Goudappel Coffeng

Master Thesis – Final Report

Phantom jam suppression through in-car speed advice

L.C.W. (Leon) Suijs

November 22, 2013

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Master Thesis study

Phantom jam suppression through in-car speed advice

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Enschede, November 22, 2013

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Summary

Congestion has been rapidly increasing during the first decade of the twenty-first century. Between 2000 and 2010 the total number of vehicle loss hours due to congestion has increased with almost 50% (Kuiper and Schuit 2012). This has resulted in increasing economic losses. Of all congestion, 22% is recognized as shockwave jams or so-called phantom jams (Noordegraaf, Faber et al. 2011)). Suppressing phantom jams can help in reducing these negative effects and can also contribute to the traffic safety on highways.

Phantom jams occur without the existence of a physical bottleneck and are caused by the imperfect driving style of road users (Járai-Szabó and Néda 2012). This study aims at evaluating to what extent in-car speed advice can help to improve the network performance with respect to phantom jams. Therefore, a model study has been performed in which various in-car speed advice systems have been simulated on a single-link network using micro-simulation software.

Phantom jams are characterized by a specific spatial-temporal pattern: a congested platoon with a length of around 0.5-1 km propagating in upstream direction with a speed of around 20 km/h. The presence of high intensity waves has been found as an important pre-phantom jam characteristic. Over 80% of all phantom jams originated during such high intensity waves. These waves are a precondition of phantom jams because of its metastable traffic state in which perturbations easily lead to congestion. This study showed that high intensity waves can be identified using its intensity, which is clearly above the queue discharge capacity and its downstream movement of around the network speed. Various algorithms have been developed which enables the identification of the spatial-temporal characteristics of both phantom jams as high intensity waves.

A total of six different advice systems have been simulated. These systems can be divided in two classes: prevention based (four systems) and dissolving based (two systems) systems. The prevention based systems are based on Kerner’s (2004) three phase theory and aim at stabilizing traffic flow in order to prevent perturbations in traffic flow to result in congestion. Therefore, a non-controlled system, which provides advice independent of the traffic state, and three “smart” variants of an intensity

wave based system have been simulated. These intensity wave based systems differ from each other in the selectiveness of providing advice within intensity waves. The dissolving based systems aim at creating “space” upstream of a jammed section by means of speed advice in order to dissolve an identified jam.

This study proved prevention based advice systems to be most successful in improving the network performance with respect to phantom jams. A significant reduction of both the number of phantom jams as the total jam weight has been measured. Consequently this also contributes to the traffic safety as traffic is stabilized and speed differences between vehicles are reduced. However, these positive impacts of the systems, are, on link-level, not evidently accompanied by an increasing average network speed. Dissolving based advice systems, on the other hand, did not result in any significant network improvements in the model environment. The circumstances under which phantom jams originated on the modelled single-link network required such high intensities that it was not able to create upstream “space” without inducing a new phantom jams.

The penetration rate and the exact speed advice are important design variables of the advice system. A higher penetration rate and a lower speed advice lead to more reduction of the average network speed. For an optimal improvement of the network performance the composition of penetration rate and speed advice is crucial. Low penetration rates require a low speed advice, which results in a relatively large reduction of the average network speed and a large speed difference between advised and non-advised vehicles. This large speed reduction is a major issue in the acceptability of the system. On the other hand, high penetration rates allow higher speed advices resulting in less reduction of the average network speed and less speed differences between advised and non-advised vehicles. However, such high penetration rates are not so much practical achievable.

It is recommended to perform further research on the effect on the average network speed on a full-scale network. It is expected that a reduction of the number of phantom jams can have a significant positive effect on the network speed due to reduced spillback effects. Furthermore it is recommended to proceed research on some of the design variables introduced during this study. This can help to come to a more detailed quantitative assessment of the effects of the advice systems, which is helpful in case of practical applications of the presented approaches to suppress phantom jams.

Preface

(Written in Dutch)

Voor u ligt het resultaat van mijn afstudeeronderzoek waarmee ik mijn Master Civil Engineering & Management aan de Universiteit Twente afrond. Hiermee komt een einde aan een geweldige studententijd die ruim zes jaar heeft mogen duren. Niet alleen heb ik goede herrineringen aan de studie zelf, maar vooral ook aan de mensen die ik gedurende deze periode heb leren kennen en de ervaringen die ik naast mijn studie heb opgedaan. Mijn bestuursjaar en een fantastische studiereis naar Singapore en Indonesië zijn slechts een greep uit de lange lijst aan mooie ervaringen uit deze periode.

Ook het laatste half jaar van mijn studietijd, waarin ik in Deventer bij Goudappel Coffeng druk bezig ben geweest met mijn afstudeeronderzoek heb ik met veel plezier doorlopen. Het verhuizen naar een nieuwe stad en het van half 9 tot 5 op kantoor zitten, moge de start zijn geweest van een geweldig nieuw leven dat voor mij staat.

Graag wil ik mijn afstudeercommissie bedanken voor de bijdrage die zij hebben kunnen leveren bij de totstandkoming van dit rapport. Lieuwe, bedankt voor het feit dat ik altijd bij je langs kon lopen voor een inhoudelijke discussie en de ondersteuning die je mij hebt kunnen bieden in het gebruik van VISSIM. Eric en Luc wil ik graag bedanken voor hun heldere kritieken die mij hebben geholpen dit onderzoek ook vanuit een breder perspectief te beschouwen.

Tot slot wil ik nog graag al mijn collega's bij Goudappel, vrienden en familie bedanken die op welke manier dan ook hebben bijgedragen aan dit eindresultaat.

Leon Suijs

Deventer, 22 November 2013

Inhoud Pagina

1

Introduction

Congestion is one of the main problems on the Dutch road network. The total number of vehicle loss hours has increased with 49% between 2000 and 2010 (Kuiper and Schuit 2012) resulting in increasing economic losses. From all congestion, 22% has been recognized as so-called phantom jams (Faber, Noordegraaf et al. 2011). Recently, the province of Noord-Brabant decided to start a pilot-project “Spookfiles” to evaluate the possibilities of in-car driving support systems in suppressing phantom jams.

Previous studies have explained the formation of phantom jams to be caused by perturbations (i.e. fluctuation in braking and accelerating behaviour of individual drivers) under metastable traffic conditions (Nakayama, Fukui et al. 2009). Such jams do not only lead to frustration under road users or to delays in travel time but they also affect traffic safety. Congestion is a known source for head-tail collisions (Marchesini and Weijermars 2010) and speed variation and high speed differences between vehicles (accelerating and decelerating) have been proved to have a negative impact on traffic safety (Beek, Derriks et al. 2007). Phantom jam suppression can therefore not only improve network performance in terms of travel times and the occurrence of phantom jams, but can also have significant positive effects on traffic safety.

To prevent phantom jams from occurring, either the cause of the perturbations or the metastability of the traffic flow can be focussed on. Dynamic speed limits, communicated by road-side systems, have been proved to be a successful instrument in stabilizing traffic flow (Smulders ,1990), increase traffic safety (Smulders ,1990) or suppressing phantom jams (Hegyi, Hoogendoorn et al. 2008). However, road-side systems are of decreasing importance to drivers as in-car advice systems are able to provide personalized advice which is much more accurate (Rutten, Weijer et al. 2013). This trend is reflected by the fact that in-car advice plays a major role in more and more traffic management projects in the Netherlands (i.e. Praktijk Proef Amsterdam (PPA) and the pilot-project “Spookfiles”).

This study continues on the use of dynamic speed advice in the battle against phantom jams. This proved concept has been combined with the rising importance of in-car advice. Therefore, dynamic speed advice has been brought to an in-car driver support system. This enables more flexibility in the design (the nature) of the advice system and makes it independent of the availability of road-side systems. However, it brings a large dependency on the penetration rate of the system. The aim of this study is to evaluate the possibilities of such in-car speed advice systems in order to suppress phantom jams. This evaluation has been performed using a single-link micro-simulation study. Various in-car speed advice systems have been simulated and their effect on the network performance has been evaluated.

First, chapter 2 introduces the research objective and questions as composed for this study. Thereafter, the theoretical background which has been used for this study is elaborated on in chapter 3. This includes the exact definition of a phantom jam as used during this study. Subsequently, the model environment is described in chapter 4. Chapter 5 describes specific phantom jam characteristics together with the development of various algorithms which help to identify phantom jams on the network. Thereafter, chapter 6 discusses an evaluation framework which has been used to assess the network performance. Subsequently, the results for all advice systems are presented in chapter 7. The analysis of these results is presented in chapter 8. Finally, chapter 9 and 10 contain the conclusion and discussion of this study.

2

Research objective and questions

This chapter presents the research objective of this study and its research questions. Subsequently the research strategy is described.

