period of the day	morning peak/evening peak/rest day
Miete (2011)[5]	Type of incidents	breakdown/accident
	Driver population	peak/off-peak/Saturday/Sunday
	Vehicle composition	Car/truck
	Weather	snow/black ice/fog/no adverse weather conditions
Schrijver et al.[6] (2004)	Type of incident	breakdown on a hard shoulder/ accident on a hard shoulder/ accident blocking 1 or more lanes
	Number of lanes	1/2/3/4
	Type of road	motorway /major road/secondary road
	Period of the day	peak/off-peak

From all these studies Snelder's et al. (2011) is the most elaborated one. Schrijver et al. (2004) and Miete (2011) base the probability on some assumptions and some general values whereas the 2 studies of Snelder determine the incident probability based on registered data for a large number of explanatory variables. Not all the variables investigated in Snelder et al. (2011) and Snelder et al. (2010b) explain that much and between the studies are some differences, probably because in Snelder et al. (2011) the calculations are based on incidents with a traffic measure and in Snelder et al. (2010b) on all reported incidents. Road geometry is a good example of the difference between the two studies.

One of the major drawbacks of Snelder et al. (2011b) is that the incident probabilities are determined for the incidents with a traffic measure. The incidents with a traffic measure only account for a small percentage (32%) of all the delay due to incidents on motorways (Snelder et al. 2011). The positive element on this study is that the relationship between traffic measures and the closing of lanes and the duration of an incident is investigated.

The incident probabilities of Snelder et al. (2011) will be used in the model for this master thesis. Only a limited amount of explanatory variables used in this study will be used in the model. Rain is also left out of the explanatory variables because it is not exactly known which influence rain has on the probability of incidents and it is more complex to deal with this possible interdependency (in the chapter 7 the recommendation, this topic will be discussed too). The differences between the regional traffic centers is also left out because it is not known if the differences are due a different registration rate or a lower probability of incident The variables where the incident probability is dependent on: number of lanes, time of the day.

[4] Based partly on Hikosake et al. (2001)
[5] The input variables are partly based on PB Farradyne, 2000
[6] Bases on AVV 2002a and AVV 2002b

$$P(incident) = f(\,number\ of\ lanes, time\ of\ the\ day) \tag{3.1}$$

The incident probabilities can be depended on what kind of incident occurs. The different classes that can be found are:

- type of incident (accident/breakdown)
- type of traffic measure
- type of vehicle (car/truck)

These incident probabilities are only valid for incidents with a traffic measure and on motorways. For non-motorway roads and for incidents on a motorway without a traffic measure less information is available about the duration and the capacity reduction. There is information about incident risks but for these incidents it is more difficult to couple these to incident duration and capacity reduction. The factors for other road types are discussed in 3.1.4.

In table 3.2 the quantitative difference in the incident probability between different studies can be seen. The chosen probabilities are low in comparison with other studies that do not filter between car breakdown and accidents with a traffic measure and without a traffic measure.

Table 3.2 Incident probabilities for different studies

Study	Vehicle breakdown 10^6 vehicle km	Accidents per 10^6 vehicle km
Snelder et al. (2011)[7]	0.054	0.11
Snelder et al. (2010b)	1.354	0.918
Snelder et al. (2010b) (traffic measure)	0.042	0.15
Miete (2011)	1.5	0.5
Schrijver et al. (2004)	2.87	0.64

3.1.2 *Capacity reduction*

The incident duration is explicitly coupled to the type of traffic measures that are taken. The capacity reduction can easily be calculated by subtracting the capacity off the blocked lanes from the original capacity. The open lanes have a lower capacity in case of a traffic incident due to distraction and unfamiliar traffic situation.

The capacity reduction is calculated by lowering the original capacity by the number of lanes that are closed multiplied by 0.54 for the less efficient use of the remaining capacity (Knoop, 2009). This figure is chosen because it is recently calculated based on Dutch motorway data. The only problem is that the efficiency of the remaining capacity is compared to the maximum capacity in congestion. The maximum capacity in congestion is usually lower than the capacity in free-flow traffic state. Because the models used are not able to handle this phenomenon the figure is not corrected for this inconsistency. The figure is estimated for a road with 3 lanes, which presumably, this relation is the same for roads with other number of lanes.

3.1.3 *Incident duration*

Preferably the duration of an incident is modeled with a probability function. The incident durations that will be simulated are from Snelder et al. (2011). The capacity

[7] Figures determined with the assumption 10% truck traffic and 90% car traffic.

reduction and the incident duration can be modeled in a deterministic way or a stochastic way. The capacity reduction and the incident duration are in reality not always the same and will vary. As there is not much information about these random fluctuations, and because a great many different incident durations for different types of incidents are used, the capacity reduction and the incident duration with a deterministic value are modeled.

3.1.4 Input variables lower leveled roads

On the Dutch main road network the incident probabilities have been investigated. In the model also non motorway roads are represented. The incident probability on those roads is likely to be different. To determine the incident probabilities on these roads a factor is used. Most roads in the main road network are motorways; the other road types are compared with these motorways. There was no accurate information about the car breakdowns and accidents on different types of roads. Instead data of the SWOV from 1998 are used to calculate the victims per vehicle kilometer. The factors are determined from data of Janssen (2005).

Table 3.3 factors for incident probity other types of road then motorways. Data: Janssen (2005)

factors different types of road	**victims/ vehicle kilometer**	**relative to motorway victims/veh*km**	**Relative victims/veh*km rounded value, used in model**
Motorway (Dutch: autosnelweg)	0.085119	1	1.0
Smaller motorway (Dutch: autoweg)[8]	0.128685	1.511821508	1.5
Country road closed for slow traffic	0.302698	3.556152385	3.6
Country road open to all traffic	0.5969	7.012496362	7.0
Major urban road	1.181534	13.88090003	13.9
Residential urban road	0.783506	9.204787872	9.2

3.1.5 Used input variables for the modeling of incidents

Car breakdowns and car accidents on the road network are simulated to forecast travel time variability. The consequences of an incident with a car or a truck differ from each other. An incident with a truck has a longer incident duration and a larger capacity reduction. Therefore a distinction is made between accidents and breakdowns of cars and trucks. To be able to link an incident to duration and capacity reduction the different types of traffic measures are linked to the incident probability. On a motorway link at a specific time 12 different temporary capacity reductions can be identified. These 12 classes are depended on two other variables that explain the incident probability.

$$\boldsymbol{P}(\boldsymbol{incident}) = \boldsymbol{f}(\ \boldsymbol{number\ of\ lanes}, \boldsymbol{time\ of\ the\ day}) \qquad (3.1)$$

[8] In The Netherlands a distinction is made between two types of motorways. Smaller motorways have normally a speed limit of 100 km/hour, and level crossings can occur. Motorways have normally a speed limit of 120 km/hour or 130 km/hour, and no level crossings are present. Motorways have a safer / more robust road design then smaller motorways.

The input variables used in the model are discussed in 3.1.1. These models are valid in a morning peak the same tables could be derived from Snelder et al. (2011) if the time between peaks or the evening peak is modeled.

Table 3.4 Input variables morning peak road with 4 lanes or more

Incident type	Probability 10^6 car/ truck km	Duration in min.
Accident with car, road closed	0.012649	25
Accident with truck road closed	0.015902	61
Breakdown with car road closed	0.005421	13
Breakdown with truck road closed	0.014456	31
Accident with car 1 lane closed	0.049016	25
Accident with truck 1lane closed	0.061621	61
Breakdown with car 1 lane closed	0.021007	13
Breakdown with truck 1lane closed	0.056019	31
Accident with car 2 with lanes closed	0.072734	25
Accident with truck 2lanes closed	0.091437	61
Breakdown with car 2 lanes closed	0.031172	13
Breakdown with truck 2lanes closed	0.083125	31

Table 3.5 Input variables morning peak road with 3 lanes

Incident type	Probability 10^6 car/ truck km	Duration in min.
Accident with car road closed	0.020677	26
Accident with truck road closed	0.025994	73
Breakdown with car road closed	0.008862	15
Breakdown with truck road closed	0.023631	30
Accident with car 1 lane closed	0.055055	26
Accident with truck 1lane closed	0.069213	73
Breakdown with car 1 lane closed	0.023595	15
Breakdown with truck 1lane closed	0.06292	30
Accident with car 2 with lanes closed	0.0588	26
Accident with truck 2lanes closed	0.07392	73
Breakdown with car 2 lanes closed	0.0252	15
Breakdown with truck 2lanes closed	0.0672	30

Table 3.6 Input variables morning peak road with 2 lanes

Incident type	Probability 10^6 car/ truck km	Duration in min.
Accident with car road closed	0.070832	28
Accident with truck road closed	0.089046	91
Breakdown with car road closed	0.030357	15
Breakdown with truck road closed	0.080951	29
Accident with car 1 lane closed	0.063568	28
Accident with truck 1lane closed	0.079914	91
Breakdown with car 1 lane closed	0.027243	15
Breakdown with truck 1lane closed	0.072649	29

Table 3.7 Input variables morning peak road with 1 lane

Incident type	Probability 10^6 car/ truck km	Duration in min.
Accident with car road closed	0.070832	28
Accident with truck road closed	0.089046	91
Breakdown with car road closed	0.030357	15
Breakdown with truck road closed	0.080951	29

3.2 Description of Marginal Computation

In this paragraph the functioning of the base and marginal traffic models is described. The result of this base model is necessary as an input for a marginal traffic model. For the marginal traffic models the necessary input and estimation errors in comparison to the base model are discussed.

3.2.1 Link transmission model

The link transmission model (LTM) (Yperman, 2007) is an algorithm for a dynamic traffic assignment. A major feature of this model is that the congestion dissipates in the upstream direction. In models with a dynamic queuing model, this is used a lot, the queue doesn't dissipate in the upstream traffic direction. The propagation of congestion in the upstream traffic direction is in line with the phenomena that are observed in reality. The link transmission model calculates link sending and receiving flows in line with first order traffic flow theory. With a fundamental diagram that has a triangular shape. The process can be described in three steps:

1. Calculate the potential sending flows of all incoming links and the potential receiving flows of all outgoing links for each node.
2. Calculate the flows that are transferred. The generic node model described in Corthout (2012) is used.
3. Calculate the new CVN of all upstream and downstream link ends.

In this way a network of 12.000 routes simulated for one hour can be calculated in 1 minute (Yperman, 2007). The time step used must be smaller than the smallest link travel time. In this thesis the LTM Leuven is used, this is an event based dynamic traffic assignment, meaning that the time step is determined for each node. In the LTM implementation in INDY (dynamic traffic model used at TNO, Bliemer, 2004) one time step is used for all the node updates in the entire simulation. For more information about the differences between INDY and LTM see appendix D.

For this master thesis the route generation and route choice of INDY is used. This is a complete route based model, in which first a route set is made (Bliemer, 2004). In this thesis the route set is created with a Monte Carlo technique. The travel time of a link is calculated with the free flow travel time and a stochastic part of the travel time. The stochastic part of the travel time is calculated by a random number from a normal distribution that is calculated with:

$$|N(0,\sigma)| \qquad with\ \sigma = \zeta_{max}\frac{(i-1)l_a}{(I-1)v_{ff}} \tag{3.2}$$

For each OD pair the fastest route is found and is added to the route set if the route is not overlapping too much with other routes that are all-ready in the route set. This check is made to exclude almost similar routes. There are three variables that influence the amount of variables found:

- Number of iterations ($\boldsymbol{I}$);
- Path overlap factor;
- Maximum dispersion factor ($\boldsymbol{\zeta_{max}}$), that has influence on the relative magnitude of the stochastic part of the route choice.

The link transmission model is often used to simulate the average traffic flows. For this purpose a route choice model is used a stochastic dynamic user equilibrium. In which the assumption is that none of the users can find a better route then his/her perceived travel time. A couple of iterations are carried out to reach a certain level of convergence. A logit based stochastic user equilibrium is performed. The formula used:

$$\boldsymbol{f_p(k)} = \frac{\boldsymbol{e^{-\mu * TT_p(k)}}}{\boldsymbol{\sum_{p'} e^{-\mu * TT_{p'}(k)}}} \tag{3.3}$$

The method of successive averages is used to determine the new route fractions between the consecutive iterations.

3.2.2 *Marginal Computation*

The MaC module (marginal computation) can marginally simulate temporary capacity differences and demand differences in routes or OD pairs. It is called a marginal simulation because only a part of the network is simulated. Only those links that differ from the base simulation are computed during those times.

The simulation in MaC follows 6 steps.

1. Read the six input files.
2. Impose the variation specified in the variation input file is on the base simulation
3. Activate part of the network
4. Simulate traffic over active part of the network and check if other parts of the network need to be activated or deactivated.
5. Write the asked output
6. Go to step 2 if there is another variation specified.

The seven input files for MaC are:

- General input file that specifies the location and names of the remaining files, the output that needs to be printed and the specification of three variables:
  - the travel time interval,
  - accuracy upstream,
  - accuracy downstream.

  The travel time interval specifies on what frequency travel times are given as output. Accuracy upstream and accuracy downstream are used to determine if a new node has to be activated or not.
- The network input file that is also used for the base simulations. In this file the links, nodes route, route fraction, dynamic OD matrix and the turning fraction interval are specified.

- The total cumulative file, in which the total cumulative curve for all links is specified, both the upstream and downstream link ends are specified.
- The turning fractions file. The turning fractions at the downstream link end towards all receiving links are specified. The time interval between two specified turning fractions are the turning fraction interval.
- The variation file in which one or multiple variations can be specified. Different variations will be simulated in different runs.
- The turning flow departures and turning flows are the last two input files. These two input files are only used if a demand variation is specified and are used to recalculate turning fractions.

The simulation in the active part of the network in the MaC module is calculated in the same way as in a LTM assignment. The time interval in which new traffic situation is calculated is the free flow travel time of the link. This is different from the MIC model in which the changes were imposed with bigger time steps.

Estimation errors in MaC
Because the simulation in MaC is much closer to LTM the results of the model are also closer to the full dynamic simulation in LTM than the MIC module. One of the few sources of errors between LTM and MaC is the fact that MaC is a single commodity model and LTM multi commodity (explanation of the terms single and multi-commodity see appendix E). In a multi commodity simulation, the flow on a link is route specific. LTM keeps track of separate route flows on each link. While in single commodity simulation, this route specific information per link is not known. Instead route fractions are used to determine the direction of the outflow of a link.

Another important aspect of the quality of the output of MaC are three parameters:
- the accuracy upstream,
- the accuracy downstream,
- the tuning fraction interval.

From Corthout (2012) it can be seen that the accuracy downstream and the turning fraction interval are the most sensitive ones. With a too high accuracy downstream, forward propagating differences are often ignored. With a too low accuracy downstream a big part of the network gets unnecessarily activated. With a too high value for the turning fraction interval the accurateness of the simulation is negatively influenced and choosing it too low leads to longer simulation times and too much input data.

3.2.3 Marginal incident computation
This section is meant to explain the MIC module in more detail. First a description of the algorithm and the input of the model are given. Secondly the estimation errors introduced are discussed.

The input for the MIC module are four files:
- Main input file, where the name and location of the other files is specified and the output that is asked need to be determined. For printing travel times a value for the interval of travel times is needed.
- A network file with nodes (ID's, and x and y coordinates) and links. For the links the ID of the link need to be specified, the capacity, the free flow travel time and the jam density the link length is optional.

- A file with the cumulative vehicle numbers (CVN) from the base simulation. The total link cumulative vehicle numbers and the total cumulative vehicle numbers towards the different downstream links. This input is needed at the upstream and downstream link end.
- A file with the incident(s). The link ID the starting time, end time and fraction of the original capacity that still can be used need to be specified.
- If route travel times are asked as output also a file with routes need to be provided as input. The consecutive links need to be specified in that order.

The MIC model exist of two parts a link model and a node model. The link model is able to propagate differences in flow (or better said the CVN) in line with first order traffic flow theory.

The second part of the MIC model is a node model. In the congestion build up phase two steps are carried out:

1. Calculate the average turning fractions during congestion build up phase.
2. The generic node model of Corthout (2012) is run with the reduction of the capacity of the affected receiving link. The demands of the sending links are determined from the results of the base simulation.

The next phase of the node model is the queue dissipation phase. It is assumed that sending links from which the flow did not change in the queue build up phase will not change in the queue dissipation phase. The turning fractions calculated in 1 are also used in the queue dissipation phase. The node model is run again without the capacity constraint of the receiving link from which the congestion spilled back. The affected links have a potential sending flow of the capacity of the link, because they are in a congested state. The time is determined till the first receiving link has the same CVN as in the base simulation. After that the node model has to be re-run because the boundary conditions have changed. This loop between node model and determining when a sending link has the same CVN as in the base simulation is carried out until all sending links have the same CVN as in the base simulation.

Estimation errors in the MIC module:
The time steps used in the MIC module are much bigger than in the base simulation, due to this the calculation time is reduced significantly but also estimation errors between first order traffic flow theory and the results of the MIC model are made.

- Averaging demand.
- Only the upstream effects of a temporary capacity reduction are covered
- Secondary or delayed spillback is not modelled
- Up and downstream bottlenecks in congestion dissipation are neglected

These estimation errors are discussed in more detail below:

The turning fraction is kept constant during the entire simulation. Demand is also averaged during queue build up phase. The used turning fractions are determined as the average turning fractions during the incident duration. So small differences in the turning fractions in the base simulation are not modeled in the MIC module (the base simulation with LTM is a multi-commodity[9] assignment where no fixed turning fractions are used and differences in turning fractions in time can occur). After the

[9] In appendix D the term multi-commodity is explained

capacity restriction due to an incident is gone, the same turning fractions are used in the calculation (the one determined as the average in the base run during the incident). After the end of the capacity reduction in the MIC module the same traffic is still present on these links that in the base run where there during the capacity reduction. Therefore the assumption of a constant turning fraction, also extended after the capacity reduction will not lead to large estimation errors.

Another estimation error is that the MIC module calculates only the upstream effects of the temporary capacity reduction whereas the downstream differences can also occur. During the capacity reduction downstream bottlenecks can be relieved because of reduced inflow. After the capacity reduction duration downstream bottlenecks can have more congestion because of increased inflow.

Delayed spillback is not correctly modelled. See where an incident at link 1 triggers a shockwave at link 2 and 3. The congestion of link 2 reaches node A, potentially reducing the inflow into link 3 and 5. This reduced inflow will have an effect on the speed of the congestion wave on links 4 and 5. This effect on the congestion is not modeled in the MIC module, for this reason secondary congestion waves are not modeled. In this would mean that the congestion wave at link 5 is not propagated into link 6 because a shockwave from link 3 entered first link 6. These estimation errors can be significant in closed loops but are limited in a real world traffic network.

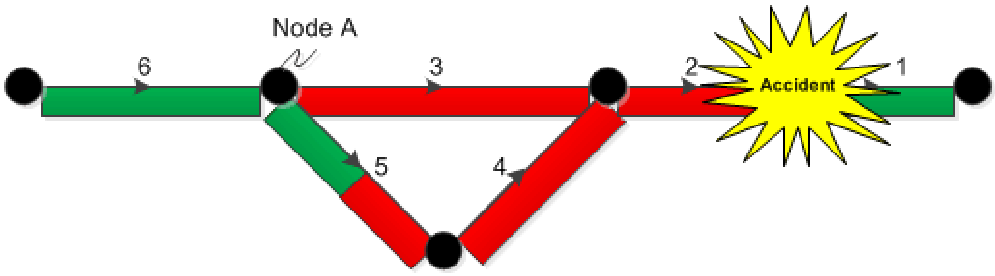


Figure 3.1: Second order spillback

The last estimation error has to do with bottlenecks during congestion dissipation. Up- and downstream bottlenecks can limit the inflow or outflow of a link. But the MIC module will not take this into account. An example is that of a 3 lane road link, which has a link with 2 road lanes somewhere downstream. In congestion dissipation the maximum outflow will be reached, when this flow reaches the link with 2 road lanes a congestion wave will be triggered. This secondary wave will not be modeled. A 2 lane road upstream of the 3 lane road link also results in an overestimation of the congestion dissipation out of the link with 3 lanes because the link inflow is lower than the outflow.

In appendix C the results of simulation of MIC are compared to analytical formulas. This comparison shows that neglecting upstream differences in the traffic flows and neglecting upstream bottlenecks can lead to significant estimation errors.

3.3 Method of incident simulation

In this paragraph the outline of the model is described. The input and output of different traffic models is discussed and the input needed for calculating the incident probabilities and travel time distribution. First the input and output for the marginal traffic model MIC is discussed. Secondly the input and output of the marginal traffic model MaC is discussed.

3.3.1 *Simulating incidents with MIC input -> output*

In the input and output for MIC and the model to calculate a travel time distribution is given. Rectangular shaped blocks are models and oval shaped blocks are input\output files. The red coloured blocks are input that is exported out of the dynamic traffic model INDY. The green coloured blocks are models that are made for this master thesis, or they are the output of the model for this master thesis. The blue coloured blocks are models or output of models developed at the KU Leuven.

The MIC model needs five input files. Three of these input files are imported form dynamic traffic model INDY. The fourth input file is a standard file, and the fifth input file specifies the incidents that need to be calculated. The information needed for a simulation in MIC consist of the following:

- A standard input file, in which the name of the input files is specified, the output that needs to be calculated and the travel time interval. The travel time interval is the time between two travel time calculations.
- The total CVN (cumulative vehicle numbers) and the CVN to all downstream links. These cumulative vehicle numbers need to be specified at the upstream and downstream link end.
- The network, that consists of nodes and links. For the nodes the location need to be specified. For links the upstream and downstream nodes, the free-flow travel time, the capacity, the jam density and optional the link length.
- The variation file in which the incidents are specified. The link on which the incident takes place need to be specified, the start time, duration and capacity reduction.
- The route file, this is an optional input file that is only needed if route travel times need to be calculated.

The links of the network file and the total CVN are used to calculate the incident probabilities. The route travel times calculated in MIC are used to calculate the travel time distribution.

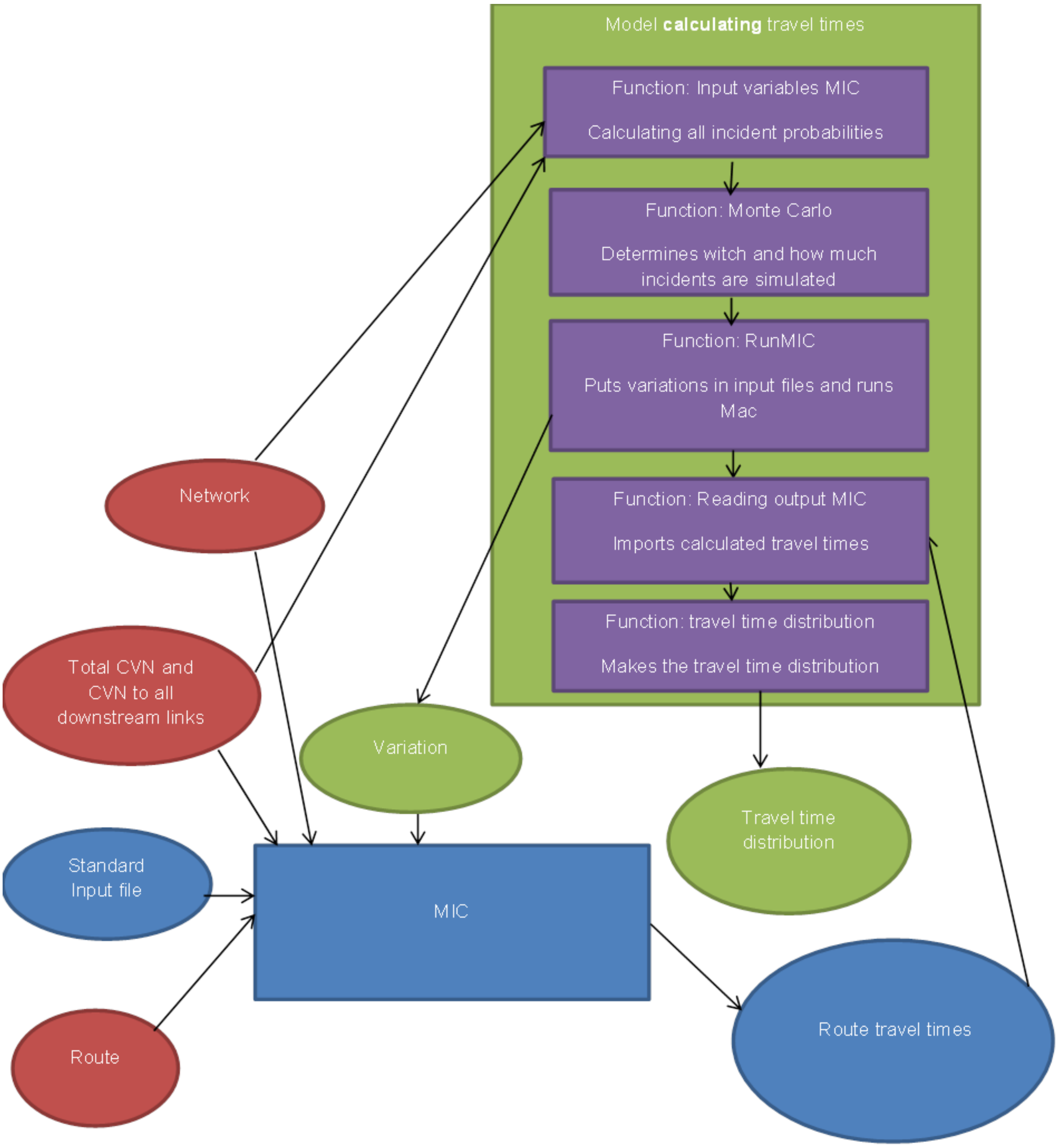


Figure 3.2: Scheme of input and outputs model calculating route travel time in MIC

3.3.2 *Simulating incidents with MaC, input->output*

Before incidents can be simulated in MaC the correct inputs are needed. The procedure to obtain all these inputs consists of multiple steps. These steps are explained in this section.

In figure 3.3 the different input/output files and models used in calculating the travel time distribution are shown. From figure 3.3 it can be seen that many files and models are needed before the MaC model can be executed. The first model that has to be run is the LTM assignment, for this model one input file is needed. In this input file all the information needed is specified. The information consists of the following information:

- The output that need to be given
- The nodes (number, location and type of node model that needs to be used)
- The links (start and end node, capacity, free-flow speed, jam density, and optional the link length)
- The routes in the model and the route fraction per timeslice
- The dynamic OD matrix
- And the timeslices

For all nodes the generic capacity proportional node model of Corthout (2012) is used. No specific information about traffic signals is used, and point queues are not used.

The network, route, route fractions dynamic OD matrix and timeslices are imported from INDY. The use of the results of an INDY run is not necessary for this model. The LTM model could be run in an iterative loop, with changing the route fractions in every assignment. Importing the final route choice from INDY is an easier solution. Output that is needed from this one base simulation are the turning fractions, turning flows and turning flow departures.

In 3.2.2 it is explained that one of the differences between MaC and LTM is that MaC is a single commodity model and LTM a multi commodity model. The differences in the CVN between a multi commodity assignment and single commodity assignment turned out to be too big so that the CVN out of the LTM multi commodity assignment could not be used for MaC. This would lead to a large part of the network in the MaC module being affected just by the difference between the single commodity and multi commodity results and not by the modelled variation. The difference between single commodity and multi commodity are due to the averaging of the turning fractions over a longer time period, although the differences are big enough to use LTM single commodity as base model, the differences between LTM single commodity and LTM multi commodity are very small (<5 veh/h in the case study). To prevent large parts of the network being unnecessary activated a second model has to be run. This is the single commodity variant of the LTM assignment. The input for this model is the network file (the same that is used for the multi commodity assignment) and the turning fractions that are calculated in the multi commodity assignment. The output of the model is the CVN and route travel times. The CVN is used for MaC and in the model that calculates travel time distributions. The travel times are only used in the calculation of travel time distribution. These travel times are used as the travel time of the base simulation.