2.1 Research Objective

The research objective of this Master thesis study is:

"*To evaluate the possibilities of in-car speed advice to improve network performance with respect to phantom jams.*"

2.2 Research Questions

The research questions which are addressed during this study are:

1. What actual traffic measurements need to be performed in order to be able to predict or identify the formation of a phantom jam?
   - *What traffic characteristics are typical for the phantom jam phase?*
   - *What traffic characteristics are typical for the pre-phantom jam phase?*
   - *How can these characteristics be measured and processed?*
2. How can the performance of the network be classified with respect to phantom jams?
3. How should the in-car speed advice system be designed?
   - *What speed advice should the driver be provided with?*
   - *On which moment the driver should be informed*?
   - *What share of drivers should follow the in-car advice?*

2.3 Research strategy

This research is executed according the following research strategy, containing a preparatory phase and an executing phase.

The preparatory phase contained a literature study which is performed to compose a clear definition of phantom jams. Consequently this definition forms a demarcation for what this research should include and exclude. Furthermore, the literature study offers an overview of both fundamental and state-of-the-art theories of traffic flow which are used to perform this research.

The executing phase is a model study. This model study contains three consecutive steps of which each step answers one of the research questions (visualized in figure 2.1). The setup of this model itself is discussed more detailed in chapter 4.

- *Phantom jam characteristics – Research question 1*

An analysis of the traffic situation during and before the origination of phantom jams has been performed in order to identify phantom jam characteristics. These phantom jam characteristics are needed to be identified in order to be able to assess network performance with respect to phantom jams. Therefore, simulation data is processed and analysed to identify characteristics and to clarify specific patterns in traffic states. Consecutively, these identified patterns have been used to create a practical tool which enables the possibility to identify such patterns during simulation. This tool contains various live and offline algorithms.

- *Evaluation Framework – Research question 2*

The network performance has been measured using an evaluation framework. The evaluation framework contains five indicators of which two indicators assess the network performance using macroscopic traffic variables. The other three indicators assess the network performance with respect to phantom jams. Therefore, the offline algorithms developed during step 1 are included in the evaluation framework.

- *Evaluation of in-car driver support systems – Research question 3*

A wide selection of in-car speed advice systems has been simulated in order to evaluate its effect on the network performance. The results for each of these systems have been analysed and compared with a reference scenario with no speed advice system active.

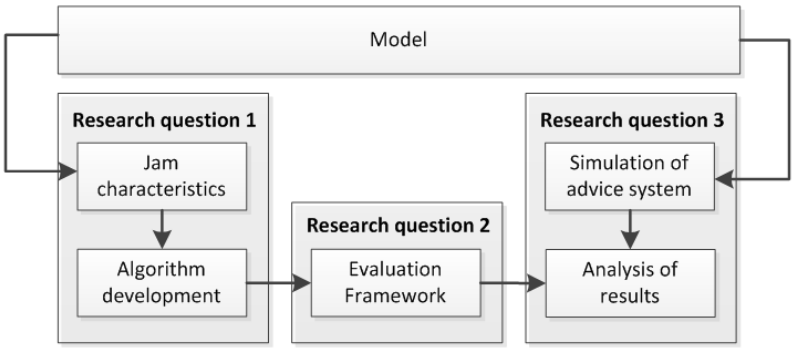


Figure 2.1: Research framework

3

Theoretical Framework

This chapter contains the theoretical framework for this study. The theoretical framework describes relevant subjects and theories which form the foundation of this study. Furthermore this theoretical framework includes the results and findings of previous research on some of these topics.

3.1 Traffic jams

A traffic jam is a condition on the road network which is characterized by slower speeds, high densities and a suboptimal flow rate. Traffic jams are part of the complex behaviour of traffic flow dynamics. Treiber and Kesting (2013) identified three factors which simultaneously cause traffic jams:

1. A *bottleneck* is a local reduction of the road capacity. Bottlenecks can be permanent attributes of the infrastructure or temporary, e.g. when caused by accidents.
2. *Disturbances caused by individual drivers*, e.g. by inattentive drivers braking abruptly, by speeding cars or by lane changes.
3. *High traffic load*: If traffic load is not substantially high, traffic flow is unconditionally stable and disturbances caused by bottlenecks or imperfect driving behaviour cannot grow to traffic jams.

Sugiyama, Fukui et al. (2008) showed experimental evidence that traffic jams can exist without the presence of bottlenecks. Within substantial high traffic flow, only small disturbances caused by individual drivers can trigger the occurrence of a traffic jam. In literature this phenomenon is frequently referred to as a *phantom jam*. However, the definition of phantom jams is not universal in literature.

From the definitions used by various authors, collected in table 3.1, it can be concluded that not only the definition of a phantom jam is not universal, also various names are used in literature to describe the phenomenon: Stop-and-go-wave, spontaneous jam, shock wave, wide moving jam, jam “out of thin air” and of course phantom jam. Besides this handful of different names for apparently the same traffic phenomenon, four characteristics of phantom jams can be extracted from these definitions:

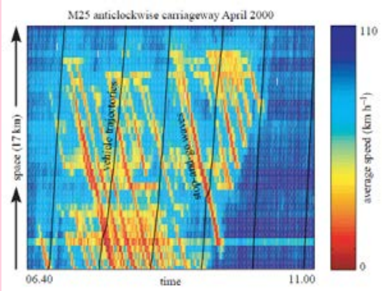
- A phantom jam is the spontaneous formation of traffic congestion with no obvious reason as an accident or a bottleneck (Kerner and Konhäuser 1993; Helbing 2001; Flynn, Kasimov et al. 2008; Sugiyama, Fukui et al. 2008; Schadschneider 2009).
- If traffic density exceeds a certain critical value, tiny fluctuation, caused by finite reaction times of drivers, lead to a positive feedback on density and speed perturbation resulting in a phantom jam (Hanaura, Nagatani et al. 2007; Sugiyama, Fukui et al. 2008; Treiber and Kesting 2013).
- The downstream front of a phantom jam is not fixed at a bottleneck and propagates backward against the flow of the traffic (Hanaura, Nagatani et al. 2007; Wilson 2008).
- A phantom jam consists of two sharp interfaces (one at which vehicles brake and the other at which vehicles accelerate) bounding a plateau of slow-moving traffic (Wilson 2008).

These four characteristics can be brought together into the following definition which is used during this research:

"A phantom jam is the spontaneous formation of traffic congestion which is not caused by obvious reasons such as an accident or a bottleneck, but by tiny fluctuations, caused by finite reaction times of drivers, which lead to speed perturbations. A phantom jam consists of two sharp fronts bounding a plateau of slow moving traffic with a downstream front which is not fixed at a bottleneck and which propagates upstream."

Table 3.1: : Definitions of phantom jams by various authors.

Author	Definition
Flynn, Kasimov et al. (2008)	"Traffic blockages that arise without apparent cause."
Hanaura, Nagatani et al. (2007)	"A spontaneous jam (or *phantom jam*) propagates backward as the stop-and-go-wave. If sensitivity of driver is lower than a critical value, the spontaneous jam occurs."
Helbing(2001)	"The spontaneous formation of traffic jams with no obvious reason such as an accident or a bottleneck."
Kerner &Konhäuser(1993)	"The spontaneous appearance of traffic congestion without obvious reasons."
Schadschneider(2009)	"In principle two types of jams can be distinguished. The first type is created by a bottleneck, i.e. locations of reduced capacity, if the inflow than this capacity. Apart from these bottleneck-induced jams, spontaneous jams or *phantom jams* exist for which this is not true, at least not in an obvious way."
Sugiyama, Fukui et al. (2008)	"A jam is generated spontaneously only if the average vehicle density exceeds the critical value. Under this condition, the free flow state is unstable and even a tiny fluctuation grows and the state transits to jamming phase by the effect of collective motion. Thus neither an apparent obstacle nor a bottleneck is needed for the formation of a jam." *Note: The authors did not mention this phenomenon specifically as a phantom jam. However, other authors refer to this research as first experimental evidence of a phantom jam.*
Treiber & Kesting(2013)	"Stop-and-go waves are caused by the delays in adapting the speed to the actual traffic conditions. These delays are the consequence of finite acceleration and braking capabilities, and also result from finite reaction times of the drivers. If traffic density is sufficiently high, this delay leads to a positive feedback on density and speed perturbation. As a result, a stop-and-go wave emerges "out of thin air" giving rise to the name *phantom jam* for this phenomenon."

Wilson (2008)	 "The pattern shown in the figure in the right. is commonly referred to as a *phantom jam* or a shock wave although in the scientific literature the terms stop-and-go wave or wide moving jam are preferred, since the structure, which propagates upstream against the flow of traffic, consists of two sharp interfaces (one at which vehicles brake and the other at which vehicles accelerate) bounding a plateau of slow-moving traffic."
Sugiyama, Fukui et al. (2008)	"A jam is generated spontaneously only if the average vehicle density exceeds the critical value. Under this condition, the free flow state is unstable and even a tiny fluctuation grows and the state transits to jamming phase by the effect of collective motion. Thus neither an apparent obstacle nor a bottleneck is needed for the formation of a jam." *Note: The authors did not mention this phenomenon specifically as a phantom jam. However, other authors refer to this research as first experimental evidence of a phantom jam.*

Apart from the phantom jam, the more obvious *stationary jam* can be identified within the world of traffic jams (Hanaura, Nagatani et al. 2007). The stationary jam is induced by slowdown or blockage of a road section (bottleneck) and typically the downstream front is fixed at this bottleneck.

Generally, every traffic jam can be classified within one of these two classes: phantom or stationary jam. However, the boundary between a bottleneck and disturbances caused by individual drivers should be clearly understood. The following example illustrates the difficulties in determining this boundary.

On a highway with traffic flow near capacity, one truck is taking over another truck. As a result, upstream drivers have to slow down their vehicles. Due to their individual delays in adapting their speed to this new traffic situation, drivers further upstream need to break harder and harder until one vehicle comes to a complete standstill. Although no real bottleneck such as changed road conditions or accident occurred, still traffic came to a standstill.

In this example, the traffic jam experienced by upstream drivers definitely fulfils characteristics (1) and (2) of a phantom jam. However, the propagation direction of the downstream front is questionable. Is the location of the overtaking trucks the downstream front? The location of the overtaking trucks is obviously propagating downstream, which does not match the third characteristic of a phantom jam. For this example, it is needed to identify both a change in traffic state upstream of the overtaking trucks as a phantom jam. First, the overtaking trucks can be seen as a bottleneck on the road. The location of the bottleneck is propagating downstream with the speed of the trucks. The upstream vehicles adapt their speed to the lower speed of the trucks. The downstream front of this platoon of following vehicles is fixed at the location of the trucks, the bottleneck. As a consequence, traffic stacks behind the trucks resulting in a platoon of highly dense traffic. Within this dense traffic, the imperfect driving behaviour of preceding vehicles leads to a standstill. A new platoon with its own downstream bottleneck has formed within the dense traffic behind the overtaking truck. The downstream front of this platoon is moving upstream, fulfilling the third characteristic of a phantom jam. After the one truck has taken over the other truck and has changed lanes back again, the high dense traffic section will solve. However, the phantom jam will continue to propagate upstream (More information on the propagation of traffic jam fronts is given in section 3.5). New upstream arriving vehicles experience a completely spontaneous traffic jam with no apparent reason. Therefore, the first characteristic of a phantom jam is mostly related to driver experience when passing such traffic jam.

3.2 Trajectories and micro- and macroscopic variables

Traffic dynamics can be described using various variables. A distinction is made between microscopic and macroscopic variables. Microscopic variables look at individual vehicles and are discussed in section 3.2.1. Macroscopic variables, on the other hand, aim to describe traffic flows. These variables are discussed in section 3.2.2.

3.2.1 Microscopic variables

At the microscopic level one looks at individual vehicles. For individual vehicles along a highway section, their position in space and time can be drawn. This is shown in figure 3.1. On the left side, x_α indicates the position of vehicle α at time t_0. The location of the preceding vehicle $\alpha+1$ at t_0 is indicated by $x_\alpha + 1$. As both vehicles move along the highway section, their position is time-dependent. The graphs $x_\alpha(t)$ and $x_{\alpha+1}(t)$ describe the location of both vehicles at time *t* and are called the trajectory of the vehicle. In this example, the rear end of the car is chosen as reference point to identify the trajectory. As long as two vehicles travel on the same lane, it is impossible for the trajectories to cross each other as this would mean both cars collided.

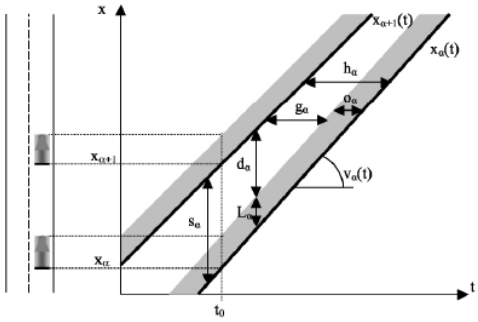


Figure 3.1: Trajectories of two vehicles along a highway section(Immers and Logghe 2002).

The derivative of the trajectory of a vehicle at time t is equal to the speed of the vehicle v_α at moment t ***(3.1)***. The second derivative of the trajectory equals the acceleration of the vehicle a_α ***(3.2)***. A horizontal trajectory corresponds to a standing vehicle:

$$v_\alpha(t) = \frac{dx_\alpha(t)}{dt} \tag{3.1}$$

$$a_\alpha(t) = \frac{d^2x_\alpha(t)}{d^2t} \tag{3.2}$$

From the space-time diagram not only individual vehicle information can be extracted, but also secondary microscopic, vehicle-to-vehicle, data can be deduced. The time headway, or shortly headway, h_α (also called Δt_α in literature (Treiber and Kesting 2013)) is the horizontal distance between the corresponding trajectories. The headway is composed by two elements: the gap-time g_α and the occupancy time o_α (May 1990; Immers and Logghe 2002). The gap-time is the time between the rear end of the car and the front end of the following car. The occupancy time is the time the vehicle occupies a road section. Time headway is an important traffic flow characteristic which affects safety, driver behaviour and capacity. A minimum headway is required in order to be able to react on any deceleration of preceding vehicles without colliding. Furthermore, on a multi-lane road section, headways determine the opportunity for lane changing, overtaking, merging and crossing (May 1990).

Besides the time headway, also the distance headway s_α can be extracted from the space-time diagram. The distance headway is the distance between the reference points of two vehicles. In the space-time diagram, the distance headway is the vertical distance between two trajectories:

3.2.2 Macroscopic variables

At the macroscopic level one does not only look at the individual vehicle trajectories, but one aims at describing traffic flows. Traffic flow is generally described by using three macroscopic variables: density, flow and mean speed. In figure 3.2 the trajectories of vehicles for a space-time region are illustrated. Such trajectory data can either be collected by camera-observation or by using floating car data. Camera based observation involves complex procedures and algorithms in order to track vehicles with sufficient accuracy, but offers the possibility to track all vehicles. Furthermore, camera observation is limited to at most a few hundred meters. For floating car data, trajectories for a small share of the total traffic flow are measured using GPS-equipment. For highway areas penetration rates of at least 0,5% are typically enough to use the data for deduction of congested areas, including their upstream and down-stream boundaries (Treiber and Kesting 2013). If trajectory data is available for all vehicles, density, flow and mean speed can be directly extracted.

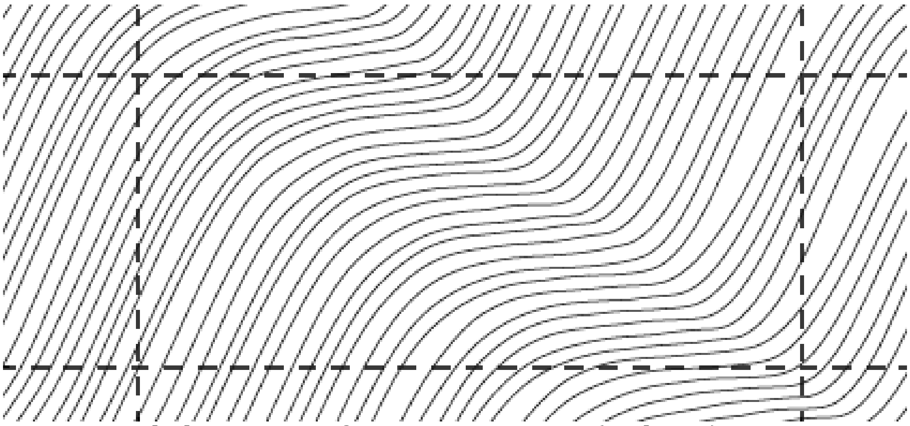


Figure 3.2: Vehicle trajectories for a space-time region (Krol 2009).

- Flow
  Traffic flow q is the number of vehicles passing a given location per time-unit (Treiber and Kesting 2013). From the space-time diagram, flow can be extracted by counting the number of trajectories crossing a horizontal line at location x ;

$$q(x,t) = \frac{N}{\Delta t} \tag{3.3}$$

  where N is the number of vehicles passing cross-section x during time-period Δt (typically in hours).