The procedure of getting six of the seven input files for MaC is explained. Only the variation file has to be specified. This is done inside the model that calculates the travel time distributions. The pre-processing steps needed to run MaC are visualized in figure 3.3.

For an explanation of the differences between single commodity and multi commodity see appendix E.

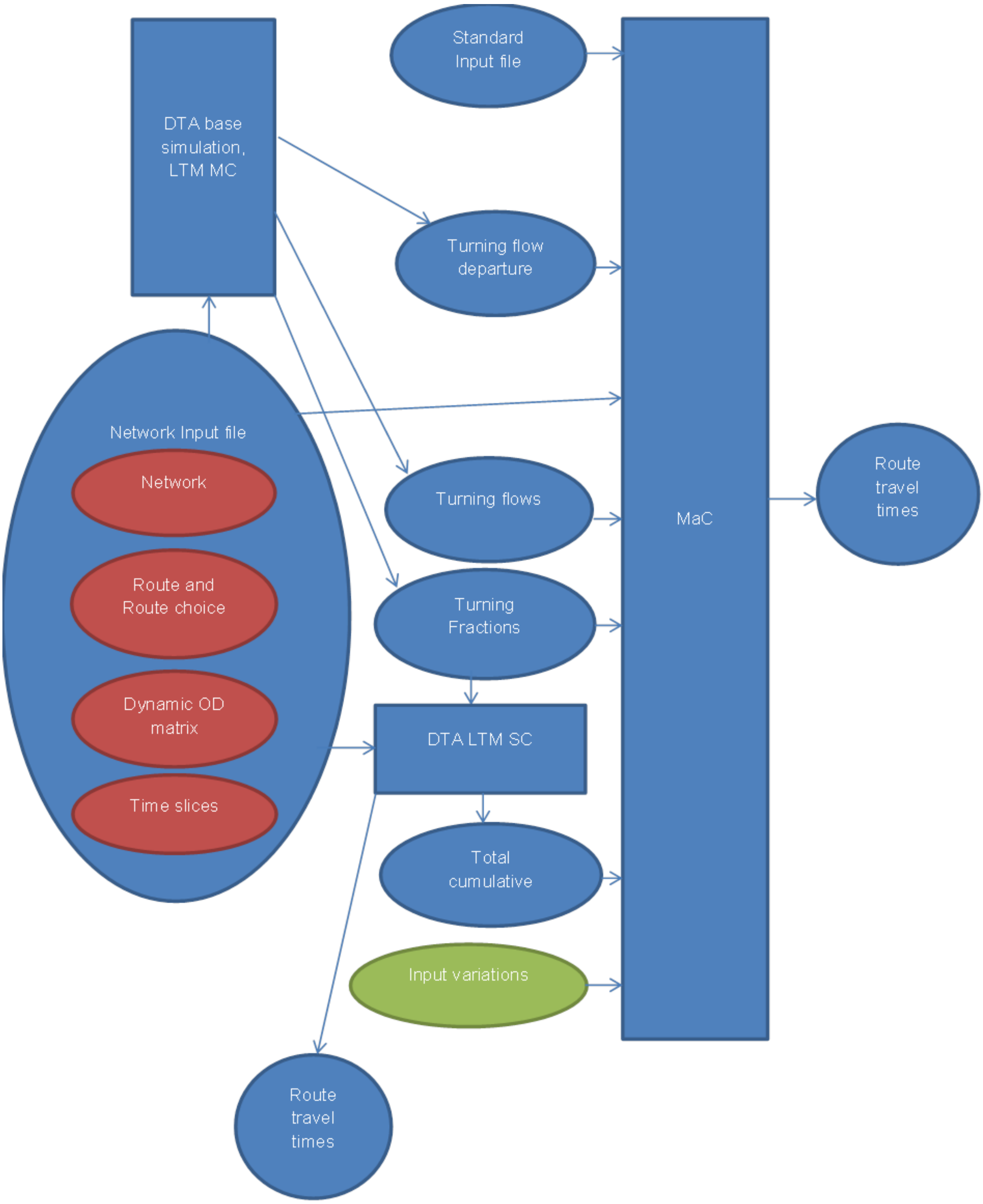


Figure 3.3 Scheme pre-processing information for simulation in MaC

In figure 3.4 the relationship between MaC and the model to calculate travel time distribution is given. The total CVN and the links are needed to calculate the incident probabilities. With these incident probabilities a Monte Carlo simulation is run. These incidents are simulated in MaC, and the output of MaC is used to make a travel time distribution. The route travel times calculated with LTM single commodity are used to determine which travel times in MaC are the same as in the base simulation.

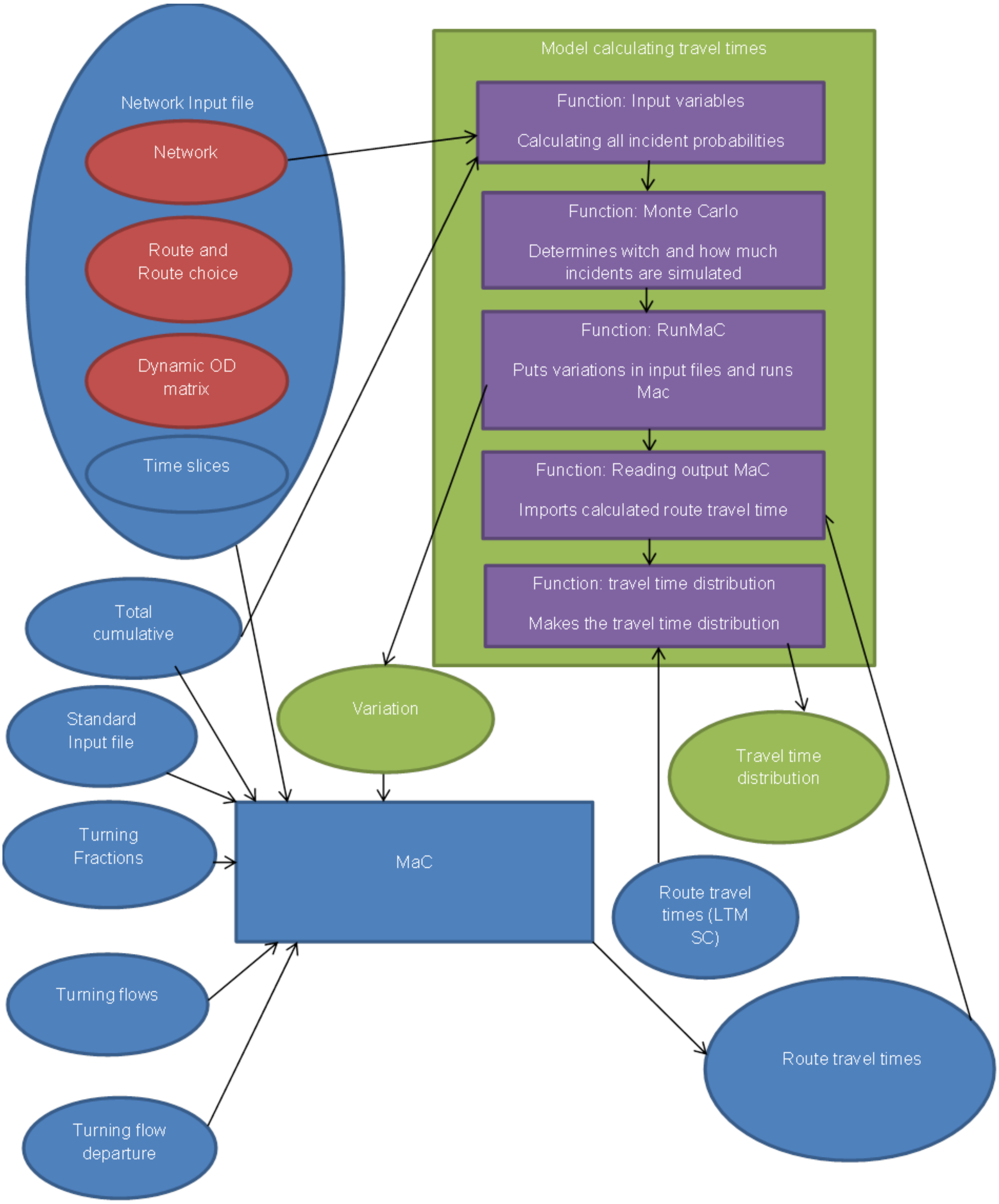


Figure 3.4: Scheme of input and outputs model calculating route travel time MaC

The procedure to calculate travel times in the MaC model turned out to be slow. In certain cases the calculation time needed for calculating and exporting travel times was 90% of the entire simulation time. For this master thesis the procedure to calculate travel times is improved. The calculation time was reduced with a factor 5, the calculated travel times were identical to the travel times in the original version.

3.4 Model calculating travel time distribution

In this paragraph the model sampling incidents and calculating a travel time distribution is explained. The model is made in the program Matlab and MIC and MaC are executed from Matlab. The model calculates the travel time distribution between every 15 minutes. This time step for observing travel time reliability/variability is used in many other studies (Peer et al. 2012 and Van der Loop 2012). A network for Amsterdam-South is used to test this model and models a morning peak. The model has a duration of 5 hours from 5:30 a.m. to 10:30 a.m. The first half hour is start up time. The last half an hour is cool down period in which no new traffic enters the network.

The model calculates the travel time distribution every 15 minutes. The time influence of an incident turns out to be long. Differences in traffic flows are still present long after the temporary capacity reduction. To get a representative travel time distribution all stages of an incident need to be incorporated. Also dissipating congestion because of an incident needs to be incorporated. Because of this the first two hours of the travel time distribution are not calculated. The model starts calculating the travel time distribution at 7:30 a.m..

In the marginal models the travel times after the end[10] of the base simulation is assumed to be the free flow travel time. The marginal models have been changed for this. In the original version no travel time was calculated in these cases. This assumption has a significant impact on the travel time distributions at the end of the simulation. After half past 8 these influences are so much that they significantly influence the calculated standard deviation.

[10] The end is defined as the moment in which the last traffic entered that link.

User equilibrium incorporating travel time reliability

The role of reliability on route choice is investigated by De Palma et al. (2005) in a stated preference survey and Lam et al. (2001) and Liu et al. (2004) for revealed travel behavior. All those papers come to the conclusion that the reliability of a route has a considerable effect on the route choice.

In literature there are many papers written on how the unreliability in travel time can be incorporated in the traffic assignment. Many papers focus on equilibrium definitions incorporating travel time variability. To name a few papers: Shao et al. (2006), Chen et al. (2010), Lam et al. (2008), Li (2009) Zhou et al. (2010). Corthout (2012) shows in a small network that an equilibrium, incorporating travel time reliability, can be reached. The output of the developed model in this research can in the same way be used for an equilibrium assignment incorporating travel time variability. In figure 3.5 the place of the presented model is shown.

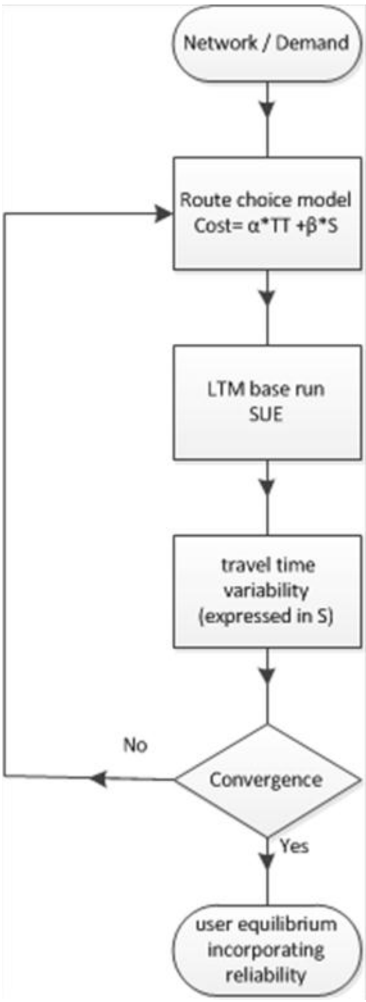


Figure 3.5: procedure for reaching user equilibrium incorporating reliability.

The model calculating travel time distribution and calculating incidents exist of 5 main parts. The working and assumptions in the model are described below:

Function 1: Input variables

On motorways the input variables described in 3.1.5 are used. On other road types the incident probability is multiplied with a factor described in table 3.3. The capacity reduction is determined by subtracting the capacity of the closed lanes multiplied by 0.54. That is the result of a study by Knoop (2009) of the less effective use of the infrastructure in case of an incident.

Assumptions:

- In the model it is assumed that 10% of all traffic is truck traffic.
- The incident starts are simulated every quarter of an hour. The first incidents are modelled after a quarter of an hour in the simulation. The last incidents start at the moment the last travel time distribution has to be obtained. In the application of this model the incidents are simulated between t=0.25 [5:45] and t=4.25 hours [9:45].
- The flow to determine the incident probability is the flow between 7.5 minutes before the start of the incident and 7.5 minutes after the start of the incident

Function 2: Monte Carlo.
In this function the incidents that will be simulated are selected randomly. The probability of an incident being selected is proportional to the incident probability calculated in function 1: input variables.

This means that in the setup of this simulation always one incident is selected. Because the marginal traffic models cannot model the consequences of two incidents or no incident. The model does incorporate the consequences of no incident (In *function 5: producing output,* the probability of no incident is dealt with). The model does not incorporate the consequences of more than one incident.

To investigate the consequences of this assumption a simulation is carried out. All possible incidents can occur on the same day. This Monte Carlo simulation is carried out 100,000 times. In table 3.8 the number of incidents per simulation is shown, the probability of more than one incident is 0.12. These situations cannot be modelled instead the model is run more often with one incident. The total amount of incidents is the same for both types of sampling.

Table 3.8: Amount of incidents

Amount of incidents in simulation	P model	P more than one incident can occur
0	0.2856	0.49
1	0.7144	0.35
2		0.12
3		0.03
4		≈0.005
5 or more		≈0.0009

Impact of simulation of one incident?
A restrictive assumption of the proposed model is that in every simulation only one incident can occur. This limitation originates from the decision for MIC and MaC, in which only one variation can be modelled in every simulation. It is investigated how restrictive this assumptions is. This will be done for the case study that is performed. For this purpose also generic formula will be derived, these formulas can be used if the model would be applied to other networks.

The question that needs to be answered is in how much of the times, two or more incidents; have an influence on the travel time? From table 3.8 it can be seen that in only 16% of the cases more than one incident would be forecasted. Only if the influence area of two or more incidents would intersect the calculated travel times would be incorrect. In paragraph 4.6 it is stated that on average 4.56% of the MaC simulation is activated.

- Assuming that for every incident 4.56% of the model gets activated.
- Assuming that the activated area is a compact area that is randomly allocated in time and space.
- Assuming that the travel time would change if the influence area of both incidents would overlap. Something that is not necessary

It can be calculated, what the probability is, that two activated areas overlap. This is investigated with simulation and for small activated areas (P_{act}) this is around ≈2*$P_{act.}$ What the probability is that the influence of an incident modelled incorrect (because if multiple incidents would be simulated, both influence areas would overlap) can be calculated with formula 3.4.

$$P_{mistake} = \sum_{i=2}^{n\to\infty} (P_n * n * \frac{n-1}{2}) * 2P_{act} * 2 \tag{3.4}$$

For the case study, using marginal traffic model MaC the formula gives 4.3%. In 4.3% of the simulated incidents one or multiple route travel times could be incorrect.

In MIC a smaller part of the network is activated, because only upstream differences are modelled. In MaC upstream and downstream differences are modelled. We assume that in MIC on average 1% of the network is activated. If the same approach as in MaC is followed. The amount of incorrect observations can be calculated. The amount of incorrect observations in MIC is estimated on 0.84%.

There is a possibility to model more than one incident. You could run a full dynamic traffic assignment with an incident and simulate the second incident in a marginal traffic model. This will lead to a longer calculation time of the whole model.

Function 3 Run MaC module
In this function the incidents sampled in the Monte Carlo simulation are exported to a text file and the marginal traffic model is run.

Assumptions:
- Only unique incidents are simulated. Incidents that are sampled more than once in the Monte Carlo simulation, are modelled once but counted more times in calculating the travel time distribution.
- The route travel times are calculated by making a trajectory through the CVN.

Function 4: import calculated travel times
In this function the calculated travel times are imported from the text files in which they are printed by the marginal traffic model. In the current version importing results is made route specific. In this function a correction takes place for incidents that are sampled more than once.

Function 5: Producing output
In this function the output is calculated. There are three alternative scripts one calculating the total system travel time and a second one calculating travel time distribution of an OD pair. The third and main output script calculates the travel time distribution of a route. The output of this script consists of a travel time distribution, the probability of the route being changed by an incident and a standard deviation of the travel time distribution. Between the calculation in MIC and MaC are a few differences

MIC:
In the MIC model the calculation of the travel time of the base simulation is made by calculating the most frequent travel time. The travel times that are less than the base travel time are erased from the results because less travel time can only occur due to an estimation error in MIC. Travel times that are no more than 1% bigger are also considered not to be changed because the calculation of travel time in MIC is not 100% accurate.

MaC:
The values that are less than 1% smaller or bigger than the travel time in the base simulation are considered not changed and are excluded from the travel time distribution.

Amount of incidents
The variability is expressed in the standard deviation. To calculate the needed amount of incidents the travel time distribution is assumed to be a normal distribution. Taking 1000 observations the probability that the calculated standard deviation (s) and the real standard deviation (σ) differ less than 5% is 0.95. This is calculated with the assumption that the calculated standard deviation s is determined from a random sample of a Normal Distribution. The base situation is only counted as one observation.

4 Results

In this chapter the results of the model are presented. First in paragraph 4.1 a general description of the case study will be given and the used network is presented. In paragraph 4.2 the results obtained with marginal traffic model MIC are presented. In paragraph 4.3 the results obtained with MaC are presented. In paragraph 4.4 the results using MIC and MaC are compared. In paragraph 4.5 the results of a system indicator are presented, in this paragraph a description of how the results could be used in a cost benefit analyses is given. In paragraph 4.6 the calculation time of both models is presented.

4.1 Set up case study

The model to simulate incidents is used on a network of Amsterdam-South, with 995 links, 3034 routes and 37 origins and destinations see figure 4.1. Not the results for all the routes and OD pairs will be presented; this would mean only for all routes, that more than 15.000 travel time distributions have to be presented. Therefore the result of only one route is presented, the results for route 1360. This is a route over the A2 and the A10 visualized in figure 4.1 (solid line). The result of one OD-pair is presented, from the A2 to the A10 east. Between this origin and destination two routes exist in the base model route one over A2 and A10 (route 1360) and one over A2, A9, A1 and A10 (route 1361), see figure 4.1.

Figure 4.1: Route 1360 (solid), route 1361 (dashed).

The consequences of incidents will not always lead to larger travel times. In section 3.4 is explained that 1000 observations are wanted to get statistical significant results (with 5% accuracy). To get significant results on route 1360 a different amount of sampled incidents in MIC and MaC is necessary, because the probability that an incident has an influence on the travel time is different in MIC en MaC (see table 4.6). This is mainly caused by the fast that MIC only calculates the changes upstream of a traffic incident and MaC calculates upstream and downstream differences. In table 4.1 the amount of sampled incidents in MIC and MaC is presented. The demand is averaged over the incident duration in MIC, something that is not done in MaC. This is the reason that the percentage of incidents that do not have an influence on the traffic system in MIC is bigger than in MaC.

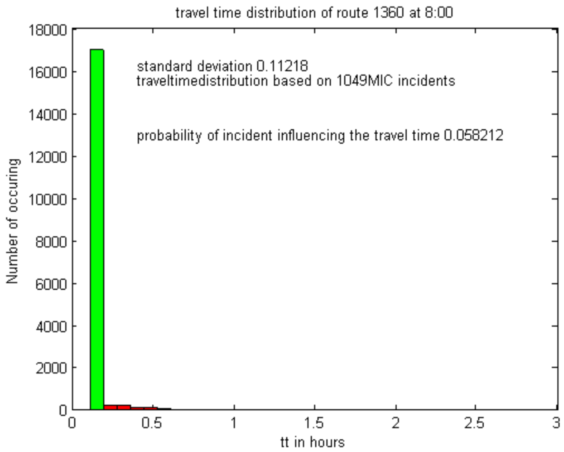
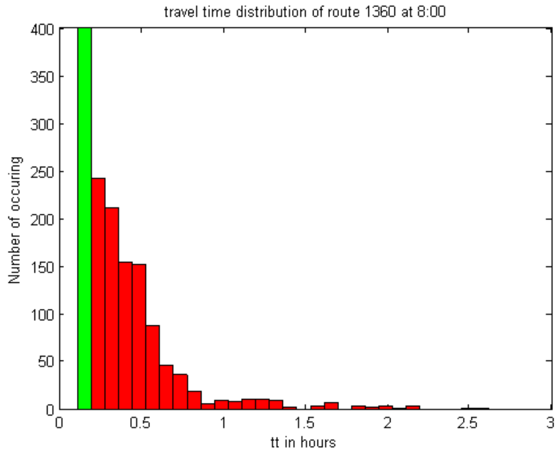
Table 4.1 Sampled and simulated incidents in MIC and MaC

	MIC	MaC
Sampled incidents	13000	5000
Simulated incidents	9531	4335
% of simulated incidents that did not have an effect on the traffic system	12.4%	10.4%

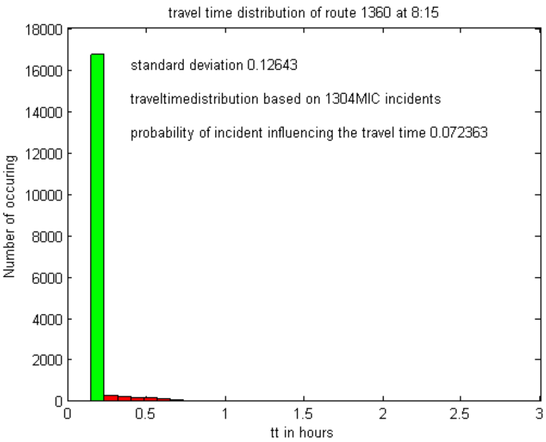
In both developed models the probability of an incident in the whole simulation is 0.71. This probability is of course the same for both models because the incident probabilities are determined out of the base simulation.

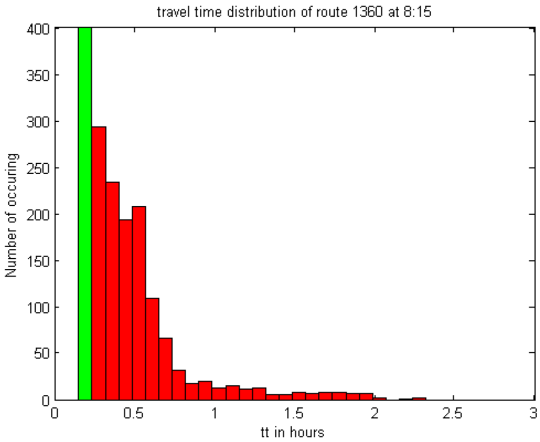
4.2 Results MIC

In this paragraph the travel time distribution due to incidents obtained with the MIC model is presented. The MIC model is not able to model elevation of congestion anywhere in the network. The green bar in figure 4.2 gives the amount of times the base travel time occurs. Most of the time (more than 90%) the travel time is the same as in the base simulation, because there is no incident (28%) or the incident does not have an influence on the travel time. In figure 4.2 the travel time distribution between 8:00 and 9:00 is given. The right picture is a zoomed travel time distribution to get a better look at the simulated differences.

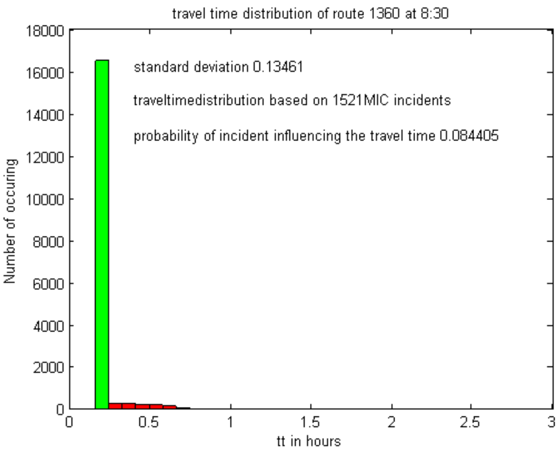
time	Travel time distribution	Zoomed in travel time distribution
8:00		

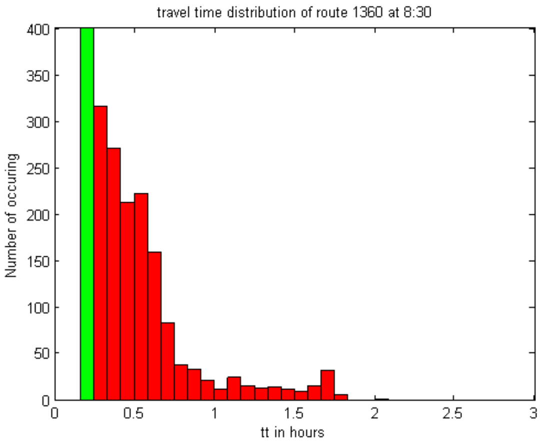
8:15


travel time distribution of route 1360 at 8:15
standard deviation 0.12643
traveltimedistribution based on 1304MIC incidents
probability of incident influencing the travel time 0.072363
Number of occuring
tt in hours

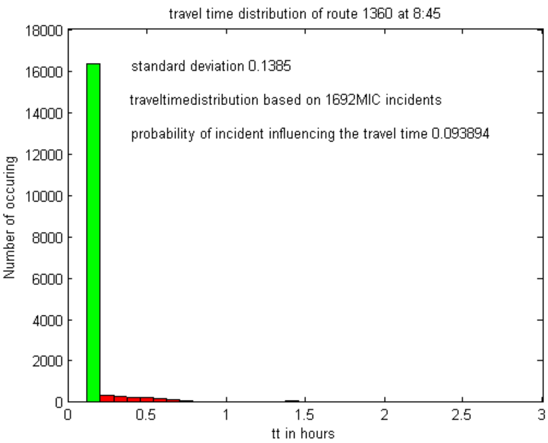

travel time distribution of route 1360 at 8:15
Number of occuring
tt in hours

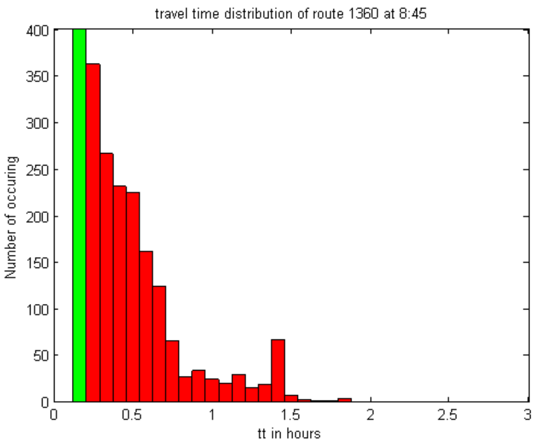
8:30


travel time distribution of route 1360 at 8:30
standard deviation 0.13461
traveltimedistribution based on 1521MIC incidents
probability of incident influencing the travel time 0.084405
Number of occuring
tt in hours


travel time distribution of route 1360 at 8:30
Number of occuring
tt in hours

8:45


travel time distribution of route 1360 at 8:45
standard deviation 0.1385
traveltimedistribution based on 1692MIC incidents
probability of incident influencing the travel time 0.093894
Number of occuring
tt in hours


travel time distribution of route 1360 at 8:45
Number of occuring
tt in hours

9:00

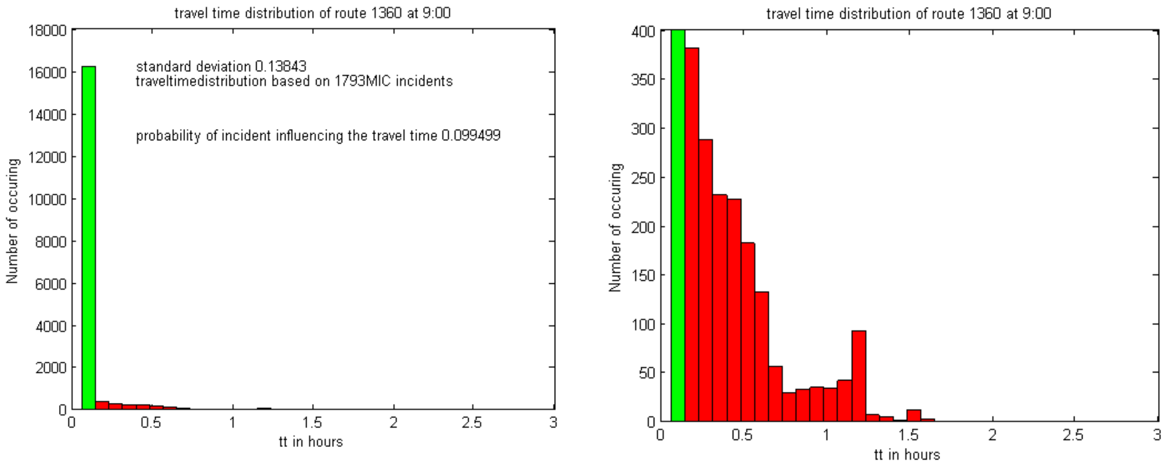


Figure 4.2: Travel time distributions of route 1360 between 8:00 and 9:00 in MIC

The axis in both columns of the pictures in figure 4.2 is kept the same. Between 8:00 and 9:00 the probability that an incident has influence on the travel time increases in time. Given that between 8:00 and 8:30, the traffic flows increase in the base simulation, leads to more incidents being sampled. And because the starting time of the incidents depends on the traffic flow of the base simulation, the capacity reduction remains average 15 minutes to half an hour. The consequences of this capacity reduction remain in the network for yet another period. In the travel time distributions at 8:45 and 9:00 really long delays do not exist due to the fact that there are no new vehicles emitted on the network after 10:15. In table 4.2 the differences in three important indicators over time are presented.