- Mean Speed
  The mean speed V is calculated by averaging the speed of individual vehicles at a specific location (arithmetic speed) or at a specific instant (harmonic speed). The arithmetic speed (also called time mean speed) is given by:

$$V(x,t) = \frac{1}{N} \sum_{\alpha=\alpha_0}^{\alpha_0+\Delta N-1} v_\alpha \tag{3.4}$$

  with ΔN the number of vehicles passing the cross-section during time-interval t and v_α being the individual vehicle speed of vehicle α (Treiber and Kesting 2013).

  The harmonic speed (also called space mean speed), corresponds (when neglecting accelerations) to the average spatial speed at a fixed time instant (Treiber and Kesting 2013). The harmonic speed is given by:

$$V_H(x,t) = \frac{\Delta N}{\sum_{\alpha=\alpha_0}^{\alpha_0+\Delta N-1} \frac{1}{v_\alpha}} \tag{3.5}$$

In order to explain the differences between arithmetic and harmonic average speed a hypothetical road section is illustrated in figure 3.3. On this road section all cars maintain a constant speed. The speed of each car is measured by the detection loop downstream of the road section. Calculating the arithmetic speed results in a speed of 85,7 km/h. However, calculating harmonic speed results in a speed of 76,4 km/h. The harmonic speed includes the factor of the time that each vehicle stays on the network. The vehicles, which drive 60 km/h, will be on the network twice as long than the vehicles driving with a speed of 120 km/h.

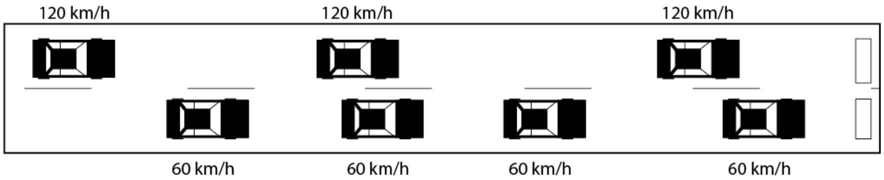


Figure 3.3: Hypothetical road section.

In case of a network loaded only with vehicles driving the harmonic speed would represent the same total time on the network as the actual total time on the network. Using the arithmetic speed results in an under representation of the total time on the network. In the example in ***(3.6)*** this is calculated for all three situations (original, arithmetic and harmonic speed) for the network situation in figure 3.3. For the ease of the calculation a network length of 10 km is used.

$$
\begin{aligned}
&TotalTimeOnNetwork\_Original &&= 4\cdot\frac{10}{60}+3\cdot\frac{10}{120}=0{,}92h &&= 55\min \\
&TotalTimeOnNetwork\_Arithmetic &&= 7\cdot\frac{10}{85{,}7}=0{,}82h &&= 49\min \qquad \text{(3.6)} \\
&TotalTimeOnNetwork\_Harmonic &&= 7\cdot\frac{10}{76{,}4}=0{,}92h &&= 55\min
\end{aligned}
$$

Only in case that all vehicles have the same speed on the network, the arithmetic and harmonic speed are equal to each other. In figure 3.4 the differences between arithmetic (time mean) and harmonic (space mean) speed are illustrated for the A9 motorway in the Netherlands. It clearly shows that the harmonic speed is always lower than or equal to the arithmetic speed.

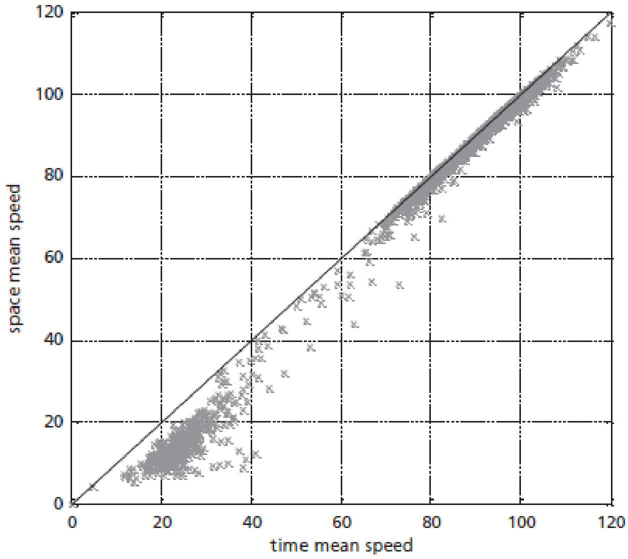


Figure 3.4: Differences between time and space mean speed for the A9 motorway (Hoogendoorn and Knoop 2012).

- Density

  Traffic density k is the number of vehicles on a road segment at a given time (Treiber and Kesting 2013). Density typically reflects to the number of vehicles per kilometre road. From the space-time diagram, density can be extracted by counting the number of trajectories crossing a vertical line at time t ;

  $$k(x,t) = \frac{N}{\Delta x} \tag{3.7}$$

  where N is the number of vehicles on the road segment at time t and Δx is the length of the road segment in kilometres.

3.3 Data collection

As described in section 3.2, traffic dynamics can be described using both microscopic as macroscopic variables. Microscopic data contains information of individual vehicles and can be measured directly on the road. This microscopic data can be aggregated to macroscopic data, which describes the traffic state on the road network. This section discusses cross sectional data collection by using detection loops on the road network and how this microscopic data can be aggregated into macroscopic variables.

3.3.1 Cross sectional data

Cross sectional data is individual vehicle data collected at a fixed cross-section on the road network. Such data is most commonly collected by use of induction loops, which are installed in the road surface. However, alternatively, also radar or optical instruments can be used to gather cross sectional data (Treiber and Kesting 2013). For this study, these alternative ways to gather cross sectional data are excluded. Therefore, this section only elaborates on the use of induction loops.

A single loop detector measures whether or not a vehicle is present on the cross-section the induction loop is installed. Therefore, it can measure two quantities:

1. The time t_α^0 at which the front of vehicle *α* α passes the induction loop.
2. The time t_α^1 at which the rear end of vehicle *α* α passes the induction loop.

Using these two quantities vehicle speed can be calculated (assuming a certain vehicle length l_α):

$$v_\alpha = \frac{l_\alpha}{(t_\alpha^1 - t_\alpha^0)} \tag{3.8}$$

As the traffic flow data which can be extracted from single loop data is limited, typically double loop detectors are installed on (Dutch) highway sections (CROW 1998). A double loop detector is nothing else than two single loop detectors close to each other with a known distance gap. From double loop detection data, speed can be calculated using formula ***(3.9)***, with the location of the upstream detection loop dl_0 and the location of the downstream detection loop dl_1. Acceleration of the vehicle is assumed to be equal to zero.

$$v_\alpha = \frac{dl_1 - dl_0}{t_{\alpha,dl1}^0 - t_{\alpha,dl0}^0} \tag{3.9}$$

For the derivation of below described secondary microscopic quantities it is assumed that vehicle speed is constant over the cross section in which both loops are located (Treiber and Kesting 2013).

1. Length of vehicle *α*:
$$l_\alpha = v_\alpha (t_\alpha^1 - t_\alpha^0) \tag{3.10}$$
2. Headway between front bumpers of vehicles:
$$h_\alpha = t_\alpha^0 - t_{\alpha-1}^0 \tag{3.11}$$
3. Time gap between rear and front bumper:
$$T_\alpha = t_\alpha^0 - t_{\alpha-1}^1 \tag{3.12}$$
4. Distance headway between front bumpers:
$$d_\alpha = v_{\alpha-1} \cdot h_\alpha \tag{3.13}$$
5. Distance gap between rear and front bumper:
$$s_\alpha = d_\alpha - l_{\alpha-1} \tag{3.14}$$

Macroscopic traffic flow data can be extracted from cross sectional data. Section 3.2.2 already discussed on how traffic flow and mean speed can be calculated from individual vehicle data. As traffic density is spatially defined, it cannot be directly measured from cross sectional data. Therefore, traffic density must be estimated using the fundamental relation with traffic flow and speed. This relation will be further discussed in section 3.4.

3.4 Traffic flow fundamentals

The fundamentals of traffic flow dynamics are constructed around the fundamental relation between the three macroscopic variables as discussed in section 3.2.2: density, flow and mean speed:

$$q = k \cdot u \tag{3.15}$$

From section 3.3 it became clear that, from these three variables, flow and mean speed at a certain location can be directly derived from cross sectional (detection loop) data. Using this fundamental relation, an estimation of the density of a road segment can be made assuming speed and flow at this segment being equal to the location measurement. The accuracy of this estimation depends on whether the arithmetic or the harmonic speed is used. Section 3.2.2 already discussed that the use of harmonic speed results in a more accurate approximation of the total time of vehicle appearance on the network. For the density estimation, using the fundamental relation, the harmonic speed therefore also results in a much better estimation than by using the arithmetic speed. This is shortly illustrated by the following example.

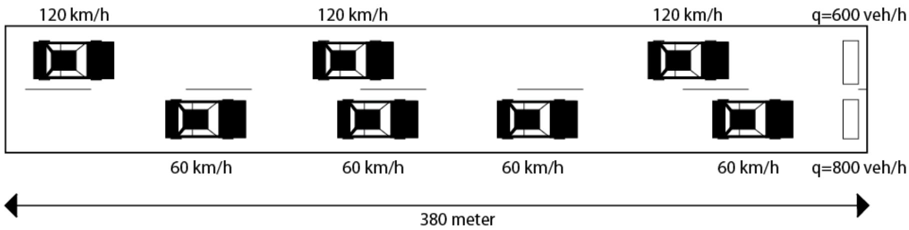


Figure 3.5: Example for density estimation.

Take the network in figure 3.5 with the vehicles on the left lane having a constant speed of 120 km/h and the vehicles on right lane having a constant speed of 60 km/h. At the loop detector a flow of 600 veh/h for the left lane and 800 veh/hour for the right lane is measured resulting in a total flow of 1400 veh/h which is for the ease of calculation equally distributed. Furthermore, individual vehicles speeds are measured at the detection loop. From these individual vehicle speeds, both arithmetic (85,7 km/h) as harmonic (76,4 km/h) speed can be calculated (see section 3.2.2). Now, using the fundamental relation, the density can be estimated for both speeds:

$$\begin{aligned} K_{Aritm} &= \frac{q}{u} = \frac{1400}{85{,}7} = 16{,}33 veh/km \\ K_{Harm} &= \frac{q}{u} = \frac{1400}{76{,}4} = 18{,}33 veh/km \end{aligned} \tag{3.16}$$

Using these densities, the arithmetic and harmonic speed result in respectively 6 and 7 vehicles for the 380 meter network. From figure 3.5 it directly becomes clear that in fact 7 vehicles are present on the network, which means that the use of arithmetic speed results in a biased underestimated density. However, in practice, available detection loop data is generally aggregated and single vehicle speed is not available.

Therefore, arithmetic speed is mostly given instead of harmonic speed. In literature therefore, although not exact, arithmetic speed is used as approximately equal to harmonic speed (Treiber and Kesting 2013). If arithmetic speed is used for density estimation it should be taken in mind that density is somewhat underestimated.

3.4.1 The traditional fundamental diagram

The publication of “A study of traffic capacity” by Greenshields in 1935 forms the beginning of traffic flow theory. Greenshields performed his research with the help of photographs with constant intervals of roadside situations (Kühne 2011). Using only seven observations, Greenshields suggested a linear relationship between speed and traffic density. From this relation and his measurements, Greenshields also deduced the relations between speed-flow and flow-density. In figure 3.6 all three relations are visualised in the fundamental diagrams in their most simple form.

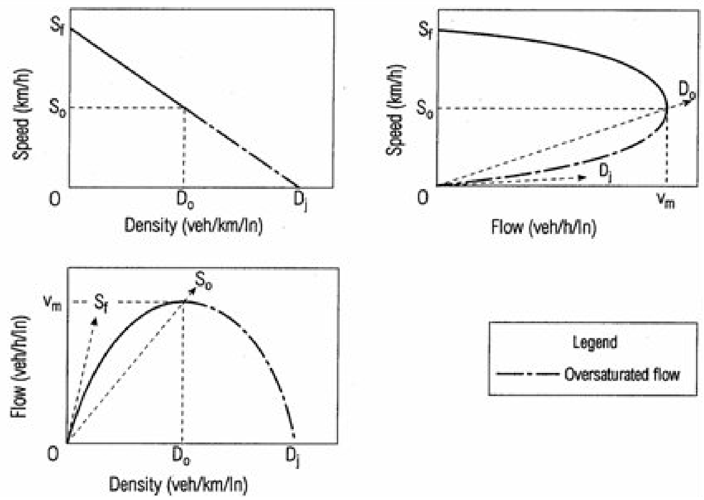


Figure 3.6: Fundamental diagrams (Federal Highway Administration).

From the flow-density diagram various characteristics of macroscopic behaviour of vehicles can be extracted (Treiber and Kesting 2013):

1. The desired free flow speed is equal to the derivative of the graph for a density k equal to zero.
2. The maximum flow rate q (the vertex of the curved graph) is equal to the road capacity. Also the corresponding density D_0 and speed S_0 can be derived.
3. Flow is oversaturated when it exceeds optimal density D_0.

3.4.2 Modern generation of fundamental diagrams

Since Greenshields’ observations in the 1930’s, a lot of research has been done on the subject of traffic flow dynamics. New and extensive observations of traffic flows resulted in an altered shape of the fundamental diagrams. Currently, the inverse-lambda shape of the flow-density diagram (figure 3.7) is considered to be the best approximation. The left “branch” of this flow-density diagram can be seen as the “free flow branch" whereas the right "branch" can be seen as the "congested branch" (Treiber and Kesting 2013).

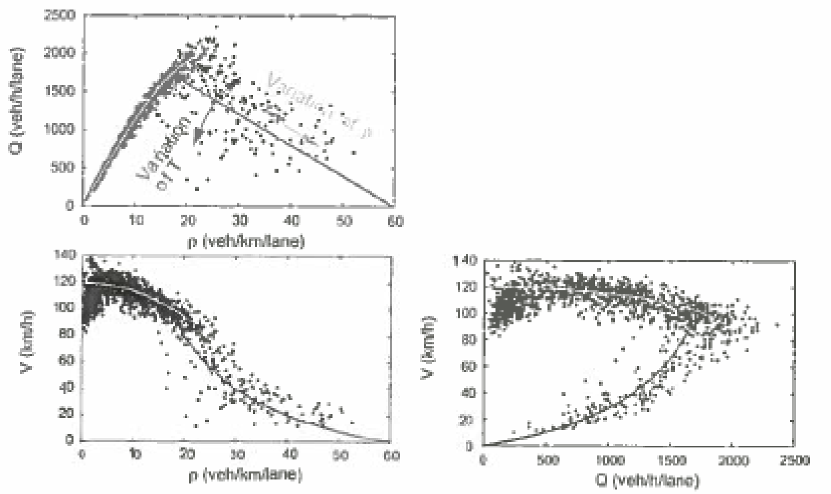


Figure 3.7: Observations of traffic flow (Treiber and Kesting 2013).

Although, modern generations of the fundamental diagram include a theoretical relation between flow and density, it is important to distinguish between the fundamental diagram and the flow-density relation. The fundamental diagram describes the theoretical relation between flow and density for homogeneous stationary traffic flows. Measured data (i.e. actual traffic flow) will however contain non-heterogeneous traffic. Therefore, it would not indisputably mean that an observed speed and flow gives a density as would theoretically follow from the fundamental relation (Kerner 2003; Treiber and Kesting 2013).

Kerner's three phase theory

Based on the difference between the theoretical relation and non-heterogeneous traffic, Kerner developed the concept of "synchronized flow" and its related three phase theory (Kerner 2003). Within the "congested branch" which can be identified in the lambda-shaped flow-density diagram, Kerner distinguishes two phases: synchronized flow and wide moving jam. Additional to these two phases, Kerner identified the free flow phase resulting in three different phases as can be seen in figure 3.8:

- Free flow (F)
- Synchronized flow (S)
- Wide moving jam (J)

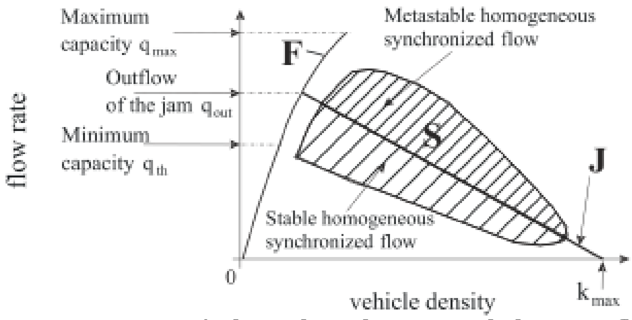


Figure 3.8: Kerner's three phase diagram including Free flow (F), Synchronized flow (S) and Wide moving jam (J) (Kerner).

The distinction which Kerner makes between synchronized flow and a wide moving jam is based on spatial-temporal features. The wide moving jam is characterized by the upstream movement of the downstream jam front with a constant speed. The downstream front of synchronized flow is normally fixed at a bottleneck. In figure 3.9 both a wide moving jam as a synchronized flow can be identified. It is clear that both phases show a specific spatial-temporal feature. The wide moving jam moves upstream through time, while the synchronized flow is fixed at the bottleneck. The distinction Kerner makes between these two phases on the "congested branch" of the fundamental diagram is comparable to the distinction between phantom and stationary jams as made in section 3.1.