Table 4.2 Results MIC

Time	Standard deviation travel time distribution (hour)	travel time in base simulation (hour)	Probability of an incident influencing the travel time.
8:00	0.112	0.237	0.058
8:15	0.126	0.275	0.072
8:30	0.135	0.287	0.084
8:45	0.139	0.248	0.093
9:00	0.138	0.191	0.099

In the network of Amsterdam-South, the time with the most congestion is a little while before 8:30. From the results of table 4.2, it can be observed that the standard deviation increases in time. After the busiest moment, the variability in travel times grows. The average travel time in the base simulation is already decreasing. A reason for this high standard deviation can be found in the probability of an incident influencing the travel time.

Of the 13000 simulated incidents 981 occurred on one of the links of route 1360. Of those 981 incidents, 291 incidents did not have an influence on the traffic system at all. In table 4.3 the amount of travel time observations are given, only the travel time observations 1% bigger than the base travel time are included. The probability of an incident influencing the travel time is also given in table 4.3. There is a direct relationship between the probability of incident influencing the travel time and the number of incidents having an influence on the travel time. The amount of incidents, that are on the route and have an influence on the travel time, are given in the third column of table 4.3. The travel time increase for those incidents is not caused by spillback of congestion from links outside the route. A third of the incidents that have influence occurred on the route itself, in two thirds of the cases, congestion due to an incident spilled back from links outside this route.

Table 4.3 Number of observations (MIC)

Time	Probability of an incident influencing travel time	Number of incidents having an influence	Incidents on the route itself that have an influence
8:00	0.058	1049	356
8:15	0.072	1304	404
8:30	0.084	1521	447
8:45	0.093	1692	501
9:00	0.099	1793	533
9:15	0.093	1669	508
9:30	0.080	1449	426

In figure 4.3 the result for the OD-pair of route 1360 and 1361 is given at 8:30. The relative importance of the travel time distributions of 1360 and 1361 are determined with the route fractions between 8:15 and 8:30.

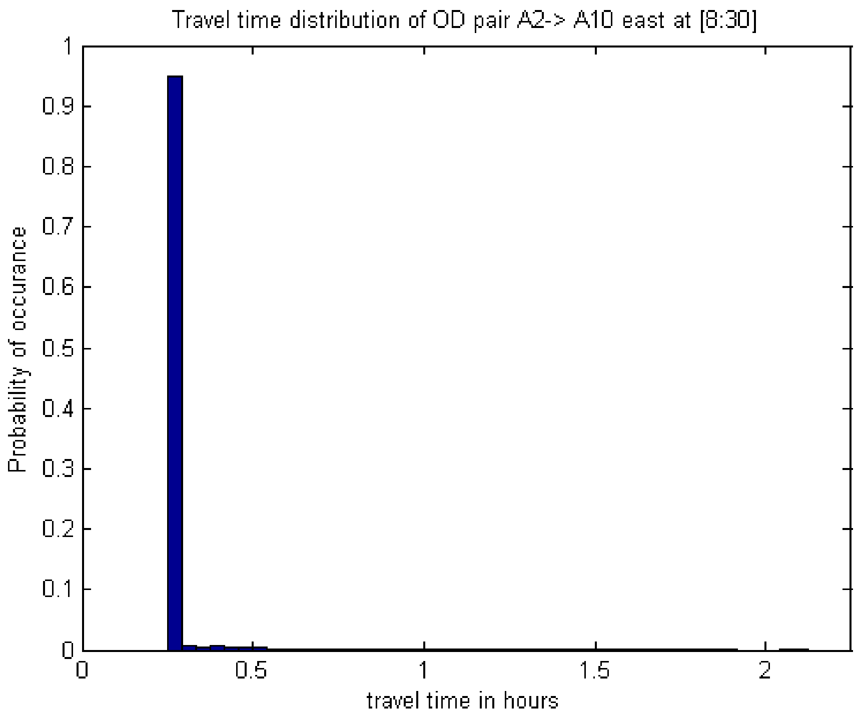


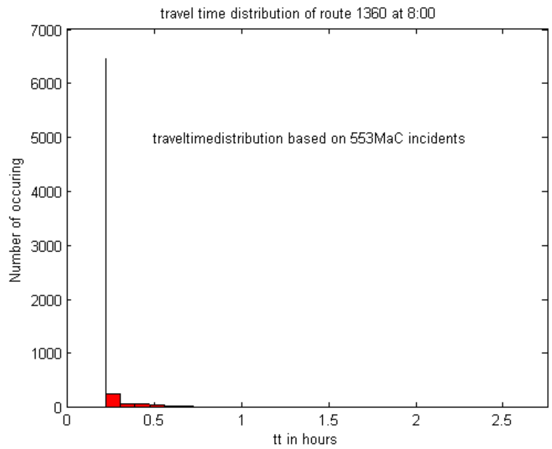
Figure 4.3: Travel time distributions of OD pair A2-> east at 8:30, with MIC

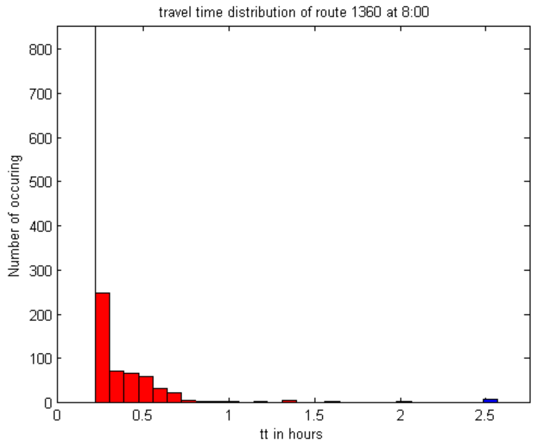
4.3 Results MaC

In this paragraph the travel time distribution due to incidents obtained with the MaC model is presented. In figure 4.4 the travel time distributions between 8:00 and 9:00 are shown. The small high bar in figure 4.4 gives the amount of times the base travel time occurs. The right picture is a zoomed travel time distribution to get a better look at the simulated differences.

time | Travel time distribution | Zoomed in travel time distribution

8:00





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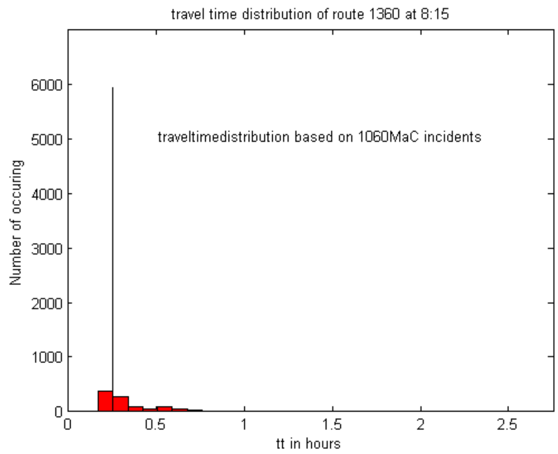

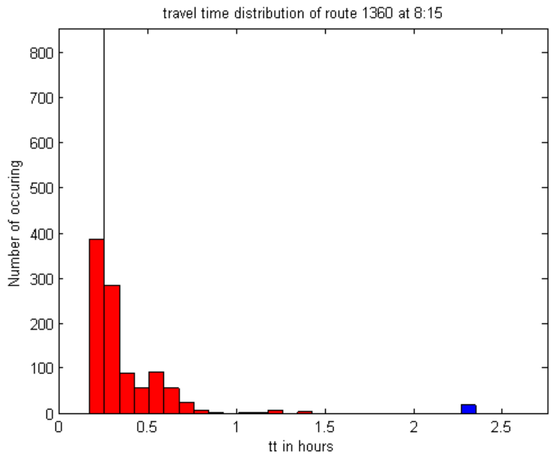

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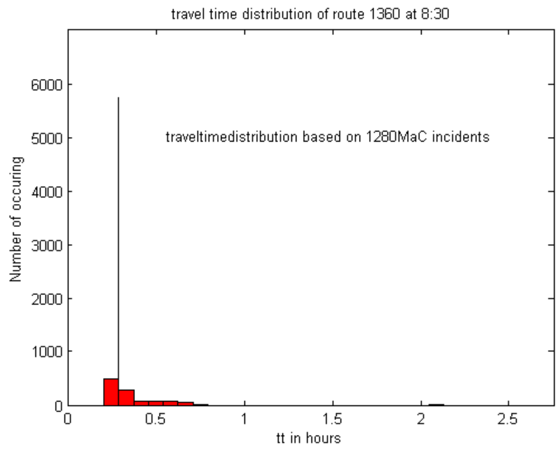
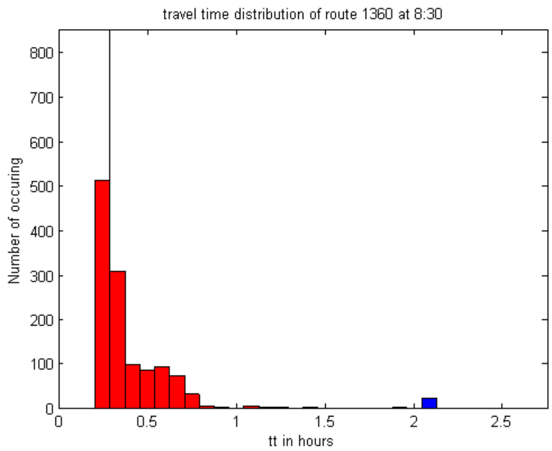




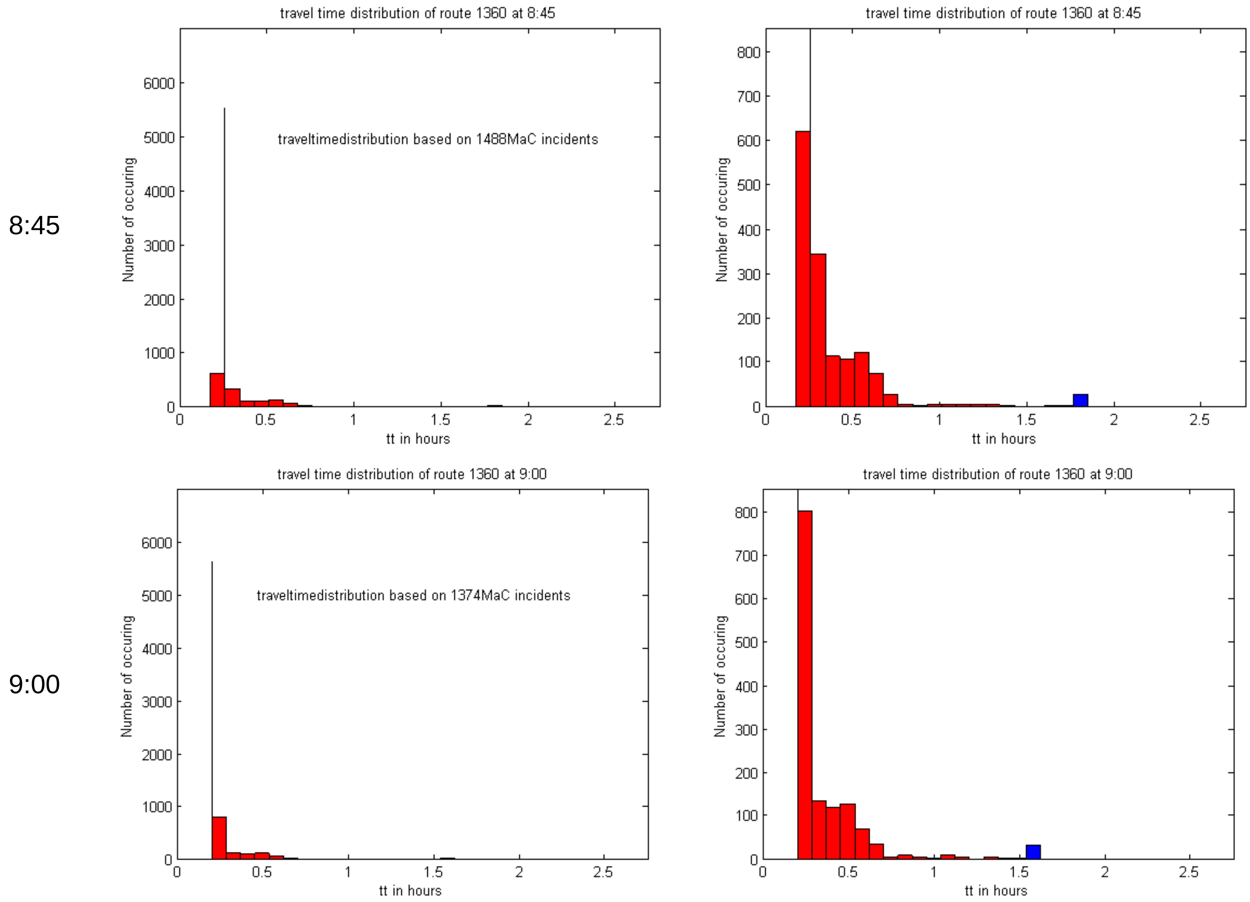


Figure 4.4: Travel time distributions of route 1360 between 8:00 and 9:00 in MaC

The axes in both columns of the pictures in figure 4.4 are kept the same. Between 8:15 and 8:45, it is clearly visible that a part of the calculated travel times are shorter than the travel time in the base simulation. In these cases, the congestion on route 1360 is dissipated. This can occur due to traffic being stopped by an incident elsewhere in the network. The results of the MaC simulation are also presented in table 4.4. The standard deviation, the travel time in the base simulation, the average travel time of, the travel time distribution and the probability of an incident influencing the travel time are given between 8:00 and 9:00.

Table 4.4 Results MaC

Time	Standard deviation (hour)	Travel time in base simulation (hour)	Average travel time (hour)	Probability of an incident influencing the travel time.
8:00	0.136	0.223	0.243	0.079
8:15	0.147	0.257	0.282	0.151
8:30	0.144	0.289	0.316	0.183
8:45	0.142	0.257	0.286	0.213
9:00	0.140	0.203	0.235	0.196

It is logical if the probability of an incident influencing the travel time is high between 8:15 and 8:45, because in the base simulation there is congestion at those times and less flow downstream of an incident can result in a smaller travel time.

Therefore, the high probability at 9:00 is an unlikely outcome; this is caused nevertheless by a large number of small delays. The calculation of travel times is based on linear interpolation between CVN; this assumption does not produce exact correct results. The high probability of an incident influencing the travel time at 9:00 can be explained with this estimation error and the fact that on average more links are activated on the end of the simulation.

The average travel time of the travel time distribution is higher than the travel time in the base simulation. This is logical because incidents results on average in higher travel times.

Of the 5000 incidents, 346 incidents took place on one of the links of route 1360. Of those 346 incidents, 60 incidents did not have an influence on the traffic system at all. In table 4.5 the amount of travel time observations is given. The probability of an incident influencing the travel time is also given. The amount of incidents on the route having an influence on the travel time is given in the third column of table 4.5. The travel time increase of those incidents is not caused by spillback of congestion from links outside the route The portion of the total amount of incidents having an influence on the travel time that are on the route itself changes in time. Spillback from other routes plays an important role in phase of dissipating congestion of the base simulation.

Table 4.5 Number of observations (MaC)

Time	Probability of an incident influencing	Number of incidents having an influence	Incidents on the route itself have an influence
8:00	0.079	553[11]	155
8:15	0.151	1060	170
8:30	0.183	1280	192
8:45	0.213	1488	203
9:00	0.196	1374	224
9:15	0.220	1541	232
9:30	0.246	1719	227

In figure 4.5 the result for the OD-pair of route 1360 and 1361 is given at 8:30. The relative importance of the travel time distributions of 1360 and 1361 are determined in the same way as in the results of the MIC model.

[11] Not significant; to get significant the calculation time mentioned in 4.6 is twice the current calculation time

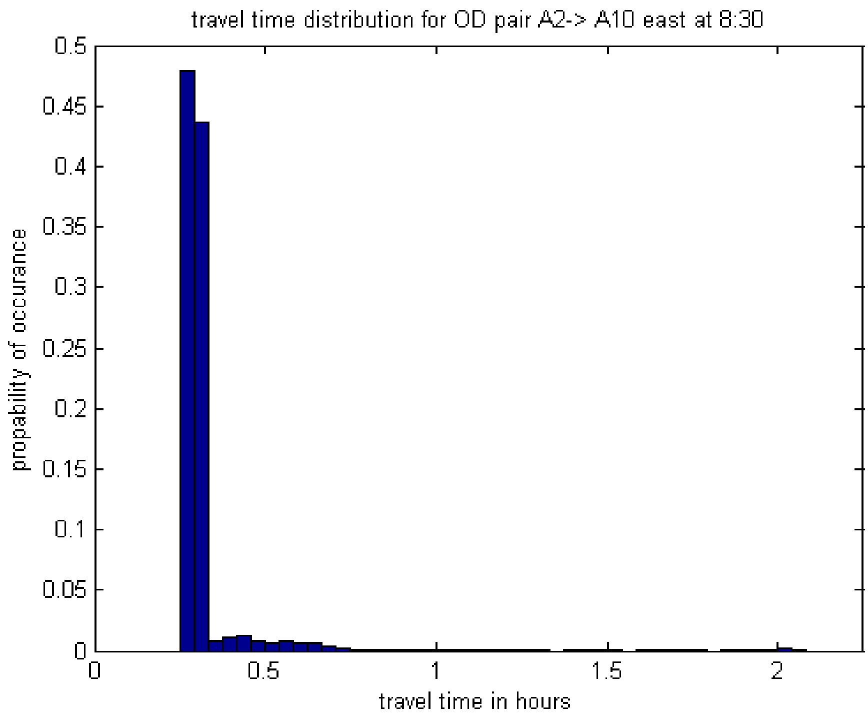


Figure 4.5: Travel time distributions of OD pair A2-> east at 8:30, with MaC

4.4 Compare MIC and MaC

In this paragraph the results obtained with MIC and MaC are compared. First the output results of MIC and MaC are compared, secondly the calculation speed. In paragraph 4.1 it is mentioned that the probability of an incident influencing the travel time in MaC is larger than with MIC. The most important reason for this difference is that MaC is able to track downstream differences of an incident. In table 4.6 this difference in probabilities is clearly visible.

Table 4.6 Differences in the probability of an incident influencing the travel time in MIC and MaC

Time	Probability of an incident influencing the travel time MIC	Probability of an incident influencing the travel time MaC
8:00	0.058	0.079
8:15	0.072	0.151
8:30	0.084	0.183
8:45	0.093	0.213
9:00	0.099	0.196
9:15	0.093	0.220
9:30	0.080	0.246

The standard deviation of the travel time distribution with MaC is higher than with MIC, see table 4.7. Because downstream differences (higher probability of an incident influencing the travel time) in MaC can be modelled, the standard deviation is also likely to be higher. There are more observations different from the base travel time.

Table 4.7 Differences in standard deviation of the travel time distribution between MIC and MaC

Time	Standard deviation MIC	Standard deviation MaC
8:00	0.112	0.136
8:15	0.126	0.147
8:30	0.135	0.144
8:45	0.139	0.142
9:00	0.138	0.139

The differences in MIC and MaC can also be seen in figure 4.6 and figure 4.7, where the delay due to incidents is given at 8:00. The biggest difference between MIC and MaC can be found by delays smaller than 5 minutes. This can be explained in the same way as the high probability of an incident influencing the travel time, in paragraph 4.3 results MaC.

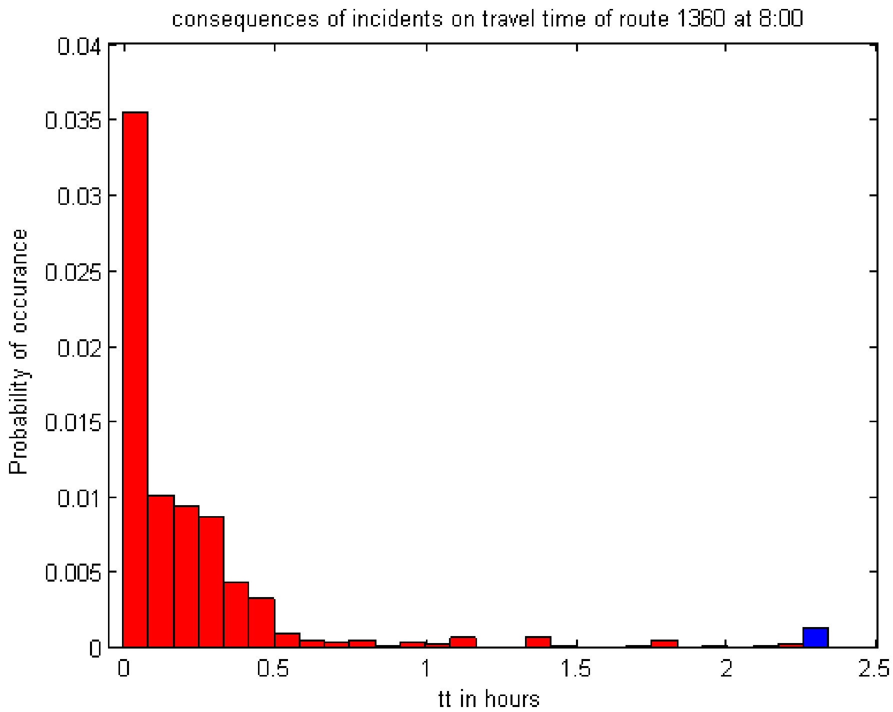


Figure 4.6: delay due to incidents in MaC

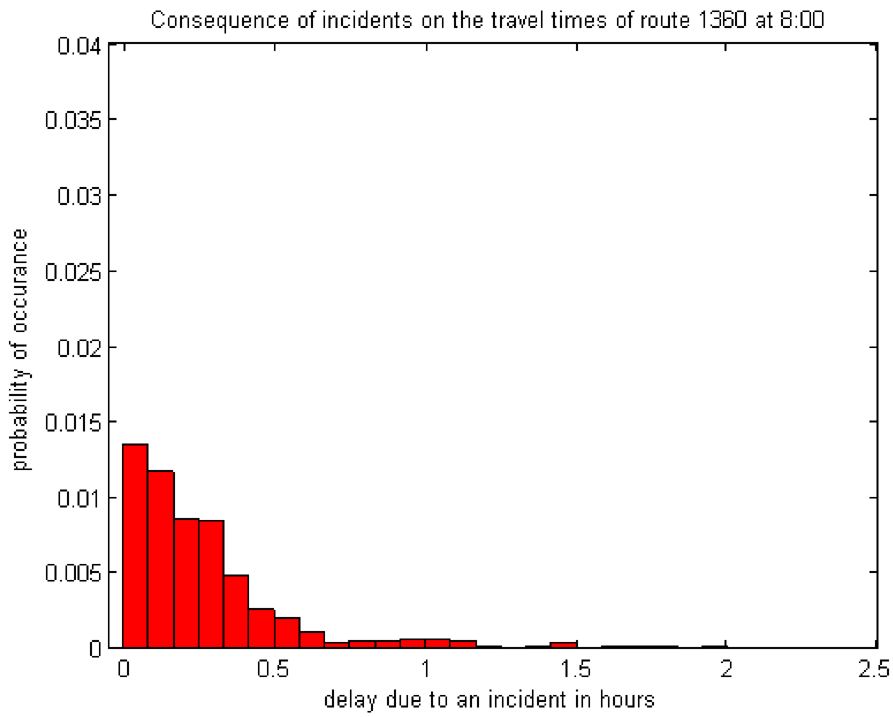


Figure 4.7: delay due to incidents in MIC

4.5 Results on basis total system travel time

The quality and the reliability of a traffic network can be investigated with the distribution of the total system travel time, in paragraph 2.4 two models where discussed that specifically aim at calculating the total system travel time, Clark et al. (2005) and Ng et al. (2011). The developed model in this research can also be used to produce the total system travel time as output.

$$\boldsymbol{TTST(k)} = \sum_{\boldsymbol{p}} \boldsymbol{TT_p\,(t) * D^{od}(k-1) * f_p(k-1)} \tag{4.1}$$

The time of a time slice and time between the calculations of route travel times is the same. This means that the demand and the route fraction change at the same moment as the calculated travel time. In the calculation the demand and the route fraction of the last time slice is used. For the total system travel time of 8:00 a.m., the demand and route fraction between 7:45 and 8:00 are used.

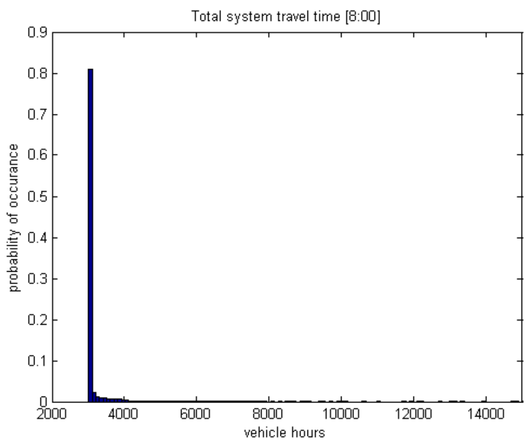
In the MIC module only the upstream differences in traffic flows are modelled. Theoretically a shorter travel time then in the base flow can only occur due to an estimation error. In the calculation of the total system travel times those system travel times that are shorter than the total system travel time in the base simulation are increased until they are the total system travel time of the base simulation. This phenomenon only rarely occurred. In table 4.8 the total system travel time of the base simulation is given and the standard deviation of the total system travel time distribution for MIC and MaC. In figure 4.8 the distributions of the total system travel time are calculated.

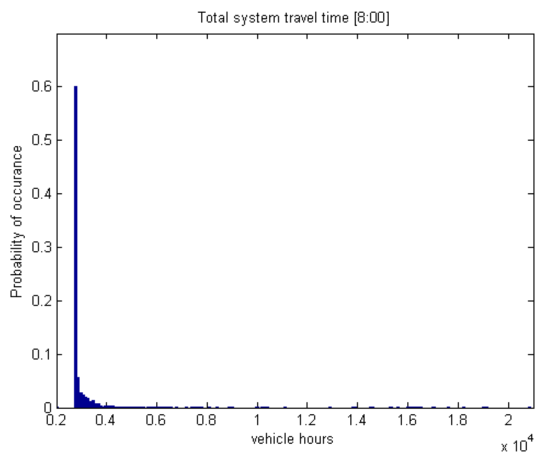
Table 4.8 Total system travel time of the base simulation and standard deviation of the total system travel time.

Time	Total system travel time [vehicle hours]*10^3	Standard deviation MIC	Standard deviation MaC
8:00	2.79	872	970
8:15	3.16	1016	1115
8:30	3.38	1073	1113
8:45	2.67	895	843
9:00	2.23	764	655

time Total system travel time MIC Total system travel time

8:00





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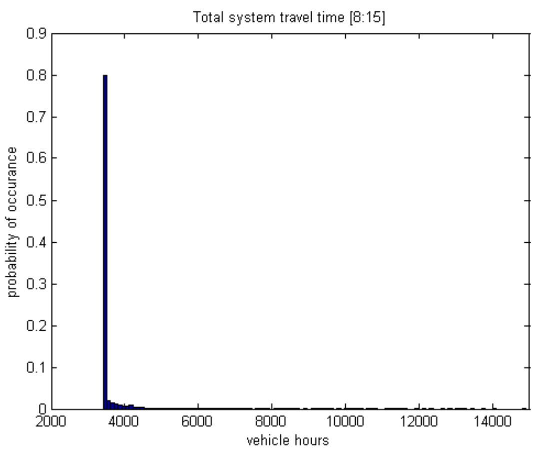

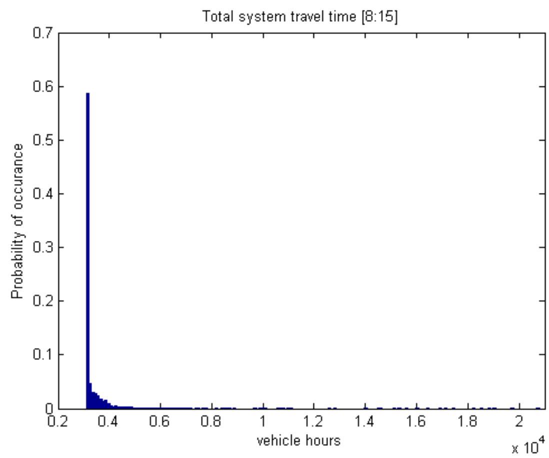

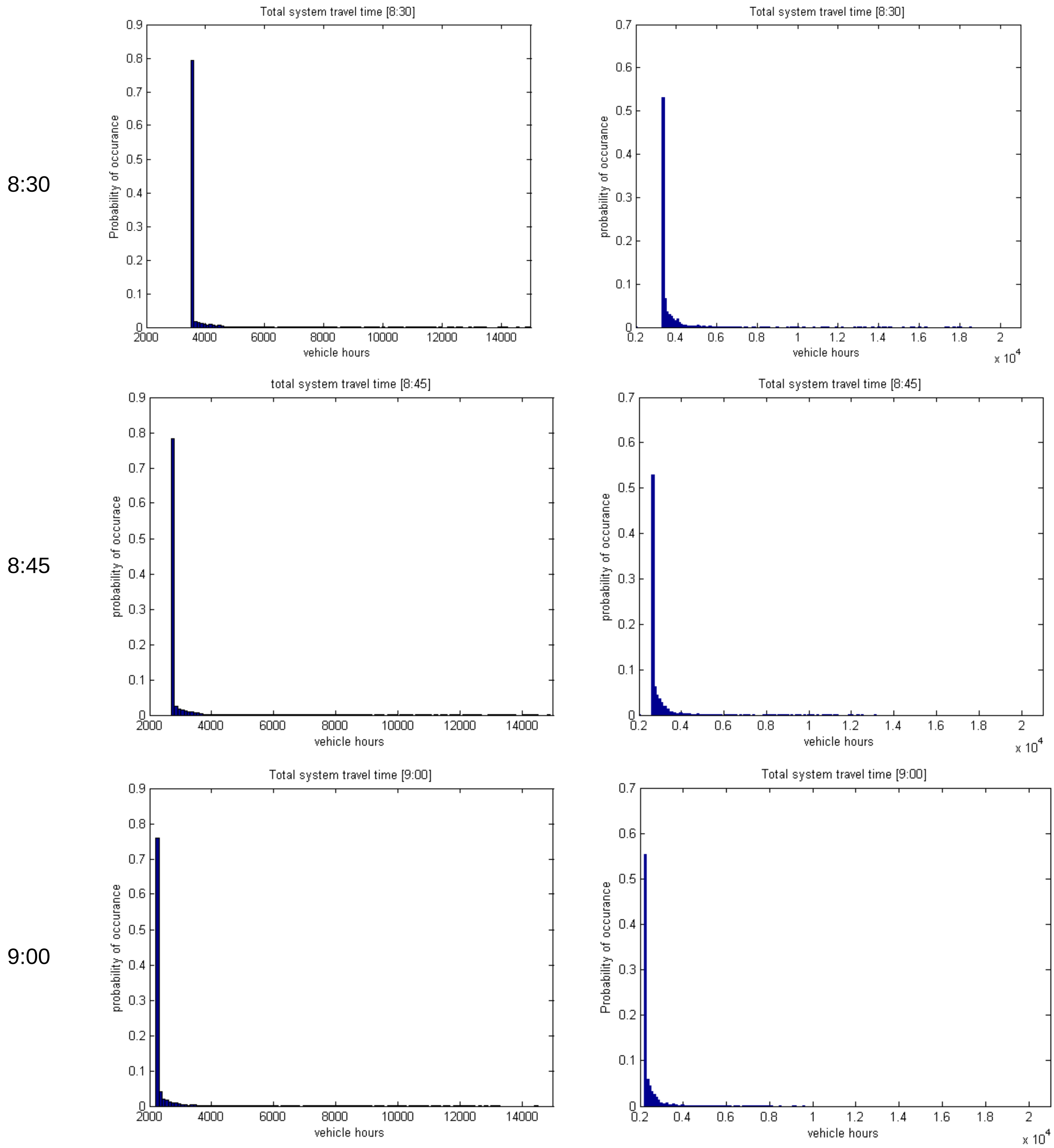

Figure 4.8: Total system travel times calculated with MIC and MaC

If the total system travel time estimated with the MIC module and the MaC module are compared with each other a few things can be seen. The probability that the TSTT (total system travel time) is others than the TSTT of the base simulation is higher in the MaC module then in the MIC module. This can be understood with the differences between the both models. The demand en the turning fractions in MIC are averaged over a longer time period then in the MaC model. This will on average lead to less links being affected upstream of the accident in the MIC module. The downstream affects are also captured in the MaC module; this leads to many links being affected; only this does not lead to many routes having a longer travel time.

In the MaC module there are also the largest total system travel times measured. In the MaC module those long travel times can be found in the total system travel time between 8:00 and 8:30. The largest total system travel times with the MIC module can however do not change that much in the presented area. That in MaC longer total system travel time occur can be explained with the fact that in MIC second order spillback is neglected and in MaC it is not neglected.

Cost Benefit analyses

The developed model can be used for a cost benefit analyses, in this box it is explained how this can be done. In paragraph 4.2 and 4.3 is showed that a travel time distribution and a standard deviation of a route and OD pair can be calculated. This calculation can be done for every route or OD pair. The standard deviation can be calculated for every route or every OD pair in two situation's the base scenario and a scenario with an infrastructure investment. The difference in standard deviation can be calculated and in this way the reliability benefits of the infrastructure investment can be quantified.

For a cost benefit analyses based on routes formula 4.2 can be used. The benefits for infrastructure investment can be quantified with the sum of the reliability benefits for all routes.

$$\boldsymbol{VoR} = \sum_{\boldsymbol{p}} \Delta \boldsymbol{S_p} * \boldsymbol{RR} * \boldsymbol{VoT} * \boldsymbol{D_{od}} * \boldsymbol{f_p} \qquad (4.2)$$

The cost benefit analyses can also be done based on OD pairs. Then the reliability benefit of the infrastructure investment is then the summation over all OD pairs, equation 4.3.

$$\boldsymbol{VoR} = \sum_{\boldsymbol{OD}} \Delta \boldsymbol{S_{od}} * \boldsymbol{RR} * \boldsymbol{VoT} * \boldsymbol{D_{od}} \qquad (4.3)$$

The two formulas 4.2 and 4.3 are not equivalent, choosing for a cost benefit analyses on basis of OD pairs or routes will result in another estimate of the reliability benefits. The question is what the right indicator for observing travel time reliability is. This question is also linked to what kind of rerouting behaviour is assumed in irregular circumstances. In this model no rerouting behaviour is assumed. Therefore interpreting reliability on a route is preferred above interpreting reliability on an OD pair. If the reliability is assessed on the basis of an OD pair the differences in the travel time of the multiple routes between origin and destination will increase the standard deviation and thus the reliability. This difference in travel time in the base model originates from the stochastic user equilibrium, and these personal preferences between routes do not relate to the social cost of reliability. Because these differences are caused by personal preferences and do not relate to the reliability of the system. For OD pair used in figure 4.3 it turns out that the reliability of the OD-pair is higher than the reliability of the routes. But this is not a general finding.

4.6 Calculation time MIC and MaC

In this paragraph the calculation time of the developed model is discussed. The calculation time for the whole procedure is given. This means that pre-processing steps before the marginal models are run and the post-processing steps for calculating travel time distributions on routes is included in the calculation time. Running the marginal models takes the most time (all route travel times are calculated in the marginal models), the pre- and post-processing steps takes around the 20 minutes. In table 4.9 the calculation time of the procedure of MIC and MaC[12] is given. From table 4.9 it can be seen that the calculation time of the model using marginal model MaC is a lot longer then the calculation time using marginal model MIC.

In table 4.9 also the calculation time if LTM would be used in this setup is given. This is the potential calculation time based on the calculation time of the simulation of one incident. The route choice of the equilibrium situation without an incident is used (in the same way as in MIC and MaC) and is assumed not to be changed when an incident is simulated. It is assumed that if LTM would be used to forecast travel time variability the same amount of incidents are simulated in LTM as in MaC.

The calculation time of MIC and MaC are clearly shorter than in LTM. This is not a surprising result because this was one of reasons to choose for these marginal models in the first place.

Table 4.9 Calculation time procedures

Model	Total procedure (hour)
LTM Leuven (potential)	267 (266sec*4335)
MaC	95.6
MIC	5.5

If the whole network would be activated in MaC the same number of node updates would be performed as in the entire simulation in LTM. The percentage of node updates in MaC is compared to the amount of node updates in full dynamic traffic assignment, on average 4.56% of the node updates of complete simulation in LTM are carried out. This means that on average 4.56% of the network is activated.

[12] The procedure to calculate travel times is changed during this master thesis. The calculation time needed to calculate travel times is reduced with a factor 5. The time necessary to calculate travel time is a significant part of the total calculation time. In the current form the calculation time of calculating all travel times is approximately half of the total calculation time.

5 Validity

In this chapter the validity of the results is investigated. In paragraph 5.1 the face validity of the results is analysed, the results of numerical comparisons are presented here. For visual comparison of the results see appendix G for MIC and appendix H for MaC.

In paragraph 5.2 the consequences of changing the three parameters in the MaC model is investigated.

In the last paragraph (5.3) the travel time distribution of the model is compared with a measured travel time distribution.

5.1 Compare results base model with marginal model

The face validity checks if the results of the model are logical. If the same incident is simulated in a marginal traffic model and in LTM model the calculated flows should be almost the same. The differences in the flows between the base simulation and the developed model using MIC and MaC due to a temporary capacity reduction are calculated (Δq^{MIC} and Δq^{MaC}). The same temporary capacity reduction is calculated in INDY and compared to INDY simulation without the incident. This difference is the expected flow difference (Δq^{exp}). In this paragraph the flow differences Δq^{MIC} , Δq^{MaC} are compared with Δq^{exp}. In 5.1.1 the results of LTM and MaC are compared. In 5.1.2 the results of MIC and MaC are both compared to LTM. The outflow calculated every 15 minutes are compared. Only flow differences bigger than 0.001 veh/h are included, to exclude inherent estimation errors in these numerical models.

The same incident is simulated in MIC, MaC and LTM. All three models have another base model to which it is compared (see table 5.1). Although the differences in the base models are small, the goal of this comparison is not to compare differences between base models but differences in the simulation of an incident with a marginal traffic model. The flow differences between the base model and the simulation of an incident in INDY (Δq^{exp}), MaC (Δq^{MaC}) and MIC (Δq^{MIC}) are calculated. In this comparison INDY is used as base model to which the results are compared. The real base model is LTM of the KU Leuven, but the differences between INDY and LTM of the KU Leuven are minimized as far as possible (see appendix D. The differences between LTM of the KU Leuven and INDY (LTM) are small enough to compare the outcomes of MIC and MaC to INDY.

Table 5.1: models to calculate the influence of an incident are compared with different base model

Incident simulated in:	Compared with base simulation:
INDY = LTM (multi commodity)	INDY = LTM (multi commodity)
MaC	LTM (single commodity)
MIC	INDY LTM

5.1.1 *Comparison results MaC model with base model*

To achieve a short calculation time in MaC, simplifications are made to the simulation. The consequences of the simplifications in the MaC model are investigated. The negative influence of these simplifications on the quality of the results will here be investigated.

In 3.3.2 it is explained that the differences between the output of LTM (multi commodity) and the MaC model are too large. The results of LTM multi commodity are changed in LTM single commodity, by calculating the output with turning fractions. The flows rather the total CVN out of LTM single commodity are the input of the MaC model. In the rest of this chapter the flows of MaC are compared with LTM single commodity (Δq^{MaC}). For this comparison 7 incidents are simulated, the 7 incidents are given in table 5.2.

Table 5.2: The seven simulated incidents

	Location incident	Hectometer spot	In the direction of	Start time capacity reduction	End time capacity reduction	Fraction of the original capacity remaining
1	A1R	10.0	Amsterdam	7:00	7:45	0.75
2	A1L	10.0	Het Gooi	6:00	6:45	0.2
3	A9L	24.0	Amstelveen	7:30	8:30	0.5
4	N522	13.0	Ouderkerk a/d Amstel	7:45	8:15	0.2
5	A2L	36.0	Amsterdam	6:30	7:00	0.4
6	A1L	16.0	Het Gooi	6:30	8:00	0.3
7	A6L	41.7	Het Gooi	8:15	8:45	0.25

The location of the different incidents is given in figure 5.1.

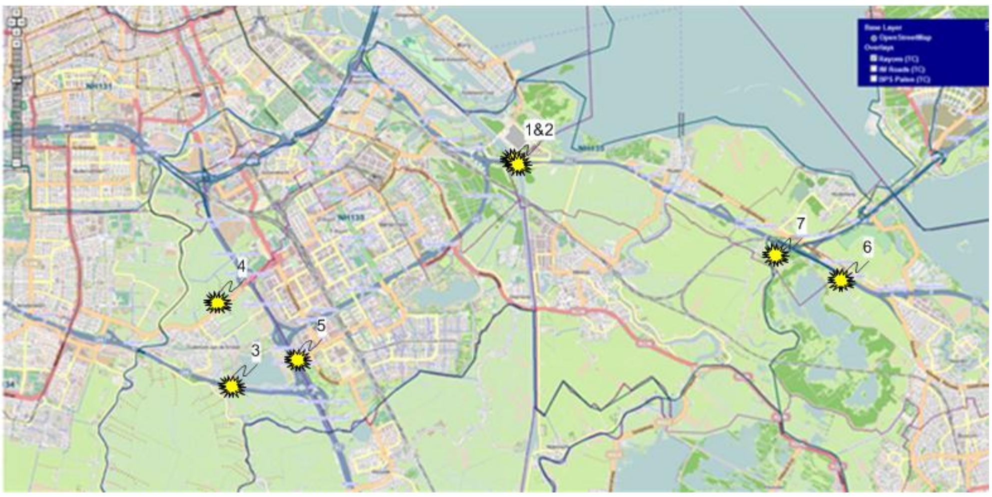

Figure 5.1: location of incident and flows on the moment of the incident

Not all the simulated incidents lead to flow differences on the same amount of links. In the complete simulation with INDY the flow differences are ranching from 21% to 0.1%. Of all the chanced flows in INDY, 30.0% is also changed in the MaC module, so 70.0% of the flows changed in LTM didn't change in the simulation in MaC.

Three types of flow differences are distinguished. The meaning of these types of flow differences can be found in table 5.3.

Table 5.3: Three types of flows in MaC

Changed in INDY	Changed in MaC	Name
Yes	Yes	Rightful affected flows
Yes	No	Wrongful unaffected flows
No	Yes	Wrongful affected flows

From figure 5.2 can be seen that rightful affected flows form the most important part of the changed flows, and that the wrongful unaffected flows are for the biggest part negligible. This means although not all changes are tracked the most important ones are.

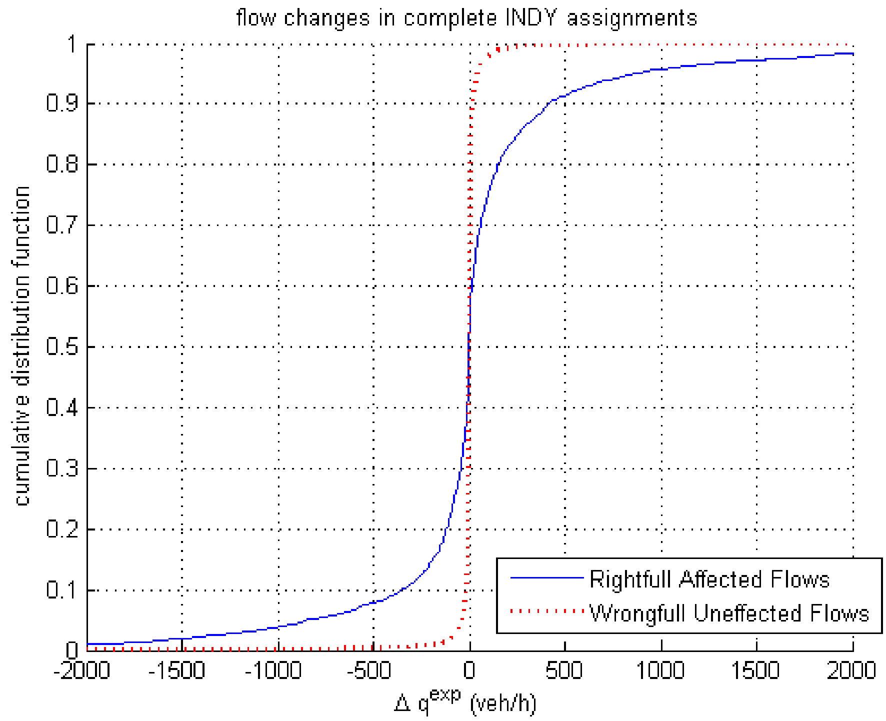

Figure 5.2: flow difference in INDY, rightful affected flows and the wrongful affected flows.

From figure 5.2 it is concluded that the most important flow changes in LTM also lead to a flow change in MaC, but what are the differences in flow changes between MaC and LTM? In figure 5.3 the difference in flow change between LTM and MaC is shown. A flow difference can be seen as an error in the MaC model.

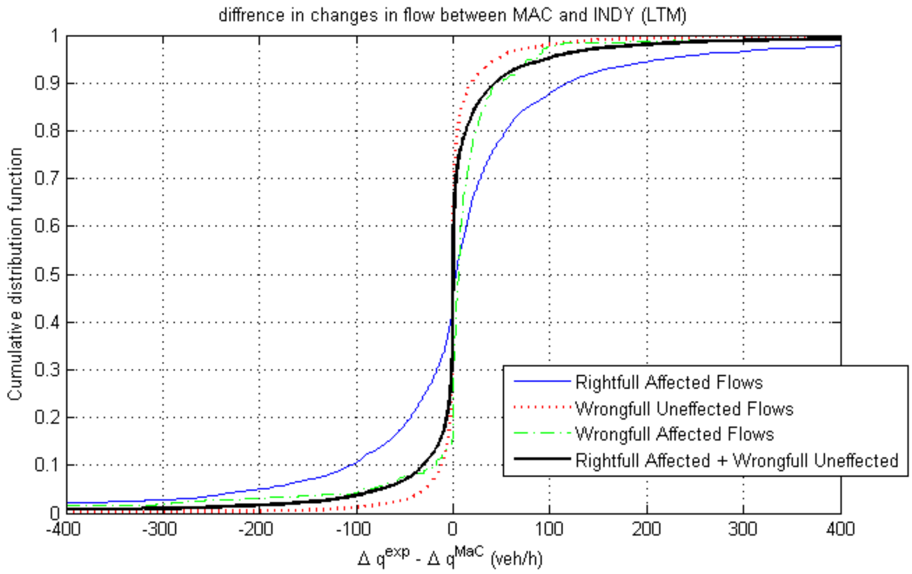

Figure 5.3: difference in flow change between MaC and INDY

There are many flows calculated with a relative small error, but do not forget a large part of the flow differences in figure 5.2 were also relative small. The errors shown in figure 5.3 are substantial. In Corthout (2012) a comparison for the MaC model is carried out for demand differences. The consequences of changing a route demand with 100 veh/hour are investigated. This procedure is carried out for 2032 variations. The calculated differences by Corthout (2012) are much smaller, most of the errors smaller than 10 veh/hour.

While making these comparisons a problem in the MaC model was discovered. The deactivation rules mentioned in Corthout et al. (2012) do not work properly with the simulation of incidents[13]. If the MaC model is run without deactivation rules the total error decreases. The total error is defined as equation 5.1:

$$\boldsymbol{TE} = \sum |\Delta \boldsymbol{q}^{exp} - \Delta \boldsymbol{q}^{MaC}| \qquad (5.1)$$

The total error without deactivation rules is reduced with 18%. In figure 5.4 the differences in estimation errors between MaC with and without deactivation rules is presented.

The deactivation rules currently implemented in MaC are not case specific, meaning that the same deactivation rules are used for the simulation of a demand difference and the simulation of a capacity reduction. For simulation of a capacity reduction the problems with the deactivation rules could be solved by adding a new deactivation rule that checks if the CVN is approximately the same as in the base simulation, as threshold the already specified variables accuracy upstream and downstream could be used. Deactivate if equation 5.2 returns true for all incoming and outgoing links of the node and all other deactivation rules are also met.

[13]The dysfunction of the deactivation rules has an influence on the results of chapter 4. The results of chapter 4 are obtained without change in the deactivation rules of the original MaC model.

$$\left|CVN^{base\ model} - CVN^{MaC}\right| < \varepsilon \tag{5.2}$$

In which epsilon(ε) is the accuracy upstream and accuracy downstream.

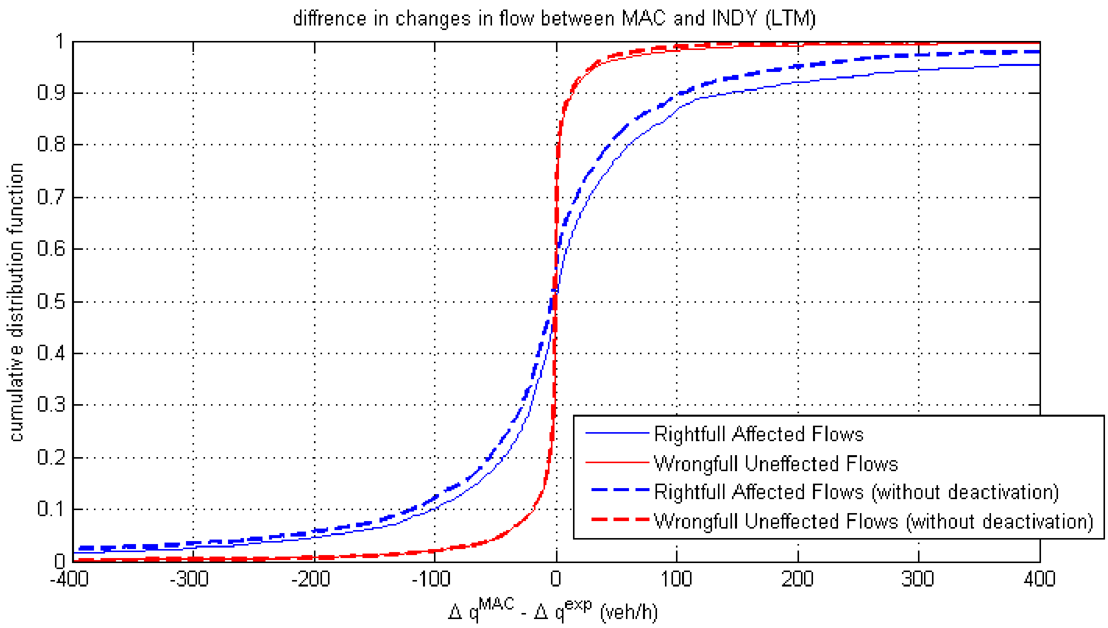

Figure 5.4: difference in flow between MaC and LTM with and without deactivation rules

5.1.2 Compare quality of upstream results MIC and MaC

The same incidents are used as in the face validity (5.1.1). In INDY there are in total over all incidents, 106 links upstream of the incident location affected. MIC is in nature only able to calculate differences in the upstream direction, therefore the comparison is only limited to those 106 links.

In the MIC module 12 of 104 links are unaffected. For these 12 links the upstream differences in LTM start and end during the incident. It is logic that the MIC module is not able to simulate these differences because in 3.2.3 is explained that demand and turning fractions are averaged over the incident duration. The congestion, in the base simulation, on those 12 links disappears before the end of the capacity reduction

The quality of the simulation of upstream moving differences in MIC and MaC is compared to full dynamic simulation of an incident in a LTM assignment In figure 5.5 the error in the flows of the marginal simulations are given. The results for MaC are calculated twice, one with deactivation rules and one without deactivation rules. From figure 5.5 it can easily be seen that the errors using MaC without deactivation rules are smaller.