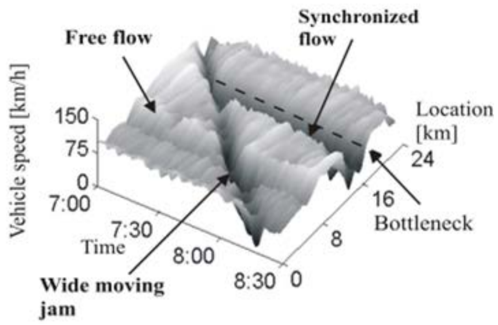


Figure 3.9: Space-time diagram including traffic speeds (Kerner 2000).

Besides this fundamental distinction between synchronized flow and the wide moving jam, Kerner also noted that two well-known effects of congested traffic can occur in both of these phases; (1) Synchronization of the average vehicle speed between different lanes and (2) a wide spreading of empirical data in the flow-density plane. Furthermore, Kerner also states that a wide moving jam has more the tendency to standstills within the traffic flow, whereas a synchronized flow has more the tendency to a synchronization of vehicle speeds across lanes with relatively higher speeds.

As can be seen in figure 3.9, transitions between the three phases can occur through space and time. However, one of the basic principles of the three phase theory is that a transition only takes place between the free flow and the synchronized phase and the synchronized phase and the wide moving jam. This means that no direct transition between free flow and a wide moving jam is possible. Therefore, the free flow traffic first has to move to synchronized flow where after it can make a transition to a wide moving jam. The same principle holds for the transition from a wide moving jam to the free flow phase.

The three phase theory can help to explain how and when moving jams propagate on roads without obstacles. First, we consider the escaping of vehicles from a moving jam from a standstill at the downstream front. A vehicle can escape once (1) the preceding vehicle has escaped from a standstill and (2) when a safety distance is achieved with the preceding vehicle. The velocity with which the downstream front of the moving jams moves upstream is described by formula ***(3.17)***.

$$v_g = -\frac{1veh}{\rho_{\max}\tau_{del}^{(a)}} \qquad (3.17)$$

where $\rho_{\max}$ is the mean vehicle density within the wide moving jam and $\tau_{del}^{(a)}$ is the average time interval between two vehicles escaping from the moving jam. The speed of the downstream front v_g is presented by the slope of line J in figure 3.8. Kerner states that the line J separates two different classes:

- If the traffic state is related to a point above line J in the flow-density plane, the traffic state is metastable. In a metastable traffic state perturbations which exceed certain critical amplitude can grow and lead to a wide moving jam. Furthermore, perturbations which do not exceed the critical amplitude can lead to a transition within the synchronized flow phase.
- If the traffic state is related to a point below line J in the flow-density plane, the traffic is stable and no wide moving jams will exist or can continue to exist.

3.4.3 Capacity drop

Kerner's three phase theory can also help to understand the phenomenon of capacity drop. Kerner (2003) describes that traffic can be either stable or metastable in the free flow state. The free flow is metastable if the flow rate is equal or higher than the outflow rate, q_{out}. For a metastable free flow, perturbations in the traffic flow can result in a transition from free flow to jam. The higher the flow rate of the free flow is compared to q_{out}, the smaller the perturbation has to be to initiate the transition to jam.

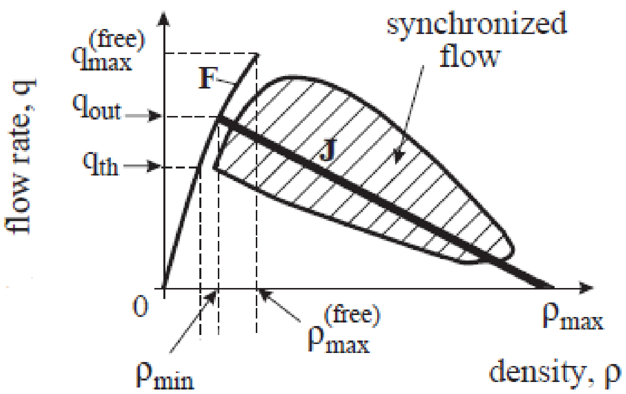


Figure 3.10: Variables of interest in case of capacity drop (Kerner 2003).

As can be observed from Kerner's three phase diagram the flow rate of the free flow state for densities between 20 to 30 veh/km is generally higher than the flow rate of synchronized flow. Because of perturbations in the metastable free flow, a transition to synchronized flow is initiated. Consequently, for the same densities lower flow rates can be achieved. This phenomenon is called capacity drop. Once the capacity drop emerged, traffic flow cannot easily "jump" back to its free flow state. Therefore, first the inflow to the jammed area has to fall to a much lower value (Treiber and Kesting 2013). The capacity drop phenomenon has been subject in various studies. Leclercq (2011) listed literature with capacity drops observed ranging from 10% up to 30%.

3.5 Shockwave theory

A shockwave describes the boundary between two traffic states which are both characterized by its own density, speed and flow rate. Shockwave theory describes how the boundary (also called shock front by Treiber and Kesting(2013)) between two traffic states propagates through time and space (Hoogendoorn and Knoop 2012). The speed c_{12} of the boundary is described by formula ***(3.18)***.

$$c_{12} = \frac{q_2 - q_1}{k_2 - k_1} \tag{3.18}$$

If c_{12} is a positive value, the boundary moves downstream. In case of a negative value for c_{12}, the boundary moves upstream, against the direction of the vehicles. The propagation speed of the boundary between traffic states can be visualized using the fundamental diagram. The slope of the line which connects the traffic states 1 and 2 in the fundamental diagram equals the propagation speed of the boundary between both traffic states. An example of this visualization is given in figure 3.11.

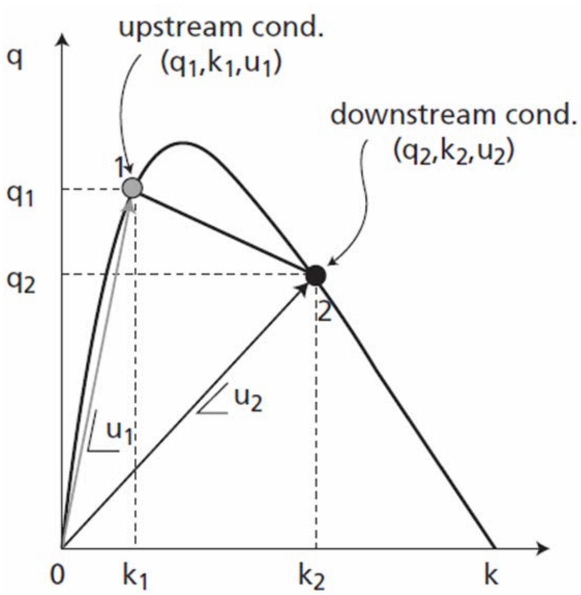


Figure 3.11: Visualization of the propagation speed of the boundary between traffic state 1 and 2 (Hoogendoorn and Knoop 2012).

Shockwave theory can be used to predict traffic conditions through time and space. The propagation speed of traffic jam fronts can be determined and traffic patterns can be followed. The ASDA model by Kerner, Rehborn et al. (2004) basically uses the shockwave theory to follow congested traffic sections (see section 3.6.2). One step further is the application of shockwave theory in traffic management. An example of such traffic management strategy is "*The specialist"* (Hegyi, Hoogendoorn et al. 2008) (Section 3.7.2).

3.6 Spatiotemporal reconstruction

Cross sectional data is basically only available for a small subset of space and time as it is limited by the number of loop detectors. Therefore, it does not offer a complete overview of the full traffic state. However, the available data can be used for interpolation to reconstruct a spatiotemporal overview of traffic states. This section discusses various methodologies which help the spatiotemporal reconstruction. First, the FOTO model by Kerner, Rehborn et al. (2004) is mentioned. This model does not so much reconstruct the spatial temporal traffic states but translates local traffic measurements in estimations of the actual traffic state. Thereafter, the ASDA model (Kerner, Rehborn et al. 2004) is described. This model uses actual traffic states (i.e. produced by the FOTO model) for interpolation to achieve a spatial-temporal reconstruction. Subsequently, the Adaptive Smoothing Method as presented by Treiber and Helbing(2002) is briefly discussed.

3.6.1 Forecasting of Traffic Objects (FOTO)

Kerner, Rehborn et al. (2004) developed the model FOTO (Forecasting of Traffic object) to recognize patterns of congested traffic. The model is based on the classification of free flow, synchronized flow and jam from Kerner's (2003) three phase theory.