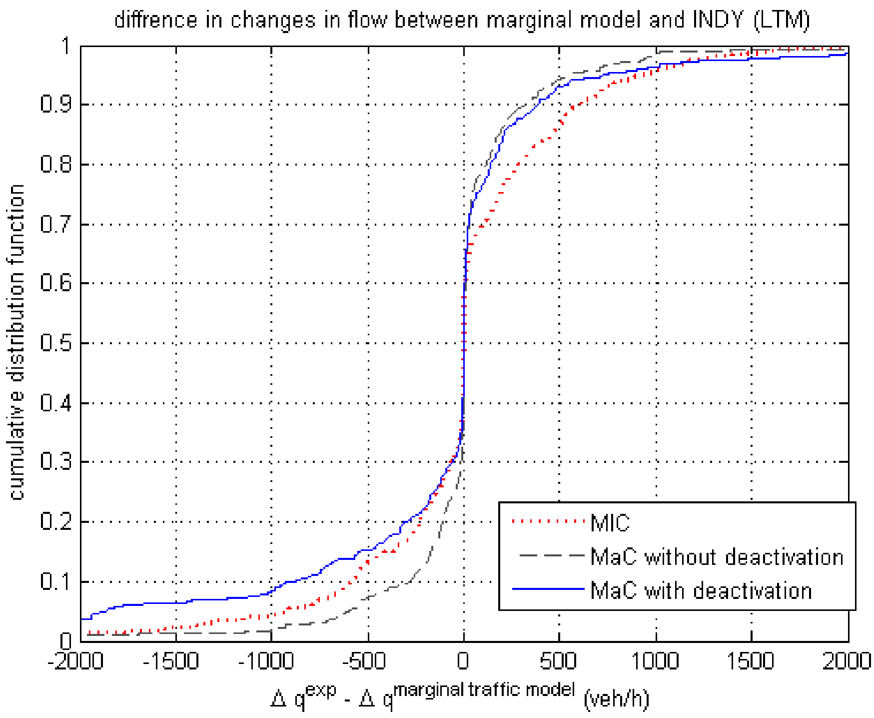

Figure 5.5: Comparison errors in MIC and MaC in the upstream traffic direction

From figure 5.5 it can be seen that MIC and MaC have almost the same accuracy. In 30% of the calculated flow differences the errors in MIC and MaC are really small. On the other hand there are also substantial errors in many cases.

The errors of MIC and MaC can be expressed in a total error, using formula 5.1. In table 5.4 the results are shown. The results show once again that MaC without deactivation rules has less estimation errors as MaC with deactivation rules. The MIC model preforms better than MaC with deactivation rules but worse than MaC without deactivation rules.

Table 5.4: Total error in MIC and Mac estimating flow differences upstream

Marginal model	Total error in (veh/hour)
MIC	$2.46*10^5$
MaC (with deactivation)	$2.89*10^5$
MaC (without deactivation)	$1.67*10^5$

5.2 Sensitivity analyses

Only the sensitivity of parameters in MaC is investigated, the MIC module does not have parameters influencing the quality of the calculation. In this paragraph the sensitivity of the results of MaC in relation to these three parameters is discussed. The three parameters and their values used in the model forecasting travel time variability are:

- Accuracy downstream (100 vehicles)
- Accuracy upstream (10 vehicles)

- Turning fraction interval (5 min)

They are mentioned before in 3.2.2. The sensitivity of the results is tested by comparing the results of MaC to the results of LTM.

For this comparison an incident is simulated at 7:24 at A9 “Gaasperdammerweg” travelling west wards, on the A9R at hectometre post 6.0, directly after motorway junction “Diemen”. The location is depicted in figure 5.6. The incident reduces the original capacity with a half. This capacity reduction remains the rest of the simulation. In appendix H the change in flow between the base simulation and the simulation of the incident is graphically presented, for LTM and MaC.

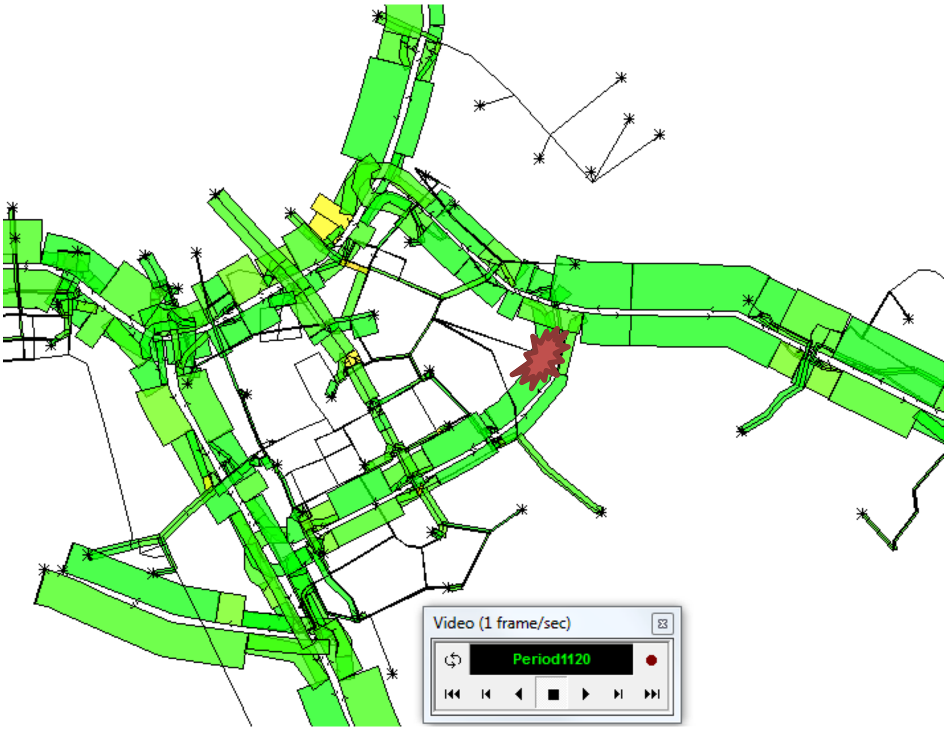

Figure 5.6: location of incident and flows on the moment of the incident

The flow differences between LTM multi commodity without and with the incident are calculated (Δq^{exp}) and the differences between MaC and LTM single commodity (Δq^{MaC}) are calculated. These two values are compared as the normalized total error (NTE). The value is normalized to the values used in the model. Below the formula of the normalized total error is given:

$$NTE = \frac{TE}{TE_{stand}} * 100 \quad (5.4a)$$

$$with{:}\, TE \sum |\Delta q^{exp} - \Delta q^{MaC}| \quad (5.4b)$$

This normalized total error is suitable to compare different values for the parameters. The parameters also have influence on the calculation time. A stable indicator of the calculation time is the number of node updates. The number of node updates is compared with running the complete model. For completeness also the simulation time is given, but this indicator is more influenced by other tasks of the computer while computing results, the main finding for the three parameters are separately discussed.

5.2.1 *Accuracy downstream*

Changing the accuracy downstream leads to differences in the quality of the results and the calculation time. The outcomes of MaC are sensitive towards the accuracy downstream parameter. Choosing the accuracy downstream higher results in a shorter calculation time, see table 5.5. The accuracy downstream has a big influence on the calculation time; downstream differences can fast propagate through the network (with the free-flow speed) leading to a large part of the network being activated.

Table 5.5: Sensitivity of ε downstream

ε downstream	NTE	Simulation time [in seconds]	Sensentivity node updates
1000	173%	25	4.61%
100	100%	51	17.09%
10	109%	104	35.97%
1	111%	89	47.17%

The results in table 5.5 show that the total error is minimal for an accuracy downstream of 100 vehicles. This is a relative high value, for demand differences Corthout (2012) advised to use a lower value between 5 and 25. Lower ε downstream leads to more flows being rightful affected and wrongfully affected flows. Although the amount of rightful affected flows increases, the total error does not decrease. This result indicates that MaC is not able to simulate flow differences upstream the same way as the LTM model. This difference can be explained with the differences between the multi commodity representation in LTM and the single commodity representation in MaC; in appendix F the difference in the results because of this difference is visualized.

5.2.2 *Accuracy upstream*

The calculation time in MaC is less sensitive to differences in the accuracy upstream, see table 5.6, because upstream differences do not propagate as fast through the network as downstream moving differences. The maximum speed of an upstream moving difference is the slope of the congested part of the fundamental diagram (around 20 km/h). For values between 1-100 the quality of the results is not influenced much, see table 5.6. The quality of the simulated results is not sensitive to the accuracy upstream, because the flow differences upstream are large. If the upstream differences propagate in a part of the network with lower flows, a lower accuracy upstream is needed.

Table 5.6: Sensitivity of ε upstream

ε upstream	NTE	Simulation time	Sensitivity node updates
1000	127%	46	15.80%
100	101%	46	16.96%
10	100%	48	17.09%
1	100%	48	17.09%

5.2.3 Turning fraction interval

The calculation time of the MaC model does not change that much with other turning fraction intervals. In the calculation of temporary capacity differences, the turning fractions are kept the same as the base simulation. The differences in calculation time are due to small differences in the links being activated. Surprisingly the normalized total error decreases with increasing turning fraction interval, see table 5.7. Corthout (2012) found the reverse pattern for demand differences. It would be logic that NTE decreases with a lower turning fraction interval because the differences between the LTM multi commodity (in which turning fraction change every node update) are minimized.

Table 5.7: Sensitivity of turning fraction interval

Turning fraction interval (min.)	NTE	Simulation time	Sensitivity node updates
10	96%	47	17.67%
5	100%	49	17.09%
3	103%	48	17.52%
1	103%	46	17.13%

5.3 Predictive validity

In this paragraph the results of the model are compared with real traffic data. In section 5.3.1, there is a discussion of which data is used. In section 5.3.2 the travel time of the data is compared with the travel times of the base model. In section 5.3.3 the travel time distribution and the standard deviations of the modelled travel times are compared with measured travel time.

5.3.1 Data

The travel times over the A2 to the A10 east are used for the predictive validity, see figure 4.1. Loop data from the Dutch National Data Warehouse Traffic Data (NDW) is used to calculate travel times. An adaptive smoothing method (Treiber et al. 2002) is used to interpolate between loop detector measurements. The speed at an unmeasured interconnecting ramp between A2 and A10 at motorway junction (Amstel) is assumed to be the same as at the A2, (hectometre 32.1). The data used is of 262 working days of 2008. The traffic model of Amsterdam-South is calibrated on data of 2008. The average travel times and standard deviations are shown in figure 5.5. The standard deviation is an indicator for the reliability of travel times. For better comparisons, the standard deviation is multiplied with the average difference between the travel time and standard deviation. In this way the area under both plots is identical.

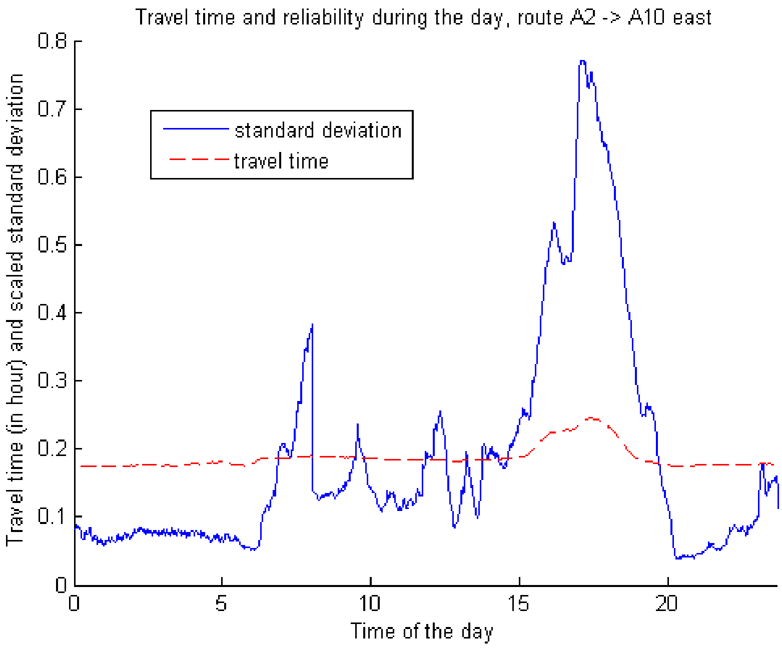

Figure 5.7: Travel time and travel time reliability during the day

For this route the most congestion is the evening peak. The reliability and average travel time increase during the evening peak period. In the morning peak, the average travel time does not change that significantly. The standard deviation does increase in the morning peak. From figure 5.7, a less stable result of the standard deviation is visible, a point that is already mentioned in 2.1.

5.3.2 Travel time

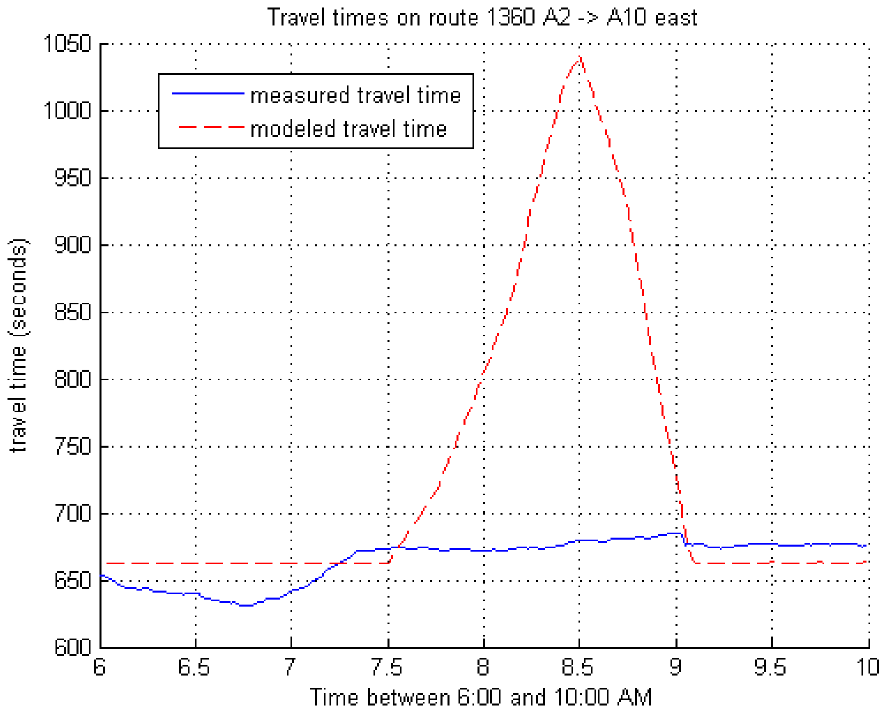

Figure 5.8: Travel time model and measured.

In figure 5.6, the travel time of the base model is compared with the measured travel times. The free-flow travel times have a good match. Only the model predicts a significant increase in travel time in the morning peak, in reality this increase is not visible. Because the travel time of the base model does not match the average travel time, the comparison of the travel time distributions of the models and reality are also more complicated. Instead of comparing the travel time distributions, the difference to the average travel time will be compared, in 5.3.3.

5.3.3 Travel time variability

In this section, the results of the model are compared with reality. In table 5.7, the standard deviation of the model and reality are shown. The standard deviation in reality is smaller than the standard deviation calculated by the models. This is opposite of what could be expected of the model, because only variability due to incidents is incorporated in the model. Adding more sources of variability will increase the standard deviation of the model further. The effects of incidents on the travel time are overestimated.

Table 5.8: Difference in standard deviation between model and reality.

Time	Standard deviation data	Standard deviation MIC	Standard deviation MaC
8:00	0.054	0.112	0.130
8:15	0.049	0.126	0.140
8:30	0.064	0.135	0.139
8:45	0.087	0.139	0.133
9:00	0.099	0.138	0.130

For an understanding of the large value of the standard deviation, figure 5.9 and figure 5.10 are useful. In these figures the average travel times are subtracted from the average travel time. The plot existing as a long vertical part is logical, because these are the observations that an incident does not have an influence on the travel time. The modelled delays of some incidents are way higher than in reality. In reality there are a few longer travel times, but with a much lower probability than calculated with the models. An explanation can be that the amount of data used for this comparison is limited. In the future, the resulting congestion due to an incident in reality and in the models should be compared. The large amount of long travel times in the model can be reduced by assuming rerouting behaviour. In this model there is chosen to model incidents where at least one lane is closed. The remaining capacity is further reduced. This set of input variables can also be an explanation for the long delays. To make the predictive validity of the model better, tweaking of the input variables is needed. A way of adding rerouting to the model is reducing the capacity reduction with the amount of traffic rerouting. The tweaking of the model would in that way mean calibrating the incident reduction

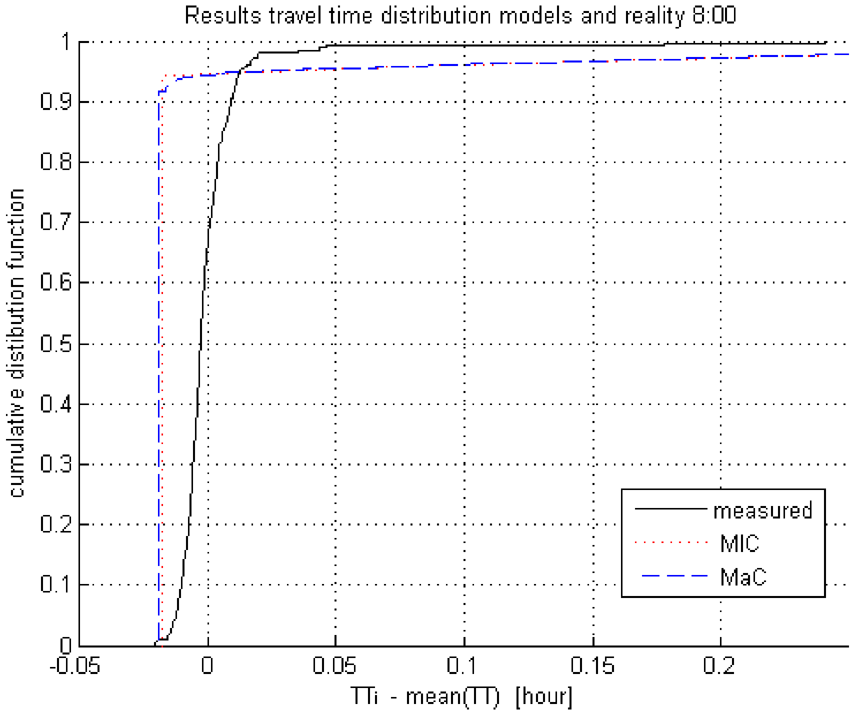

Figure 5.9: Cumulative distribution function at 8:00 AM

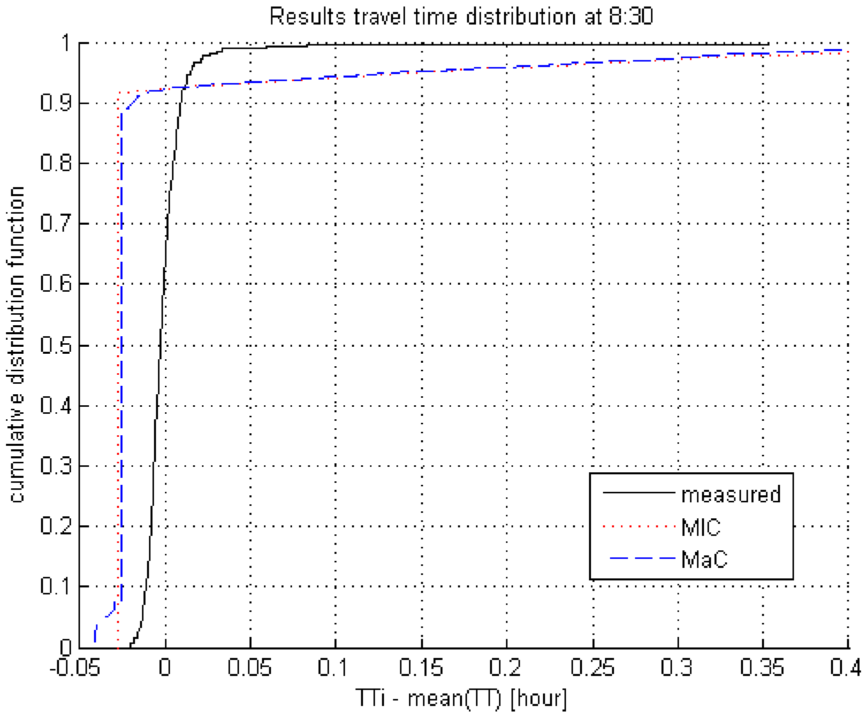

Figure 5.10: Cumulative distribution function at 8:30 AM

6 Conclusion

In this chapter the most important findings of this research are mentioned. This is presented as answers to the research questions.

Which indicator could best be used to describe travel time reliability and the societal costs of reliability?
The standard deviation is the best indicator to describe travel time reliability because it is a well-known test that incorporates early and late arrivals, can be translated to a monetary value and the analytical expression of the indicator with an assumed log-normal distribution is increasing convex. This means that the value of the indicator increases with a wider and more positive skewed (large right tale) travel time distribution.

The fact that reliability can be translated into a monetary value is important because in practical policy and related applications, the travel time reliability is one of the multiple indicators used in policies. All these indicators are translated to a monetary value to compare their relative importance.

It is argued that strong positive skewed travel time distribution (large right tale) increases the travel time reliability, because travellers value late arrivals stronger then early arrivals and large delays result in not only being late for an appointment but in completely missing the appointment.

There are arguments against the use of the standard deviation because it does explicitly take the skew of the travel time distribution into account and the mean is used in the calculation of the standard deviation and the mean is sensitive to outliers of the travel time distribution. None of the investigated indicators for travel time reliability do meat all the criteria. The standard deviation is the best because it meets the most and most important criteria for the travel time reliability indicator.

What are the current problems in forecasting door-to-door travel time reliability on a network?
There are two directions in forecasting travel time reliability:
1 A relationship between travel time reliability and average travel time, based on regression analyses;
2 Repeated modelling of travel times in a traffic model.

The forecasts of travel time reliability are based on an aggraded relationship between reliability and travel time. The rule of thumb, 25% of the travel time benefits can be seen as reliability benefits, is used or a relationship is calculated with a regression analyses. The problem with these forecasts is that they do not incorporate the spatial and temporal characteristics of the traffic system. One of these temporal and spatial characteristics of the traffic system is the congestion propagation.

In traffic models, part of these temporal and spatial characteristics can be incorporated. Challenges in forecasting travel time reliability with a traffic model is finding the right mixture between: calculation speed, accurate modelling of traffic flows and quality of the input variables. For an accurate forecast of travel time variability, one needs an accurate representation of congestion patterns. A dynamic traffic model with an accurate description of the spatial and temporary characteristics of congestion has clear advantages over static models, but dynamic models also have a longer calculation time. Most travel time reliability forecasts with traffic models are based on the repeated explicit simulation of one or multiple sources of variability. The traffic model must be able to accurately model these variations.

Which methods/models are promising methods/models to forecast door-to-door travel time variability due to incidents on a network, and can be further investigated?
Promising methods to forecast travel time variability due to incidents are marginal traffic models, MIC (Marginal incident Computation) and MaC (Marginal Computation) (Corthout, 2012). MIC and MaC are promising methods to forecast travel time variability because they combine an accurate representation of traffic flows with fast computation times.

The representation of traffic flows in the marginal models is accurate because the spatial and temporal characteristics of congestion are modelled. This is done with the link transmission model (LTM) (Yperman, 2007), based on first order traffic flow theory.

The calculation time of the marginal traffic models is small because only in a small part of the network traffic flows are calculated when an incident is simulated. Marginal traffic models calculate the flow difference between a base situation and the flows in case of (for instance) an incident. As input for the marginal traffic models, the output of a dynamic traffic model is needed. This base model only has to be run once, where the marginal traffic model is run multiple times.

How can door-to-door travel time variability be forecasted due to incidents on a network?
Two options to forecast travel time variability are investigated, simulating incidents in marginal traffic model MIC and marginal traffic model MaC. Twelve different incident types are identified; these incidents are simulated with a weighted Monte Carlo sampling. After a start-up period of two hours every quarter of an hour, a travel time distribution and a standard deviation is calculated. This output can be generated for all or a specific selection of routes or OD pairs. Travel time distribution for the total system travel time can also be calculated.

How accurately can door-to-door travel time variability due to incidents on a network be forecasted?
The developed models are investigated in two ways, based on how accurate they forecast travel time variability:
1 The results of the marginal traffic models are compared with results obtained with the base model.
2 The results of the model are compared with a measured travel time distribution.

In both cases, the accuracy of the forecast is investigated by using it on a network of Amsterdam-South. The model has 965 links, 3034 routes with 37 origins and destinations.

The model simulating traffic flows in marginal traffic model MIC is only capable of calculating the flow differences upstream of the incident location. The congestion upstream of the incident location is reasonably accurately modelled. The model simulating traffic flows in marginal traffic model MaC models upstream and downstream differences. For seven incidents the accuracy of the results are determined, 30% of the flows are rightfully affected. These 30% of the flows rightfully affected are the most important flow changes in MaC. The errors in the calculation of the traffic flows is up to 2000 vehicles/hour, which is significantly larger than the errors in simulating demand (100 veh/h) differences in MaC. The calculation of downstream flow differences in MaC has many errors; a reason for these errors is the assumption of constant turning fractions and the difference between the base model that is multi commodity simulation and MaC that is single commodity simulation. Due to an incident, specific traffic is delayed, resulting in an incorrect modelling of traffic flows downstream of the incident location.

The forecast of the travel time distribution is compared with a real travel time distribution. The modelled travel time distribution does not resemble reality, it lacks realism, due to the fact that only a limited amount of all variability is modelled and the modelled variation lacks realism. In the current version, no rerouting behaviour is assumed. The validity of the input variables in these traffic models is not investigated.

Which of the researched models is the most suitable model to forecast travel time variability from door-to-door due to incidents on a network?

The MIC model is of the researched models the most suitable model to forecast door-to-door travel time variability caused by incidents. Because the MIC model is more than 18 times faster, and the accuracy of the simulation of the upstream flow differences in and MIC and MaC are almost comparable. The ability of MaC to calculate downstream differences is less important because the most important changes in the travel time are upstream of the incident location.

In this research it is shown that door-to-door travel time variability caused by incidents can be forecasted with explicit simulation of incidents in marginal dynamic traffic model MIC within reasonable amount of time.

7 Recommendation

In this chapter recommendations and directions for further research are indicated.

7.1 Using existing marginal traffic models for travel time variability studies

In this research marginal traffic models MIC and MaC are used to estimate a travel time distribution due to incidents. For these studies, the use of marginal traffic model MIC is recommended because the calculation time of the procedure is more than 18 times faster than MaC. In the current small network, the calculation time of the procedure in MaC is a bit more than a weekend; the same results in MIC can be obtained in several hours. Both models have almost the same accuracy if the upstream flow differences are compared.

7.2 Direction for further research

Direction for further research can be divided into two directions, improving the current setup with MIC and MaC, or starting with a new approach.

7.2.1 In the current setup

- Adding rerouting behaviour in the model. Corthout (2012) described en-route rerouting model in MaC. This complete en-route rerouting model will be unpractical in travel time variability studies in larger networks due to the increase in calculation time. With pre-processing the input or post processing the output, rerouting behaviour can be added in a simplified manner. In Snelder et al. (2012), a methodology of pre-processing the input is discussed. The capacity of the incident location is increased with the amount of traffic rerouting. Validating / calibrating the input variables. Checking if the input variables used also result in the right amount of congestion. It is recommended to combine this with adding some kind of rerouting behaviour. The capacity reduction and then mainly, the less efficient use of the infrastructure, is based on result found in literature. If this factor also leads to a correct modelling in a traffic model is not known. The relation between the incident types and the predictive validity also needs to be investigated further. A study that systematically compares traffic data with the model in recommended.
- Research on how the problems in MaC modelling the downstream flows of an incident, can be reduced. A solution is changing the turning fraction in the simulation, possibly this can be done in the same way as modelling demand differences in MaC. Only without assuming the travel times constant. The turning fractions have to be changed until they satisfy route demand; this iterative procedure is not implemented in MaC, for more information about updating turning fractions see, Blumberg et al. (2009).
- Research on how the deactivation rules in MaC could be adjusted. The current deactivation rules do not give satisfactory results if temporary capacity reductions are simulated. An extra deactivation rule could be added that checks if the CVN (cumulative vehicle numbers) of the base simulation and the simulation in MaC are the same (whit a certain accuracy threshold).
- A way to reduce the length of the start-up period and cooling down period. In the current set up, a long start-up period is needed to also have incidents where the capacity reduction is gone, but still, congestion due to the incident is

present. These long start-up periods and cooling down periods make the time output is generated unnecessary short.

- Investigating how more sources of variability could be incorporated in the model. In order to get a forecast of travel time reliability and not only the variability due to an incident. A methodology to incorporate rain in the model set-up is to create two base simulations one for dry circumstances and one for heavy rain fall. In the base model with rain the capacity (and the free-flow speed) of all links is reduced. In both models incidents could be simulated. The obtained travel time distributions can then be combined, in the same way as with an OD pair, but then not with the route fraction but with the probability of rain. With this methodology the possible interdependency between rain and the occurrence of rain can also be incorporated.

7.2.2 Other models with the same philosophy

In this research, the marginal traffic models MIC and MaC and their base model LTM are used for the travel time reliability forecast. There are a few problems with the match between base and marginal models. The simulation in MIC and MaC is a single commodity simulation and in the base model a multi commodity simulation; this leads to estimation errors, or rather the absence of updating the turning fraction so that they are consistent with route demands. The current base model has a fixed and a priori route generation. For an accurate modelling of the consequences of an incident, one needs a model with a flexible route set to enable en-route rerouting. The small time steps (in INDY in order of 5 seconds) that are needed for accurate working of the LTM algorithm leads to a computationally demanding base model. For an accurate working of a marginal model the algorithms of the base model and marginal model need to be closely related, this results in small time steps in the marginal model (this is how marginal model MaC works).

If all these problems in the current models are analysed it is good idea to investigate to possibilities to forecast travel time variability/reliability with other base model. The fixed point model (Gentile et al., 2007) for a DTA seams a promising model to investigate for travel time variability/reliability forecasts (Tampère, 2012).

With a fixed point solution algorithm for a dynamic traffic model, a coarser description of traffic flows in time is possible. An update frequency of 12 per hour (5 minutes) is possible with this algorithm. This is possible because the proposed model for a DTA does not use continuous dynamic network loading as a sub problem. With continuous dynamic network loading the time step needs to be smaller than the free flow travel time of a link (or in case of a cell transmission model smaller than the free flow travel time of a cell). The fixed point model is compared with two other earlier proposed cell based DTA models (Gentile et al., 2007). The calculation time of the fixed point formulation is 35-200 faster than the other cell based approaches[14]. The model proposed by Gentile et al. (2007) exist of multiple iterative procedures, the spillback of congestion is modeled in an iterative procedure satisfying link demand and capacity. The model uses a single commodity environment in which the turning fraction are in an iterative procedure changed until day satisfy the route demand. The third iterative procedure determines the route choice. This model to calculate a DTA is more closely related to the idea of

[14] In Ypermann (2007) it is also stated that the link transmission model has a lower computation time or a more accurate description the cell transmission models but the saving in calculation time is less than the amount of cells defined per link (so not in the order of 35-300).

marginal simulation then INDY with LTM, with these iterative procedures only those links and route fractions are recalculated that are changed due to the simulation of an incident. The advantages of using the fixed point formulation of Gentile et al. (2007) are the fast calculation time, the iterative procedures, because of these iterative procedures not all flows have to be recalculated.

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Appendixes

A. Traffic states, reliability and travel time distribution

In this appendix three relationships are discussed. The first relationship is the shape of the fundamental diagram during the day. The second relation is between the travel time reliability and mean travel time during the day. The third relationship is the relation between travel time reliability and traffic states. The difference in the definition of traffic states and the difference in outcome are discussed.

The shape of the travel time distribution during the day
Van Lint et al. (2008) state that in onset and dissipation of congestion the travel time distribution is heavily positive-skewed (large right tale of the distribution) and that in free flow the travel time distribution is symmetrical and narrow. In heavy congestion the travel time distribution is symmetrical or a bit negative-skewed and wide. Eliasson (2006) found that there are more positive-skewed then negative-skewed distributions. Eliasson (2006) found more positive-skewed distribution with high congestion and high standard deviation. The correlations found by Eliasson (2006) are not strong. At least it can be said that the findings of Van Lint et al. (2008) and Eliasson (2006) are not in contradiction with each other.

Relation between travel time reliability and mean travel time during the day
Fosgerau et al. (2008) plots the travel time against the standard deviation. In figure a.1 there is a specific pattern recognizable. In the peak period with congestion these two variables make a counter clockwise round. In the dissipation phase of the congestion still high standard deviations are measured but mean travel time is already rapidly deceasing. Later Fosgerau (2010) analytically proved that in a Vickery bottleneck the expected delay and the variance of the delay make a counter clockwise round. The results are only valid for the case that random variations of demand and capacity are not within one period. In reality this assumption does not hold in a road network, because there are capacity and demand differences from one day to another. Further the outcome only holds for the specified variation in capacity and demand that in reality does not have to hold. Van Lint (2005) finds the opposite of Fosgerau et al. (2008): in onset of congestion the travel time are less reliable then in the dissipation phase of congestion, instead of less reliable travel times in the dissipation phase of congestion, as seen in figure a.2. The indicator to express travel time reliability used by Van Lint et al. (2005) and Fosgerau et al. (2008) is different. Van Lint et al. (2005) express the reliability in the skew and width of the distribution while Fosgerau et al. (2008) used the standard deviation.

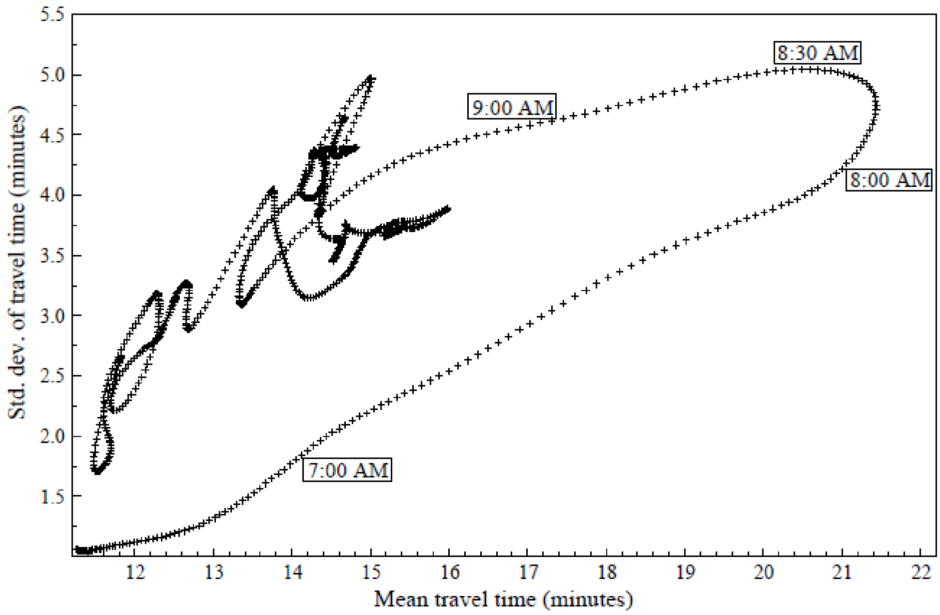

Figure A.1: standard deviation of travel times plotted against the mean travel time, Fosgerau et al. (2008)

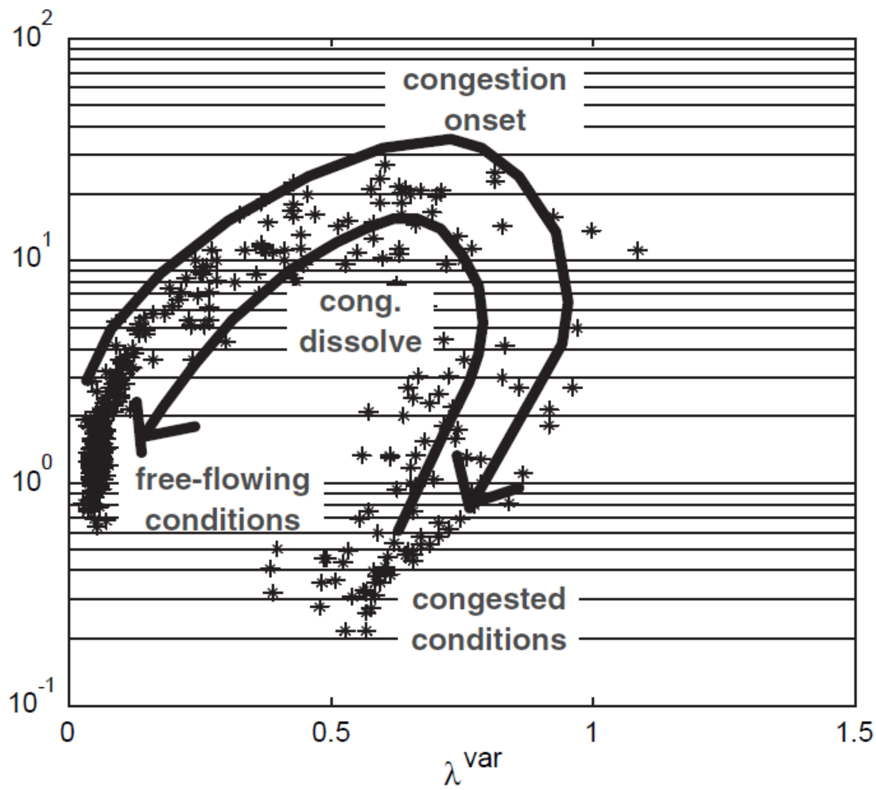

Figure A.2: The variability of travel times, described in the skew and width indicator, during a peak period, Van Lint et al. (2005)

Travel time variability and different traffic states

There are three papers that try to estimate a relation between travel time variability and different traffic states. The papers are from Peer et al. (2012), Eliasson (2006) and Tu et al. (2006). The names and the definitions of the traffic states differ per paper. Peer distinguish between three traffic states: free flow being measurements above 0.9 times the free-flow speed, congestion being measurements between 0.9 times the free-flow speed and the speed at capacity, and hyper-congestion being measurements lower than the speed at capacity. Eliasson does not divide his data set into different categories, but plot his results in the same way as Peer does. Tu makes another distinction between traffic states. Free flow being measurements lower than a certain inflow. Transition flow being measurements between two critical inflow levels, and capacity flow measurements with an inflow above a certain threshold. The different traffic states are plotted in a fundamental diagram in figure a.3. The conclusion of Peer is that with higher congestion the relation of mean delay and travel time variability is decreasing. A one minute decrease in mean delay has a bigger impact on variability in free-flow then in (hyper-) congestion. Eliasson draws another conclusion for low congestion levels the relation between relative increase in travel time and relative standard deviation is stable. In congestion this relation is increasing and for high congestion levels decreasing. Tu also concludes that in free flow the variability is stable, in transition flow the variability is increasing with the inflow, and in capacity flow decreasing with the inflow. The conclusion of Tu has a lot of similarities with the conclusion of Eliasson. Only the definitions of the different traffic states are different. The result of Tu is logic with a look at the fundamental diagram. In reality there are rarely measurements really low at the congestion branch of the fundamental diagram. The dotted part of the fundamental diagram in figure a.3. For these low measurements there need to be gridlock, but Tu always determined inflow so far upstream that at that spot there was no congestion. This means that gridlock was by setup of the experiment not possible.

The strange thing about the definitions used by Peer et al. (2012) is that some minimum and maximum travel time in a certain categories are defined by the boundaries of the categories. The differences between Peer et al. (2012) and Eliasson (2006) con not be explained by different definitions because they were almost the same.

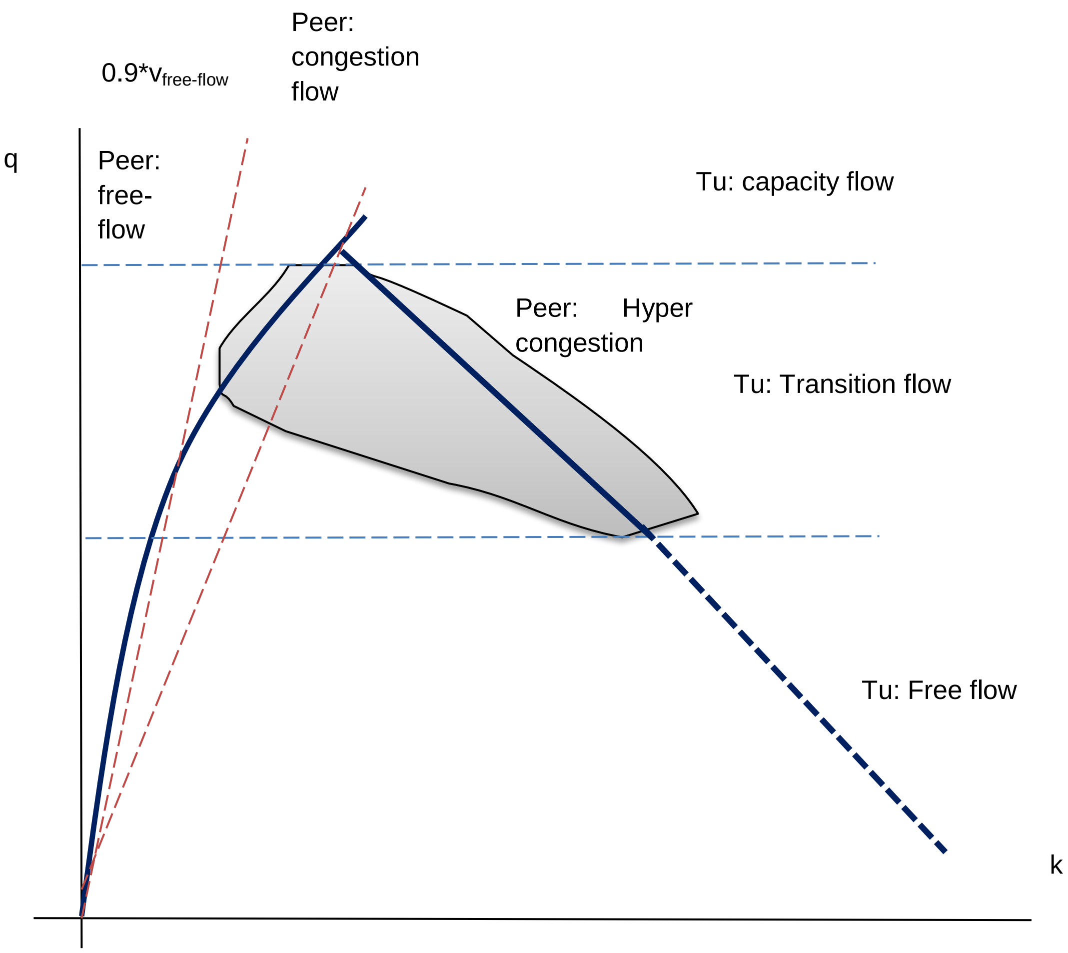

Figure A.3: Definitions of different traffic states plotted in a fundamental diagram

B. Analytical formulas travel time indicator

For three indicators it is investigated if they are increasing convex with the scale parameter of the log-normal distribution. The three indicators under consideration are:

- The second probability indicator.

$$PR_2 = P(TT_i \geq 10 + TT_{50}) \tag{2.9}$$

- The width of the travel time distribution

$$\lambda^{var} = \frac{TT_{90} - TT_{10}}{TT_{50}} \tag{2.10}$$

- The skew-width indicator

$$SW = \begin{cases} \dfrac{\lambda^{var}\ln(\lambda^{skew})}{L_r} & \lambda^{skew} > 1 \\ \dfrac{\lambda^{var}}{L_r} & \text{otherwise} \end{cases} \tag{2.12}$$

With:

$$\lambda^{skew} = \frac{TT_{90} - TT_{50}}{TT_{50} - TT_{10}} \tag{2.11}$$

The investigation in this appendix is following the same approach as Pu (2011). An analytical relationship for travel time reliability indicators will be found. Pu investigated the other travel time reliability indicators mentioned in section 2.1.2, equation [2.3- 2.8] and 2.11. For the misery index (equation 2.7) it was not possible to come up with an analytical relationship. Pu (2011) assumed that the travel time distribution is log-normal distributed.

$$f(x)=\frac{1}{(x-\theta)*\sigma*\sqrt{2\pi}} * e^{-\frac{\ln\frac{x-\theta}{m}}{2\sigma^2}} \qquad x \geq \theta; m, \sigma > 0 \tag{2.1}$$

Where:
σ = shape parameter
θ = location parameter
m = scale parameter

For simplicity Pu (2011) assumes the location parameter to be zero (*θ=0*). The definition of the log-normal distribution used in the derivations is.

$$f(x)=\frac{1}{x\sigma\sqrt{2\pi}} * e^{-\frac{\left(\ln\frac{x}{m}\right)^2}{2\sigma^2}} \qquad x \geq \theta; m, \sigma > 0 \tag{B.1}$$

In these indicators percentiles are used many times. A percentile of equation B.1 can be calculated with percent point function B.2.

$$G(p) = me^{\sigma\Phi^{-1}(p)} \qquad 0 \leq p < 1; m, \sigma > 0 \tag{B.2}$$

Φ^{-1} = probit function
Φ = the cumulative distribution function of $N(0,1)$
$\mathrm{p} = \frac{\text{percentile}}{100}$

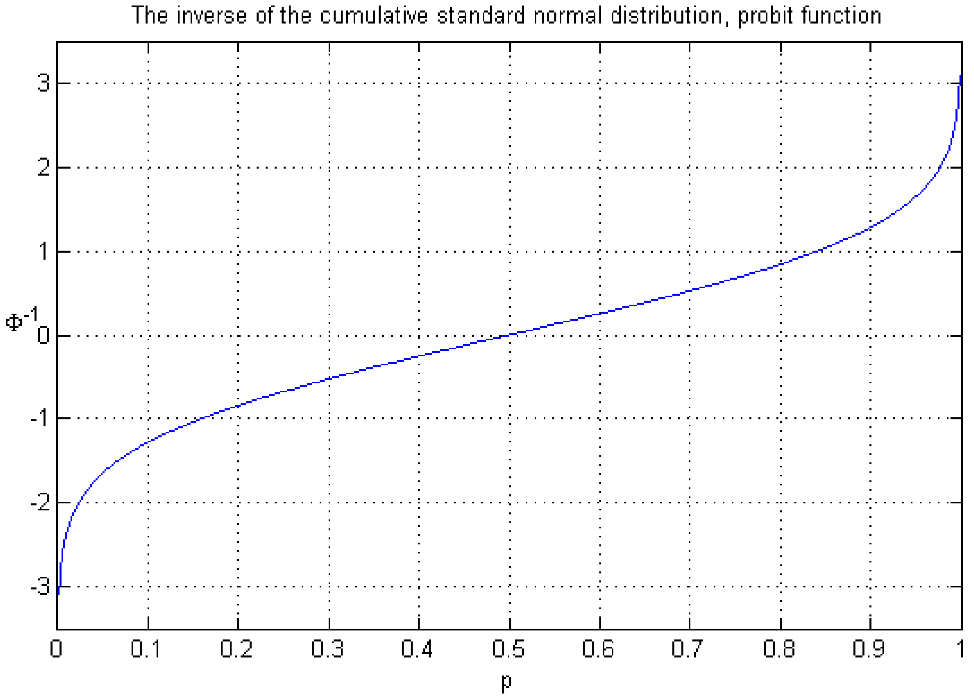

Figure B.0.4: the inverse of the cumulative distribution function of the standard normal distribution, also called probit function

Calculating the median travel time is straightforward, filling in formula (B.2) in with p=0.5:

$$\Phi^{-1}(0.5) = 0 \tag{B.3}$$

$$G(0.5) = me^{\sigma*0} \tag{B.4}$$

$$G(0.5) = m \tag{B.5}$$

Probability indicator
Let *p* be the probability that the travel time is < 10 + mean travel time. The 10 minutes delay is replaced by variable a. The following relationships hold:

$$G(p) = a + m \tag{B.6}$$

$$me^{\sigma\Phi^{-1}(p)} = a + m \tag{B.7}$$

$$e^{\sigma\Phi^{-1}(p)} = \frac{a}{m} + 1 \tag{B.8}$$

$$\sigma\Phi^{-1}(p) = \ln\left(\frac{a}{m}+1\right) \tag{B.9}$$

$$p = \Phi\left(\frac{\ln\left(\frac{a}{m}+1\right)}{\sigma}\right) \tag{B.10}$$

The second probability indicator can then be expressed as:

$$f(\sigma) = 1 - p \tag{B.11}$$

$$f(\sigma) = 1 - \Phi\left(\frac{\ln\left(\frac{a}{m}+1\right)}{\sigma}\right) \quad \sigma > 0, m > 0 \tag{B.12}$$

Φ Is the cumulative distribution function of the standard normal distribution. Because Φ is increasing for increasing σ and $\left(\frac{\ln\left(\frac{a}{m}+1\right)}{\sigma}\right)$ is decreasing for all $\sigma > 0$, the function is increasing with the shape parameter. The function is not convex increasing for increasing shape parameter. For increasing shape parameter the function approaches 0.5.

Width indicator
The 90th percentile can be expressed as:

$$TT_{90} = G(0.9) \tag{B.13}$$

$$G(0.9) = m\, e^{1.282\sigma} \tag{B.14}$$

The 10th percentile can be expressed as:

$$TT_{90} = G(0.1) \tag{B.15}$$

$$G(0.1) = m\, e^{-1.282\sigma} \tag{B.16}$$

The analytical expression of the width indicator is:

$$f(\sigma) = \frac{m\, e^{1.282\sigma} - m\, e^{-1.282\sigma}}{m} \tag{B.17}$$

$$f(\sigma) = e^{1.282\sigma} - e^{-1.282\sigma} \tag{B.18}$$

To investigate if the function is increasing the first derivative has to be taken. To investigate if the function in convex the second derivative has to be taken.

$$f'(\sigma) = 1.282e^{1.282\sigma} + 1.282e^{-1.282\sigma} > 0 \qquad \sigma > 0 \tag{B.19}$$

$$f''(\sigma) = 2.564e^{1.282\sigma} - 2.564e^{-1.282\sigma} > 0 \qquad \sigma > 0 \tag{B.20}$$

The width indicator has an increasing convex shape with an assumed log-normal distribution.

Skew width indicator
The expression for the skew is given in Pu (2011) eq. 11

$$\boldsymbol{\lambda^{skew} = e^{1.282} > 1 \qquad \sigma > 0} \quad \text{(B.21)}$$

Because for $\sigma > 0$, $\lambda^{skew} > 1$ the skew width indicator becomes:

$$\boldsymbol{SW = \frac{\lambda^{var}\ln(\lambda^{skew})}{L_r}} \quad \text{(B.22)}$$

Most of the used indicators for travel time reliability are unit less, of the indicators mentioned in section 2.1.2 only the standard deviation and the skew- width indicator are not unit less. To compare the results the skew width indicator is made unit less. The results of this indicator are not the reliability per unit distance but say something about the whole route. The indicator that is tested is:

$$\boldsymbol{SW = \lambda^{var}\ln(\lambda^{skew})} \quad \text{(B.23)}$$

The analytical expression of this indicator is:

$$\boldsymbol{f(\sigma) = e^{1.282\sigma} - e^{-1.282\sigma} * \ln(e^{1.282\sigma})} \quad \text{(B.24)}$$

$$\boldsymbol{f(\sigma) = 1.282\sigma e^{1.282\sigma} - 1.282\sigma e^{-1.282\sigma}} \quad \text{(B.25)}$$

The first end second derivative of this function is calculated to find out if the function is increasing convex.

$$\boldsymbol{f'(\sigma) = 1.282e^{1.282\sigma} + 2.564\sigma e^{1.282\sigma} - 1.282e^{-1.282\sigma} + 2.564\sigma e^{-1.282\sigma}} \quad \text{(B.26)}$$

$$\boldsymbol{f'(\sigma) > 0 \quad for\ \sigma > 0} \quad \text{(B.27)}$$

$$\boldsymbol{f''(\sigma) = 5.128e^{1.282\sigma} + 3.287\sigma e^{1.282\sigma} + 5.128e^{-1.282\sigma} - 3.287\sigma e^{-1.282\sigma} > 0} \quad \text{(B.28)}$$

The skew width indicator is increasing convex with the assumed log-normal distribution.

Conclusion
In this appendix an analytical expression for the second probability indicator, the width indicator and the skew-width indicator are found, with the assumption that travel times are log-normal distributed, equation B.2. The derived function for the second probability indicator is increasing concave, the function of the width and the skew-width indicator are increasing convex. In table B.1 the results of these analyses are given.

Table B.1: Overview results analytical analyses

Indicator	$f(\sigma)$	Properties, $\sigma > 0$
Second probability indicator	$f(\sigma) = 1 - \Phi\left(\frac{\ln\left(\frac{a}{m} + 1\right)}{\sigma}\right)$	Increasing, concave (for $\frac{a}{m}$ >1)
Width indicator	$f(\sigma) = e^{1.282\sigma} - e^{-1.282\sigma}$	Increasing, convex
Skew-width indicator	$f(\sigma) = 1.282\sigma e^{1.282\sigma} - 1.282\sigma e^{-1.282\sigma}$	Increasing, convex

C. Comparison results MIC with analytical formulas

In this appendix the results from a MIC simulation are compared with analytical derived formulas based on first-order traffic flow theory. This comparison is made to give insight in the situations where estimation errors in the MIC module have significant impact on the results. Two situations are discussed:

- Homogeneous and stationary traffic situation with an incident
- An incident upstream of a junction.

Scenario 1: homogeneous and stationary road

A formula originally derived by Olmstead (1999), later by Knoop (2009) using horizontal queuing:

$$\boldsymbol{Total\ Delay} = \frac{\mathbf{1}}{\mathbf{2}}\frac{\boldsymbol{C_2} * \Delta \boldsymbol{T^2} * (\boldsymbol{r}-\mathbf{1}) * (\boldsymbol{r} * \boldsymbol{C_2} - \boldsymbol{D})}{\boldsymbol{C_2} - \mathbf{D}} \qquad \text{(C.1)}$$

The meaning and the values for the different variables are given, in table c.2

Table C.2: variables scenario 1

variable	meaning	Value
ΔT	Duration of the capacity reduction	0.25 hour
r	The capacity reductions	0.5
C2	Capacity of the road	1500 veh/hour
D	The damand	2000 veh/hour

This reduction is also simulated in the MIC module with two links of 10 km. The results of the analytical formula is 31.25 hours and of the MIC module 31.2500000000002 hours. The MIC module and the analytical formula give the same output in this scenario. The MIC module makes a small mistake with rounding within the calculation.

Scenario 2: Incident upstream of a junction.