The FOTO model processes local traffic measurements $q(t)$ and $v(t)$ in a fuzzy inference system. This fuzzy inference system includes the fact that flow rate in synchronized flow is usually much higher than flow rate in wide moving jams as well as other empirical features of the traffic phases synchronised flow and jam. With the speed and the flow fuzzified into the values low, medium and high (figure 3.12), fuzzy rules are implemented in order to identify whether traffic is free flow, synchronized flow or wide moving jam. The fuzzy rules used in the FOTO model are:

1. If the vehicle speed is ''high'', the traffic phase is ''free flow''.
2. If the vehicle speed is ''medium'', the traffic phase is ''synchronized flow''.
3. If the vehicle speed is ''low'' and the flow rate is ''high'', the traffic phase is ''synchronized flow''.
4. If both the vehicle speed and the flow rate are ''low'', the traffic phase is ''wide moving jam".

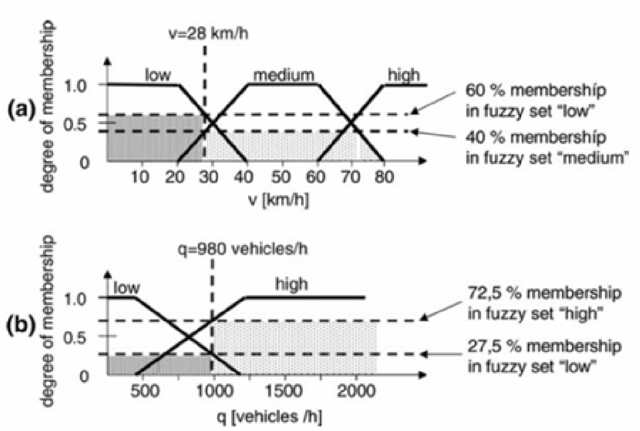


Figure 3.12: Illustration of FOTO fuzzification(Kerner, Rehborn et al. 2004).

3.6.2 Automatic Tracking of Moving Traffic Jams (ASDA)

Additional to the FOTO model, Kerner, rehborn et al (2004) developed a model which is able to track a moving jam at all time; even in between detection loop locations (figure 3.13). Once the upstream front of a wide moving jam has passed a stationary detector, the propagation speed of the upstream front is calculated using the shock-wave theory (The basic principles of shockwave theory are discussed in section 3.5). This is described by formula ***(3.19)*** with which the location of the upstream jam front $x_{up}^{(jam)}$ can be calculated. In the right hand side, the formula to calculate shockwave propagation speed (formula ***(3.18)***) can be recognized.

$$x_{up}^{(jam)} = L_{i+1} - \int_{t_0}^{t} (i+1) \frac{q_0^{(i)}(t) - q_{\min}}{\rho_{\max} - \left(\dfrac{q_0^{(i)}(t)}{w_0^{(i)}(t)} \right)} \tag{3.19}$$

L_{i+1} is the co-ordinate of the corresponding detector. The flow rate for the wide moving jam (which is typically close to zero) is expressed by $q_{\min}$ and the density for the wide moving jam (which is typically a predefined maximum of vehicles per km) is expressed by $\rho_{\max}$. The measured flow rate $q_0^{(i)}(t)$ and the average vehicle speed $w_0^{(i)}(t)$ at detector *"i"* are furthermore included in this formula. For the propagation speed of the downstream front a similar approach is used in the ASDA model with the outflow of the wide moving jam determined based on downstream detector data.

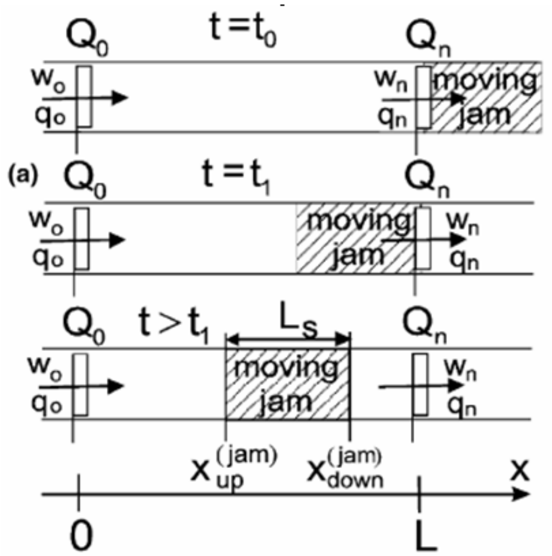


Figure 3.13: Illustration of ASDA: tracking wide moving jams (Kerner, Rehborn et al. 2004).

3.6.3 Adaptive smoothing

The Adaptive Smoothing Method also uses stationary traffic detectors (loop detection) to obtain an estimation of the full spatial-temporal traffic data (Treiber and Helbing 2002). The method uses the fact that perturbations and boundaries between traffic states propagate in different directions in free traffic (downstream propagation) and congested traffic (upstream propagation) with speed which is relatively constant. Therefore, the method estimates whether or not traffic is in free flow or congested state at the stationary detector using the velocity measured by these detectors. With this estimation of the traffic state, a filter for either congested or free traffic is used. Figure 3.14 shows a visualization of the effects of using the free flow or congested state. It is clearly seen, that the propagation direction of the traffic state is either downstream (free traffic) or upstream (congested). The method uses fixed propagation speeds of 80 km/h for free flow and -15 km/h for congested traffic.

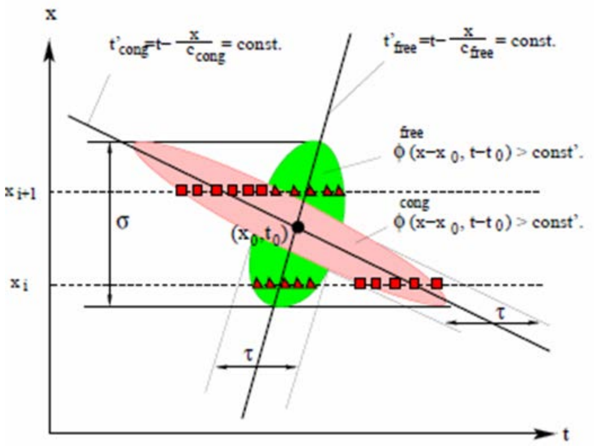


Figure 3.14: Visualization of the effects of either using the free flow filter or the congested filter (Treiber and Helbing 2002).

3.7 Traffic management

Traditional traffic management measures in case of congestion are rerouting of traffic, reducing speed limits and, however less traditional, opening peak hour lanes. Control by means of variable speed signs is not often considered in literature. Smulders (1990) looked into the effects of variable speed signs on the stability and homogeneity of traffic flow. Furthermore, Hegyi, Hoogendoorn et al. (2008) developed an algorithm (the SPECIALIST) to resolve so called shockwaves (or phantom jams) using dynamic speed limits communicated to road users by using variable message signs above roads.

3.7.1 The effect of variable speed signs on traffic flow stability

According to Smulders (1990), variable speed signs can result in a significant improvement of the traffic stability. Especially the fraction of small time headways is reduced significantly. Furthermore, the number of serious speed drops was reduced with up to 50%. This improved traffic stability is not accompanied by a decrease in capacity or by effects on other traffic characteristics such as mean speed, speed difference and distribution over lanes.

3.7.2 The SPECIALIST

The SPECIALIST is an approach to apply dynamic speed limits specifically to resolve shock waves / phantom jams. This theory is based on shockwave theory (section 3.5). Knowing the different traffic states on the road network (measured by for example by detection loops), the propagation of traffic jam fronts can be predicted (similarly to the ASDA model). Figure 3.15 illustrates the resolving strategy of the SPECIALIST and its corresponding traffic states. Once a traffic jam (state 2) is detected, upstream speed limits are switched on. This results in a changed traffic state from state 6 to 3. The boundary between these traffic states is moving upstream. The boundary between state 2 and 3 propagates upstream slower than the boundary between state 1 and 2. Therefore, after a while, the initial traffic jam is resolved. However, there remains an area with reduced speed. A basic assumption in this theory is that traffic flows out more efficiently from traffic state 4 than from congested traffic state 2. This efficient outflow of traffic is represented by traffic state 5. At last, a downstream propagating boundary between state 5 and 6 remains. The initial traffic jam has been resolved and new arriving vehicles do not experience any delays of this initial traffic jam.