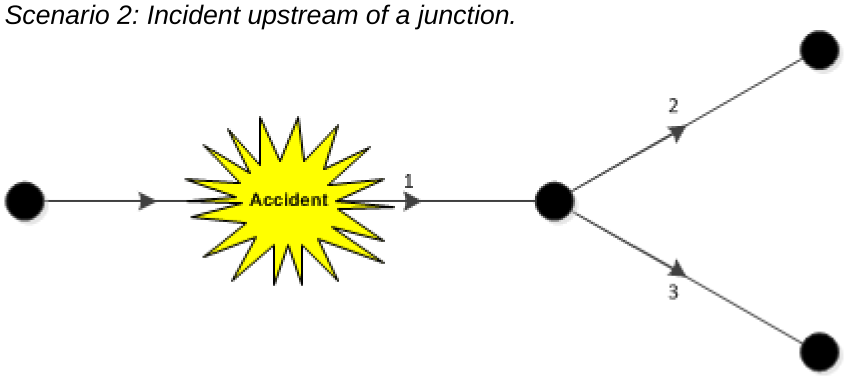

Figure C.1: Incident before junction

In this scenario there is an incident upstream of a junction. Link 1 has 4 lanes and link 2 and 3 has 2 lanes. At the junction more people choose link 2 then link 3. The analytical formula is given with the formula below.

$$\boldsymbol{Total\ Delay} = \frac{1}{2}\frac{\Delta T^2(r^2\psi C_1^2 - C_1\psi rD - rC_1C_2 + C_2D)}{C_2 - \psi D} \tag{C.2}$$

Table C.3: variables scenario 2

variable	meaning	value
ΔT	Duration of the capacity reduction	0.25 hour
r	The capacity reductions	0 (total blockage)
ψ	Fraction of travelers using link 2	0.6
C_1	Capacity of link 1	8000 veh/hour
C_2 (C_3)	Capacity of link 2 (3)	4000 veh/hour
D	Demand	6000 veh/hour

This scenario is also modeled in the MIC module, link 1 is divided into 3 links all links are 6 km. The incident is simulated at the upstream end of the third link of link 1. The analytical formula results in 1875 vehicle hours lost where the MIC module calculates 750 vehicle hours lost. In this simple scenario the MIC module cannot calculate the new congestion wave at the junction after the incident duration. This estimation error is due to the fact that MIC does not model flows upstream of the incident location. The result of the MIC module is equal to the results of the analytical formula of scenario 1. The MIC module is not able to forecast traffic state G in figure C.2 and figure C.3. This scenario shows that the MIC module is not able to reproduce the results of a simple analytical formula.

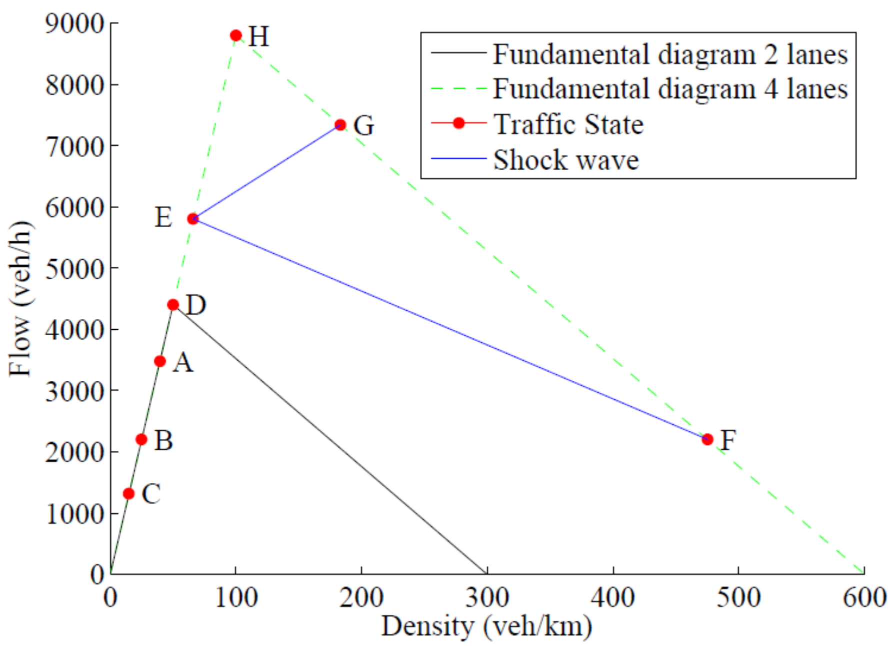

Figure C.2: Fundamental diagram of C1 and C2, (Knoop, 2009)

In this appendix three relationships are discussed. The differences and similarities found by different authors will be discussed. The first relationship that will be discussed is the shape of the fundamental diagram during the day. The second relationship is that of the travel time reliability and mean travel time during the day. The third relationship is the relation between travel time reliability and traffic states. The difference in the definition of traffic states and the difference in outcome are discussed.

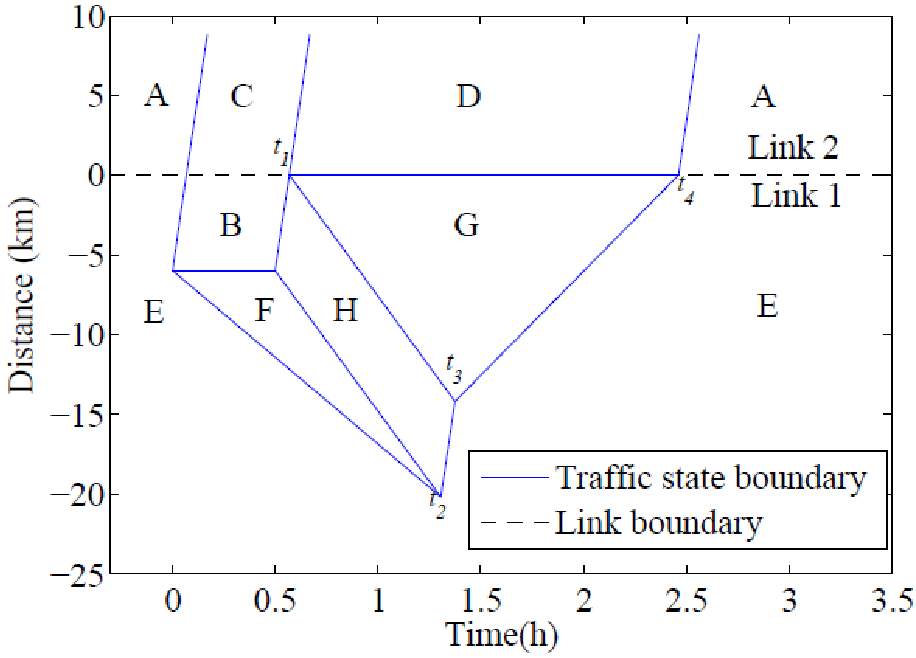

Figure C.3: Resulting traffic situation because of scenario 2, (Knoop, 2009)

D. Difference between LTM KU Leuven and LTM TNO

For MIC the total CVN out of INDY (the LTM model is implemented in INDY) are used, for MaC the total CVN out of LTM Leuven are used. There is investigated what the differences between those two models is. Differences between the outputs of the both models are investigated only on the dynamic network loading. Route choice is not considered in this comparison. The differences between LTM Leuven (in the remainder also called LTM) and INDY are:

- The dynamic OD demand is in INDY changed a factor Indy.loading factor (4.01 is used), this factor is not used in LTM
- Values in the dynamic OD matrix that are smaller than 0.5 veh are removed in INDY in LTM this is not done.
- The node model in LTM and INDY is different. In LTM the generic node model described in Corthout (2012) is used. The node model in INDY is not exactly known. It is not the generic node model described in Corthout (2012) or the node model described in Bliemer (2007) as stated in Corthout (2012).
- Numerical approximation is different. LTM of the KU Leuven is an event based model, meaning that node and link update frequency is dependent on the free-flow travel time of the link(s). In LTM a user defined update frequency is used. If the frequency is too high there is no congestion modeled on the links that have a smaller free-flow travel time then the update frequency.
- In INDY the CVN of t=0 or t=1000 (start point value in LTM and INDY is different) are actually the CVN at t= timestep_IndyOutput.
- The difference between LTM and INDY is that origin and destination links in LTM don't have a physical length. In LTM origin and destination links don't have a travel time in INDY origin and destination links have a travel time. This results in other assignment because not all origin links have the same free-flow travel time.

In figure D.1 and figure D.2 the difference in flow between LTM_Leuven and INDY are shown, only 3.6% of all flows differ more than 10 vehicles. From a closer observation of the results the differences between LTM Leuven and INDY are mainly due to the fact that origin links don't have travel times in LTM and INDY they have. In figure D.1 and figure D.2 the results of INDY are scaled with 5 minutes and the outputs are corrected for the loading factor.

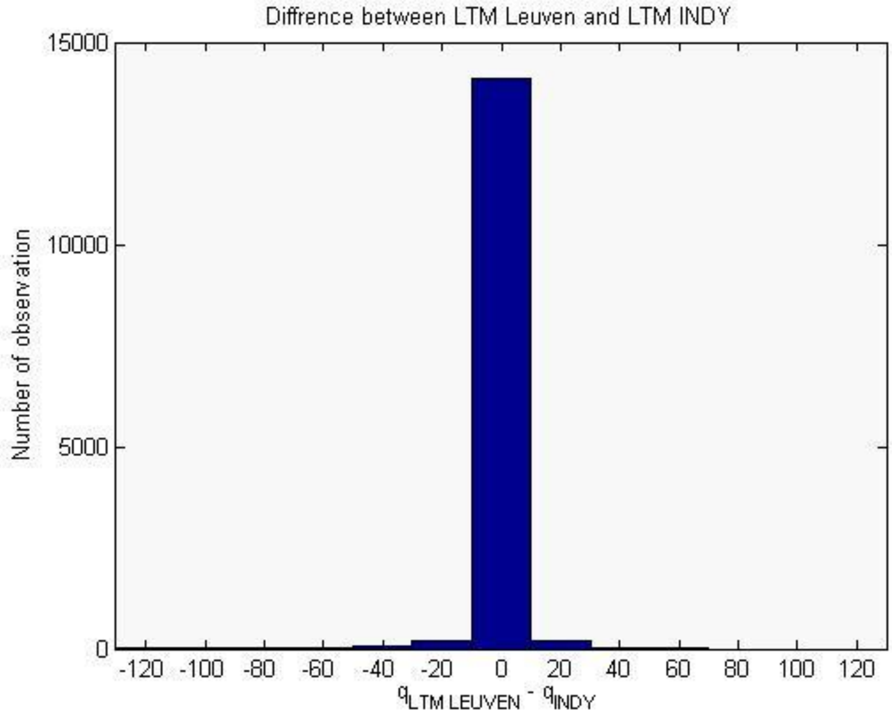

Figure D.1: Difference flow between LTM Leuven and LTM INDY.

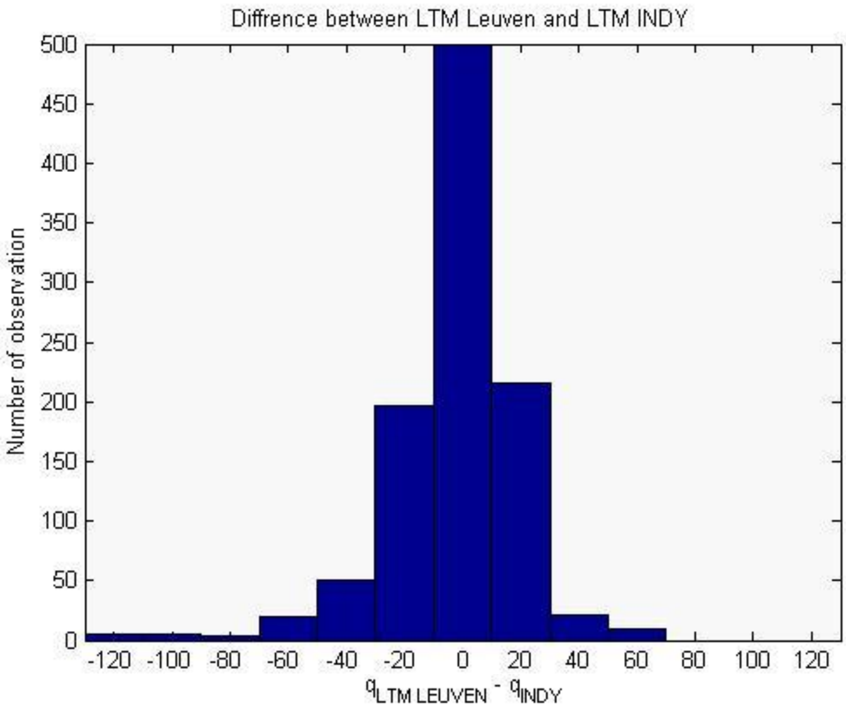

Figure D.2: Zoomed in difference flow between LTM Leuven and LTM INDY.

The differences between LTM Leuven and Indy are further investigated. All origin and destination links are given the same length. In the comparison the time scale is corrected for the travel time on those origin and destination links. Secondly the loading factor in INDY is set in such way that this is not a difference between both models anymore, (equal to 4, or generic set the frequency of timeslices in [$hour^{-1}$]). The differences between LTM Leuven and LTM INDY are presented in

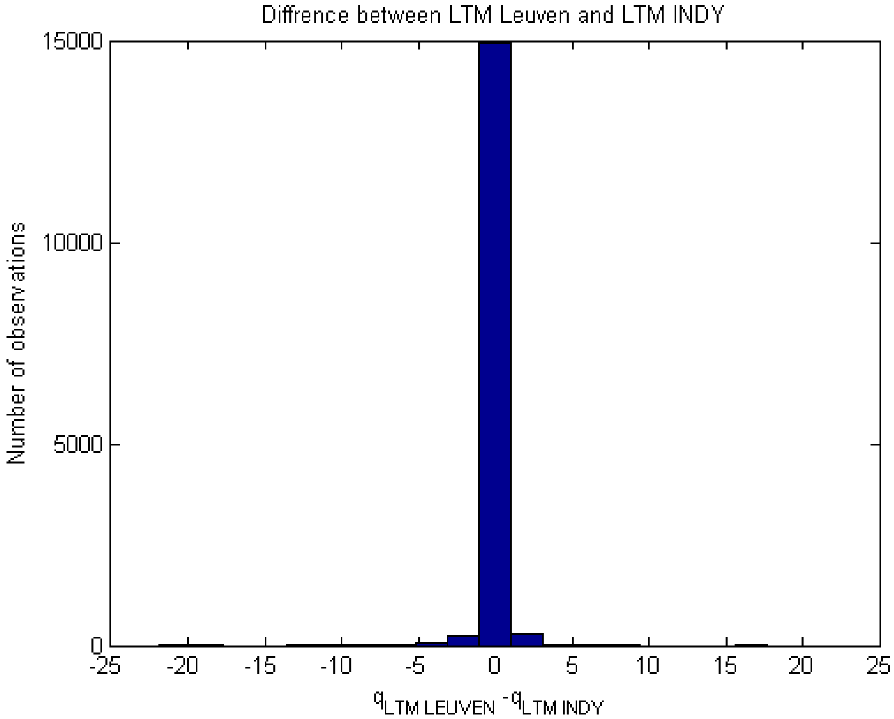

Figure D.2: Difference in flow between LTM Leuven and LTM INDY, with adaptations

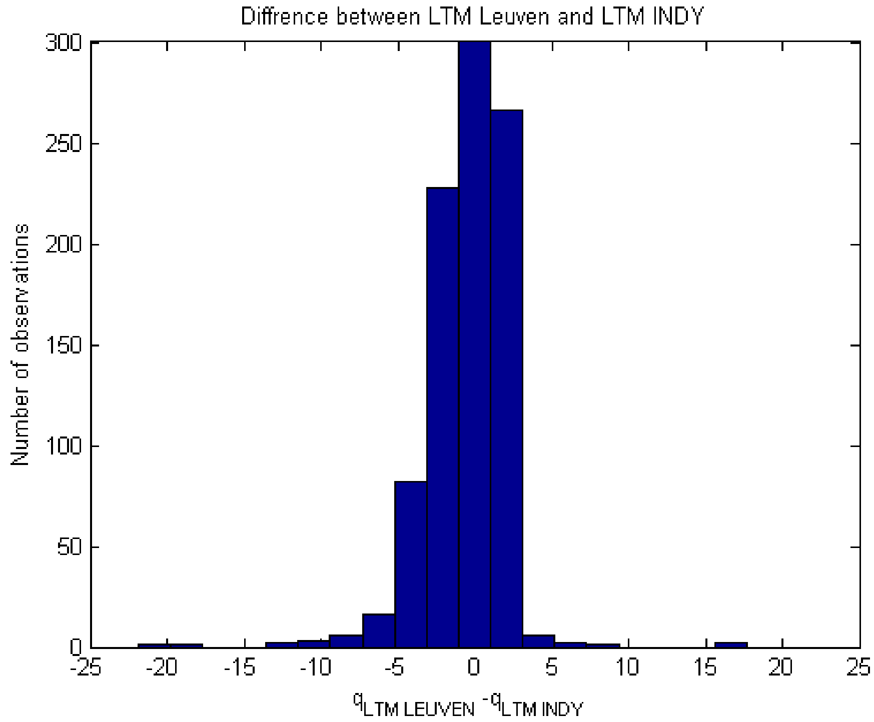

Figure D.2: Zoomed in difference in flow between LTM Leuven and LTM INDY, with adaptations

E. Single commodity and multi commodity

In this appendix the difference between single commodity simulations and multi commodity simulations is explained.

In a single commodity simulation the propagation of traffic through the network is based on turning fractions. These turning fractions are input for a single commodity simulation.

In a multi commodity simulation the paths are remembered during the simulation. At a node the demand from the sending links to the receiving links can be calculated with knowledge about the paths.

The traffic in a single commodity simulation on a link is seen as one flow where in a multi commodity simulation the flow on a link is subdivided in path specific flows. The consequences of this difference at a node are schematically shown in figure E.1.

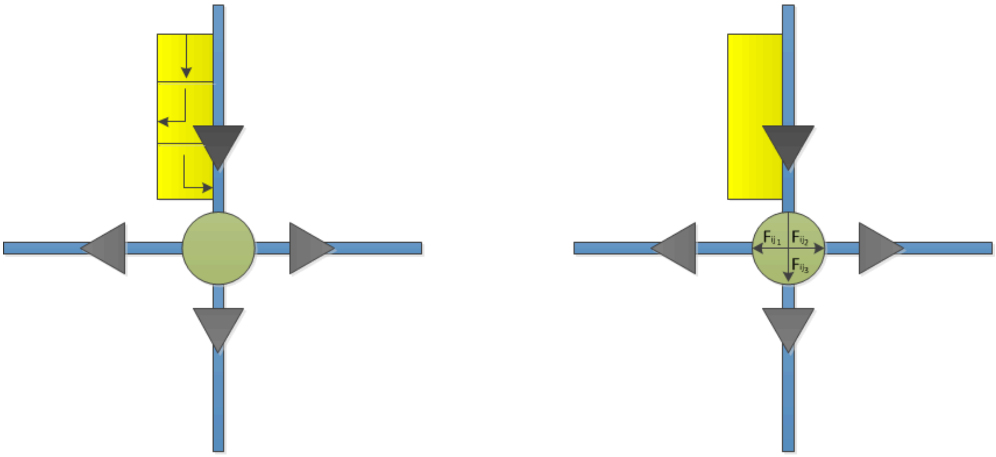

Figure E.1: Difference between multi commodity (left) and single commodity (right).

If in a single commodity simulation a couple of iterations are needed to get route demand consistent with the turning fractions. The turning fractions can be calculated by propagation of route flows based on the link travel times. These turning fractions can then be used to calculate new flows and new link travel times. In the first iteration the turning fraction can be based on the free flow travel time. This concept is used in Blumberg et al. (2007) and Gentile et al. (2007).

F. Visual representation of errors in MaC

Because in the simulation in MaC fixed turning fractions are used, downstream differences due to an incident are not accurately modeled. Specific traffic is delayed due to an incident, this results in changes in the turning fractions. Due to the single commodity simulation in MaC and the assumption of identical turning fractions as in the base simulation. In this appendix a graphical illustration of this estimation error is provided.

For an understanding of this estimation error, no exact description of the simulated incident is necessary. In figure F.1, figure F.2, figure F.3, and figure F.4 the flow difference between the base simulation and the simulation of an incident are given. A downstream moving difference is propagating from left to right. In figure F.1 the difference between the base simulations and the simulation of an incident in LTM multi commodity is given. In figure F.2 the difference between the base simulation (LTM single commodity) and the simulation of an incident is given. In figure F.2 the downstream moving difference is turned to the other side of the motorway. This phenomenon is not visible in figure F.1. In the simulation of an incident in LTM multi commodity this does not occur because there is no route in the simulation that uses the on- an off-ramp to turn to the other side of the motorway. It is also an illogical route. In a single commodity simulation the downstream moving difference is propagated to the onramp, because other traffic is turning left, (at node 1, see figure F.2).

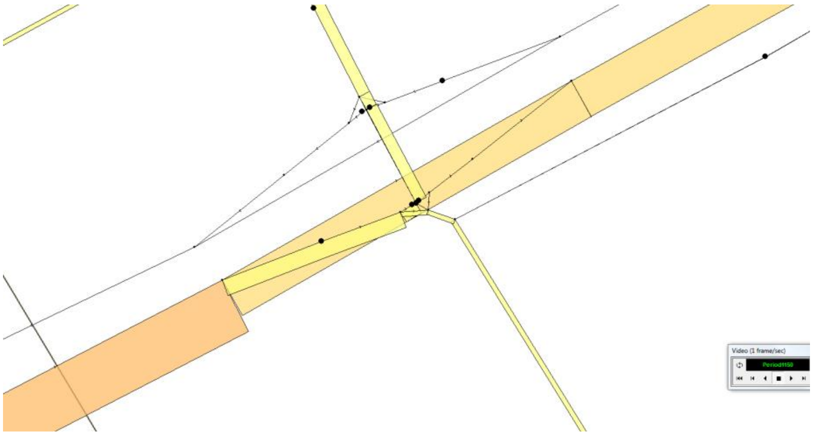

Figure F.1: Flow reduction propagating downstream in LTM multi commodity

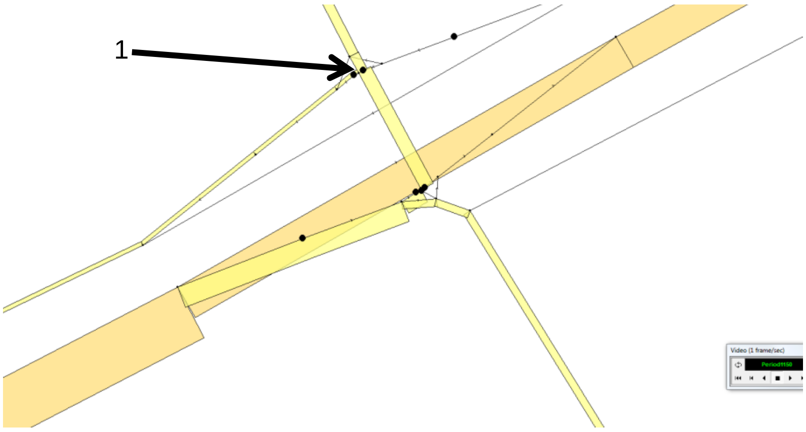

Figure F.2: Flow reduction propagating downstream in LTM single commodity

The same phenomenon can be seen in figure F.3 and figure F.4.

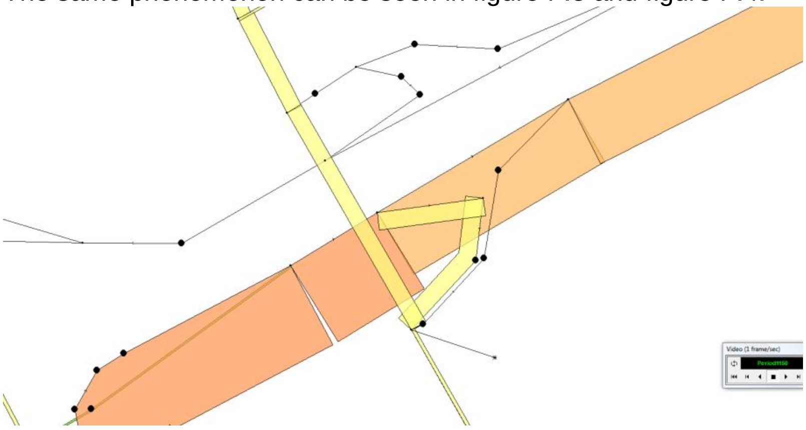

Figure F.3: Downstream propagating difference in LTM multi commodity

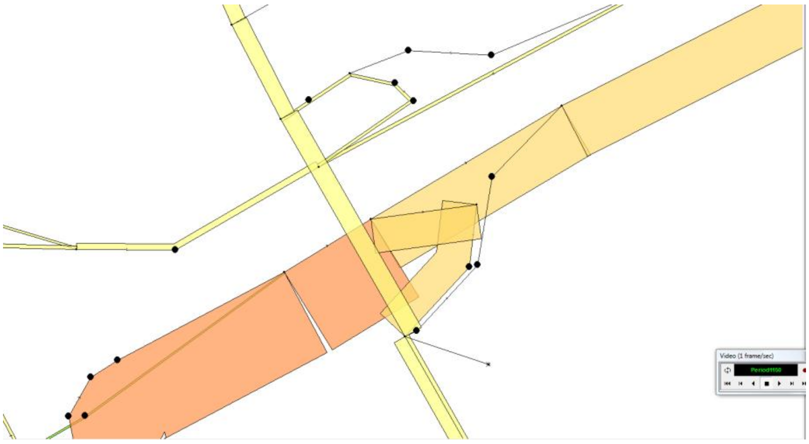

Figure F.4 Downstream propagating difference in LTM single commodity

This phenomenon causes links in MaC are wrongfully and unnecessarily activated, resulting in less accuracy and longer calculation time. This problem can be reduced by using higher value accuracy downstream. The result is that small differences are not calculated.

G. Visual comparison results MIC with LTM

The results of simulating one incident are compared for different models. The same incident is used in 5.2. The figures show the differences in the flow between the base simulation and the simulation of an incident. The upper figure show the differences in the flow in base simulation and the incident simulated in LTM. The bottom figure show the differences between LTM single commodity and the results of an incident simulated in MaC.

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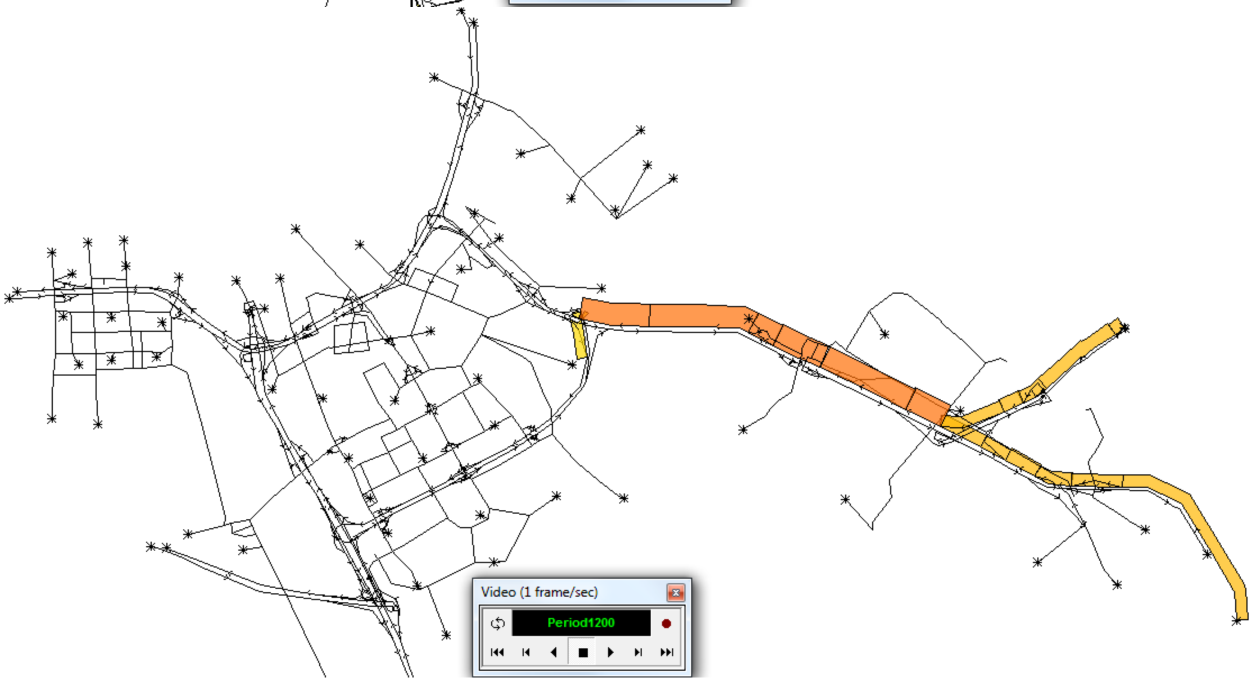

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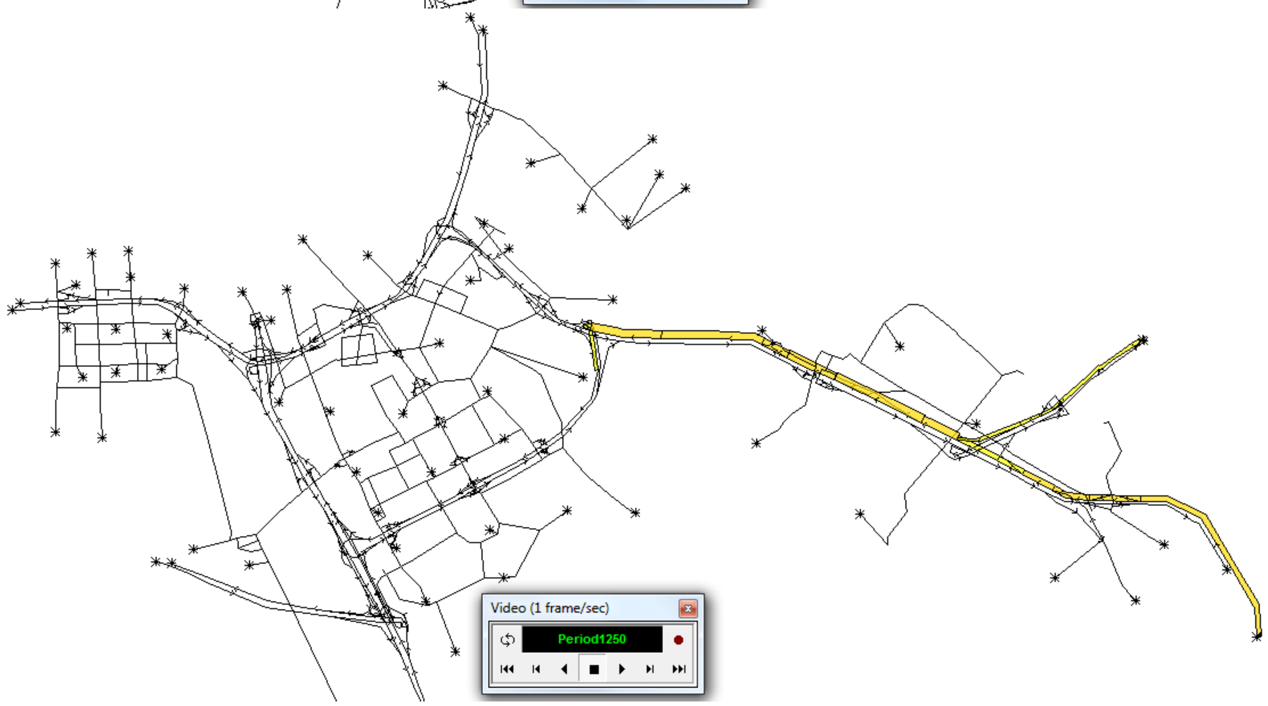

H. Visual comparison results MaC with LTM

The results of simulating one incident are compared for different models. The same incident is used in 5.2. The figures show the differences in the flow between the base simulation and the simulation of an incident. The upper figure show the differences in the flow in base simulation and the incident simulated in LTM. The bottom figure show the differences between LTM single commodity and the results of an incident simulated in MaC.

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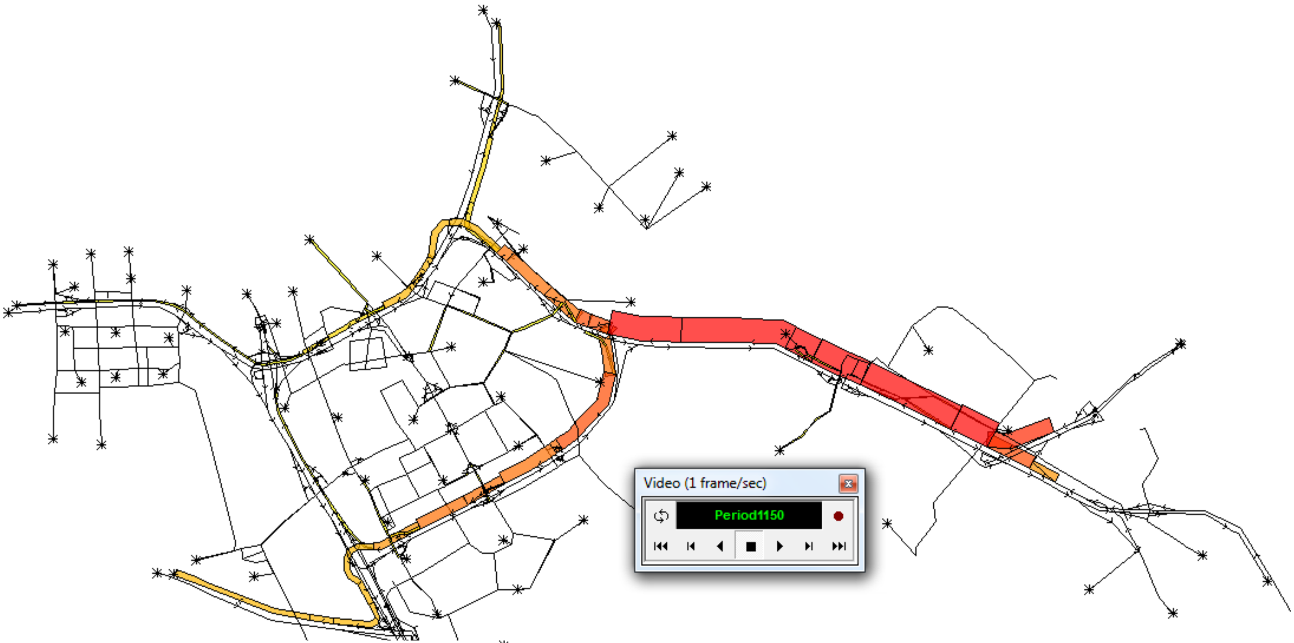

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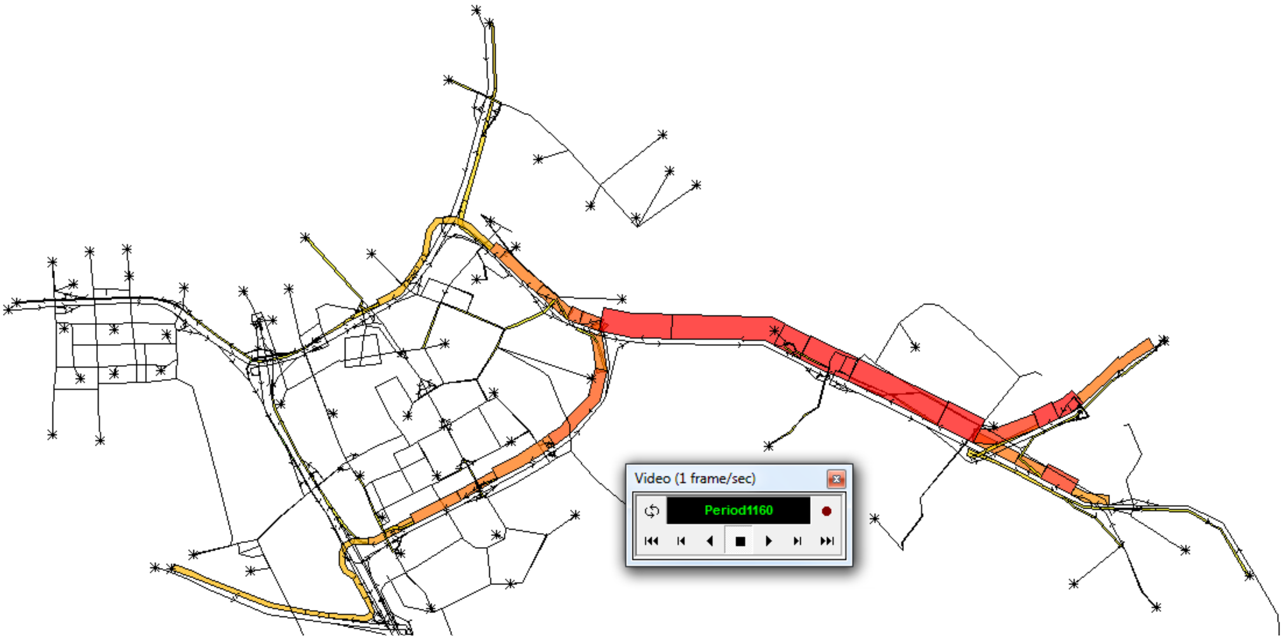

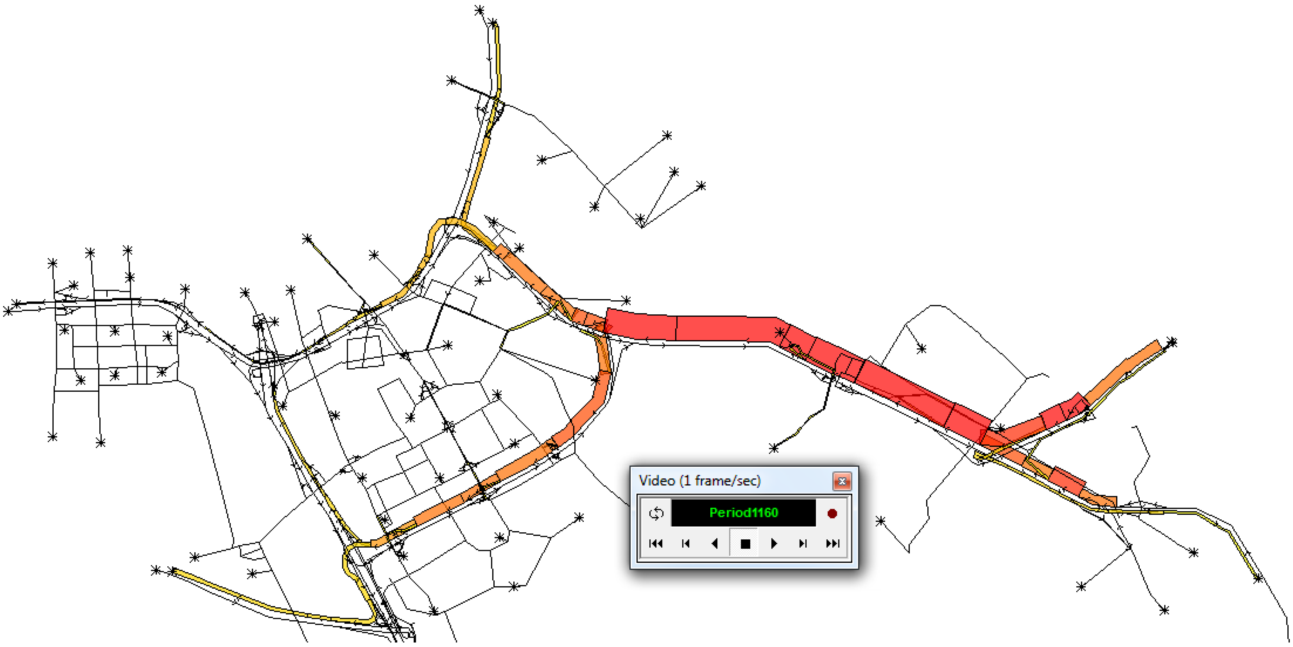

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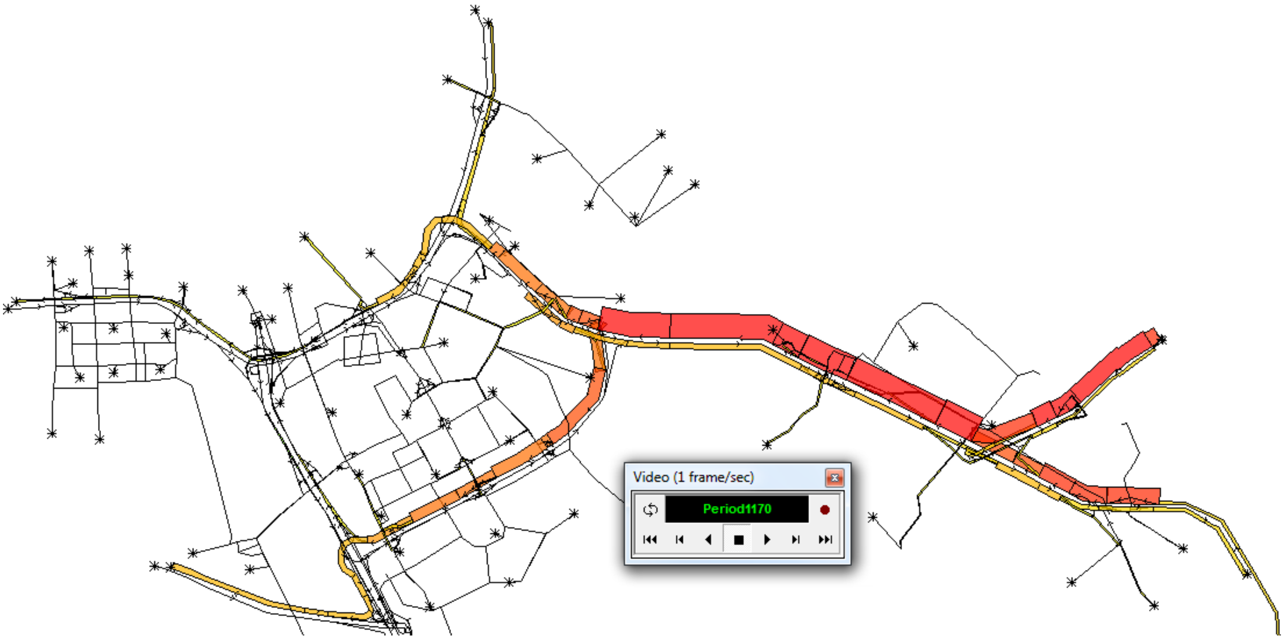

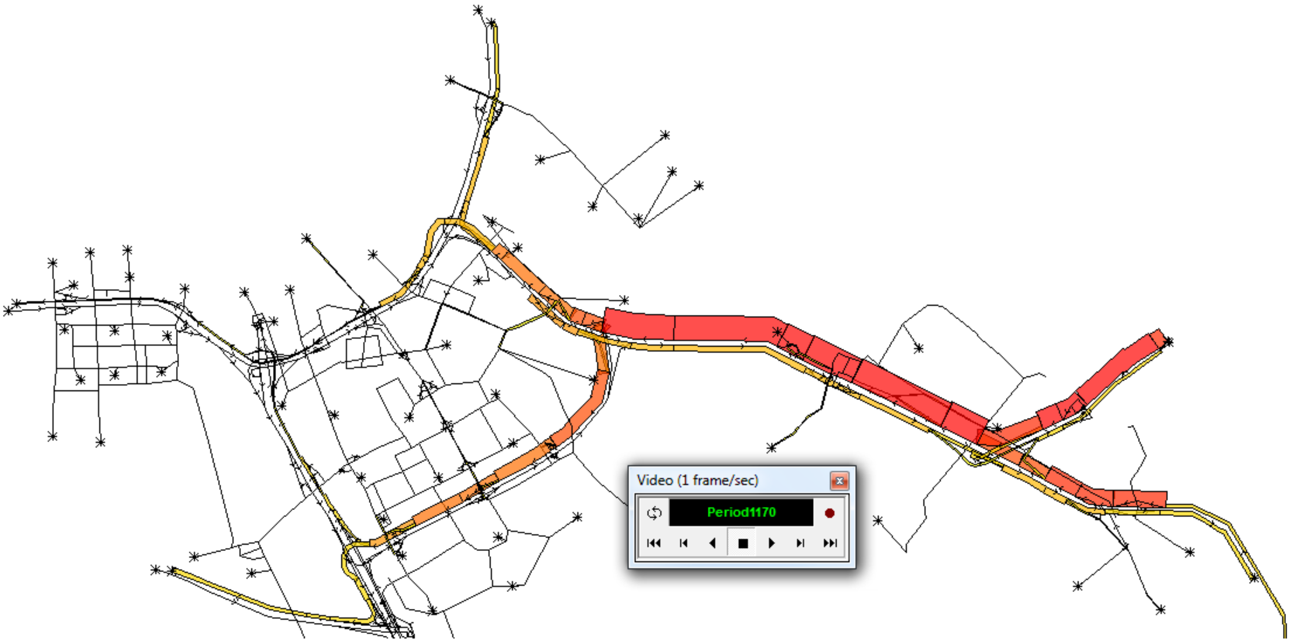

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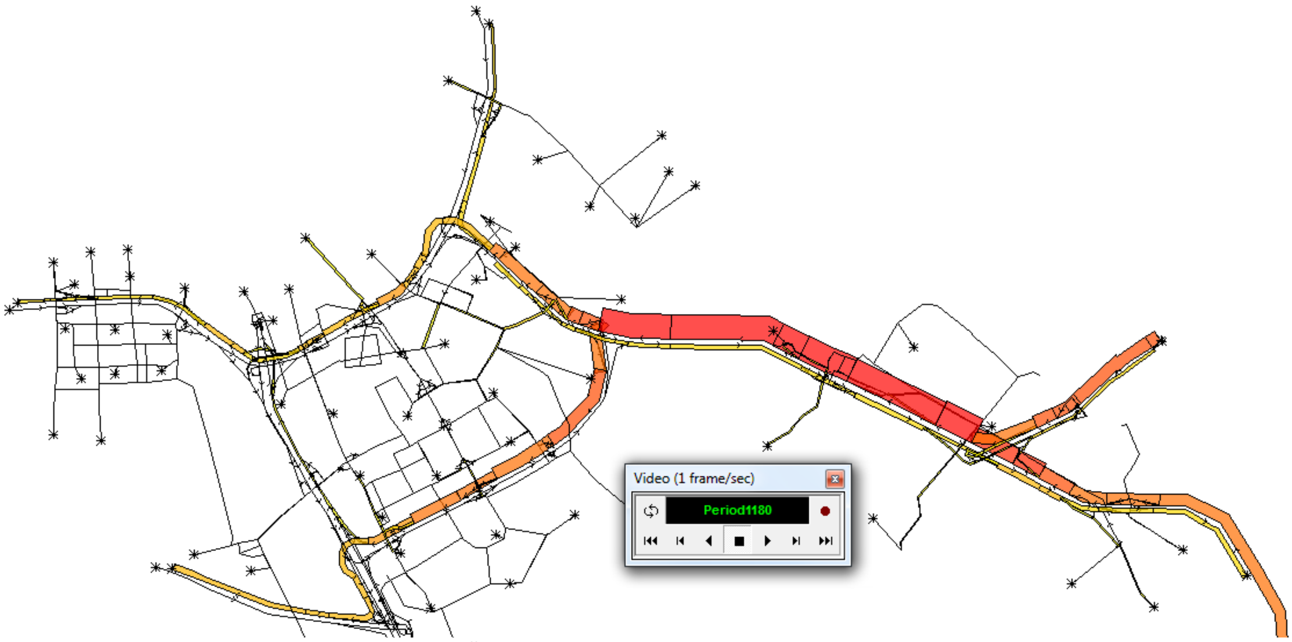

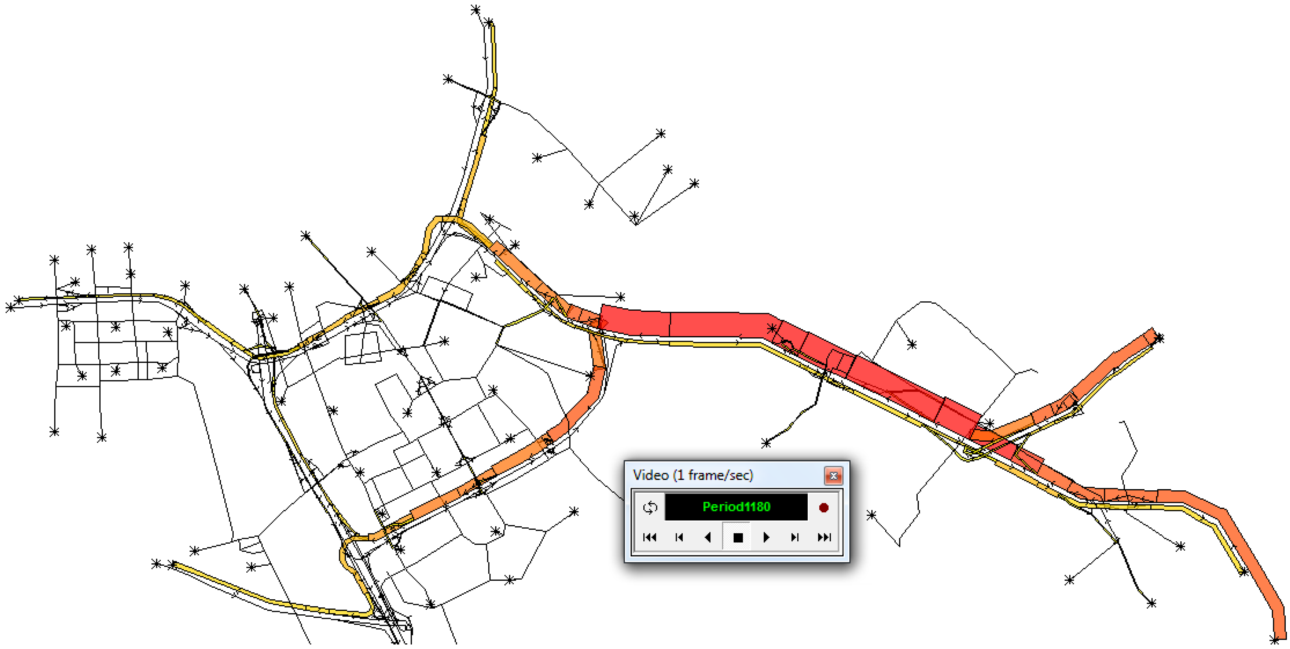

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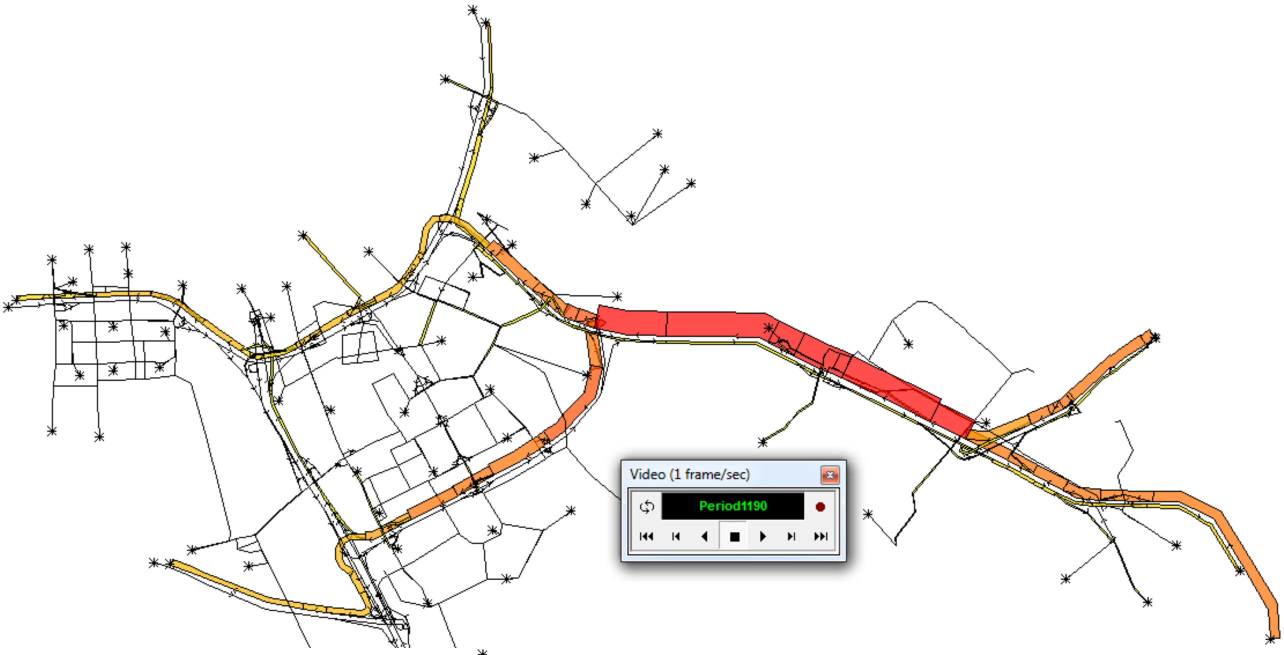

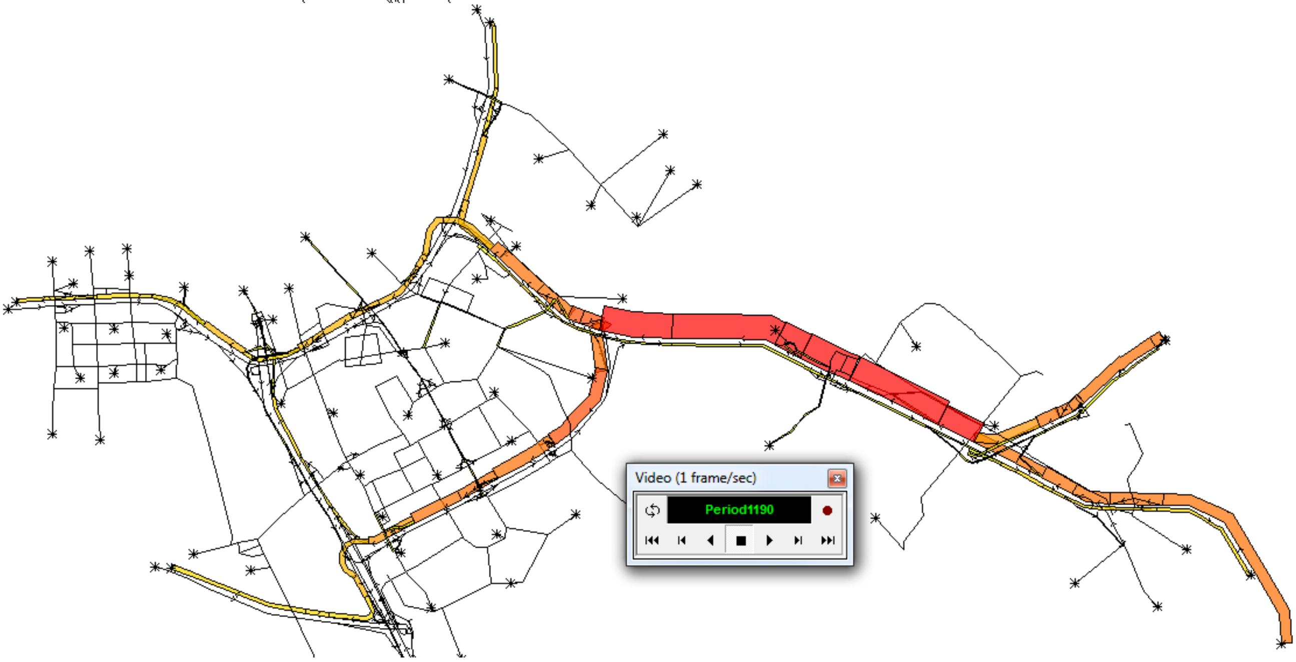

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