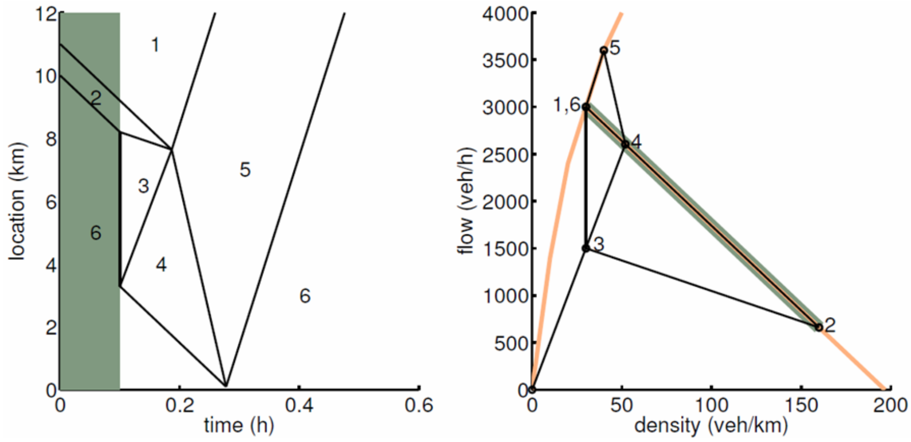


Figure 3.15: The SPECIALIST. Various traffic states in resolving a traffic jam (Hegyi, Hoogendoorn et al. 2008).

The dissolving strategy of the SPECIALIST has some known restrictions. The upstream network conditions are decisive in the successfulness of this strategy. If upstream intensity is too high, there is no "space" available upstream to resolve the identified shockwave. Upstream traffic can be very metastable and disturbances due to the speed advice can lead to new phantom jams. In practice, the SPECIALIST is only appropriate to be used in around 10% of all identified shockwaves, fulfilling the spatial-temporal characteristics of a phantom jam with a success rate of 80% (Burgmeijer, Eisses et al. 2010). Therefore, it needs to be remarked that this mainly includes so called congestion-tails. Congestion tails are characterized by the same spatial temporal characteristics as phantom jams but do have an infrastructural cause (i.e. onramp or lane closure). In case of such congestion tail the intensities upstream of the jammed area is likely to be less dense than in case of a real phantom jam. Note that in case of a real phantom jam, the jam specifically originated due to a perturbation under extremely metastable (high intense) network conditions. For congestion tails on the other hand, only capacity restrictions on the bottleneck are required and not on link level.

3.7.3 Cooperative driving

Another approach to prevent phantom jams can be through the introduction of cooperative driving systems. Such systems can be helpful in both reducing the number of perturbations due to imperfect driving behaviour and in stabilizing the traffic flow. In 2010, TNO performed a field operational test in which a similar system (cooperative adaptive cruise control, CACC) was tested. This proved to have a large potential in preventing and resolving phantom jams (Broek, Netten et al. 2010). A decrease of 10% on average in vehicle loss hours has been measured with a fully equipped car park. Such system however, requires considerable technological developments in the car industry before a reasonable share of the total car park is ready for cooperative driving (systems).

3.8 Traffic models

Traffic models aim to simulate traffic in order to be helpful in answering traffic flow related questions such as: What is the travel time between A and B during peak hour? What is the fastest route between A and B given specific network conditions? When does congestion occur on the road network? How will this congestion propagate? Or how long does it take before congestion has disappeared?

A widely used classification between traffic flow models is the classification based on aggregation level (Treiber and Kesting 2013):

- *Macroscopic models* are locally aggregated to macroscopic variables such as density, flow rate and mean speed. Macroscopic models are not able to describe phenomena as the propagation or evolution of congestion or the propagation of shock fronts. As dynamical variables are aggregated, macroscopic models do not describe the interactions between individual vehicles on the road.
- *Microscopic models* include the individual driving behaviour on the road. Such models describe the reaction of each driver on the road network depending on its individual behaviour and the surrounding traffic.
- *Mesoscopic models* combine macroscopic and microscopic into a hybrid model.

3.8.1 Microscopic models

For this study a microscopic simulation is performed in order to be able to both simulate the imperfect driving behaviour of traffic participants which are cause of the formation of phantom jams and the propagation of phantom jams. The two main elements of which a microscopic model consists are related to the two main driver tasks: the longitudinal (acceleration, deceleration, headway etc.) and the lateral task (changing lanes, overtaking etc.). The longitudinal task is described by the car-following model, whereas the lateral task is described by the lane-change model. For this study, the VISSIM software package has been used for simulation. Therefore, the focus in this section is on the design of both elements in VISSIM.

Car following model

The car following model describes the longitudinal movements of a vehicle on the road network. It describes acceleration and cruising in both free traffic as in traffic with a direct or indirect (approaching) predecessor (Treiber and Kesting 2013). Pipes (1953) developed the first car following model assuming that drivers maintain a safe distance to their predecessor. Later, Chandler et al. (1958) also included the assumption that a driver’s acceleration is proportional to its relative speed with his predecessor into his model. A more modern car-following model, which is widely used in modern microscopic models, is the Wiedemann model, which is based on the psycho-spacing theory (Treiber and Kesting 2013). The psycho-spacing theory is explained below using the Wiedemann approach.

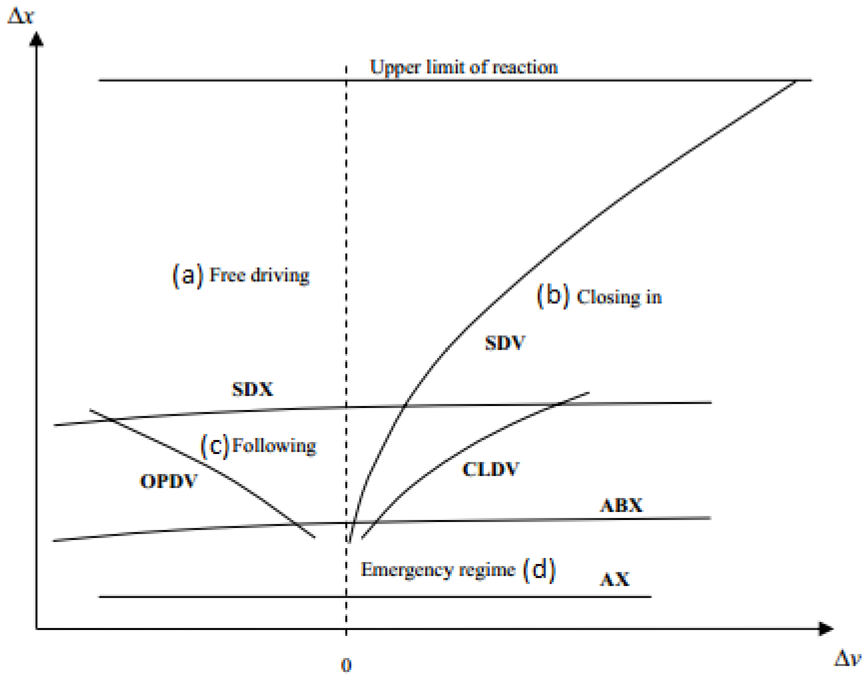


Figure 3.16: Illustration of the Wiedemann car following model (Olstam & Tapani, 2004).

The Wiedemann model includes the psycho-physiological aspects of four driving regimes: (a) free driving, (b) closing in, (c) following, and (d) emergency regime. These regimes are separated by the functions *AX, ABX, SDX, SDV, CLDV* and *OPDV*.

AX is the desired distance between stationary vehicles. It contains the length of the front vehicle and the desired front-to-rear distance and is defined is in formula ***(3.20)***.

$$AX = L_{n-1} + AXadd + RND1_n \cdot AXmult \quad \textbf{(3.20)}$$

Where $AXadd$ and $AXmult$ are calibration parameters and $RND1_n$ is a normally distributed driver dependent parameter.

ABX is the desired minimum following distance at low speed differences. This threshold is described by formula ***(3.21)***.

$$ABX = AX + BX$$
$$BX = (BXadd + BXmult \cdot RND1_n) \cdot \sqrt{v} \quad (3.21)$$

Where $BXadd$ and $BXmult$ are calibration parameters.

SDX is the maximum following distance which is described by a formula similar as those for the desired distance between stationary vehicles and the desired minimum following distance. The approaching point, *SDV*, is the point from where an approaching vehicle notices that it is approaching a slower vehicle. The *OPDV* function describes the point from where a vehicles notices that it is travelling with a lower speed than the leading vehicle. The *CLDV* function is assumed to be equal to the approaching point in VISSIM.

The acceleration or deceleration of a vehicle depends on the regime the vehicle is in. For convenience of the reader, deceleration functions are not presented in this report. However, the functionality of these deceleration functions are described per regime. In the free driving regime, vehicles use its maximum acceleration to reach its desired speed. When desired speed has been reached a small deceleration or acceleration is determined for the vehicle in order to simulate inaccurate handling of the throttle. If a vehicle enters the *closing in* regime, the vehicle gets a deceleration which depends on speed and acceleration/deceleration of the leading vehicle and the distance between both vehicles. In the following regime a vehicle only receives a small random acceleration or deceleration in order to simulate inaccurate handling of the throttle. Finally, when a vehicle enters the emergency regime, a strong deceleration is assigned to the vehicle based on the actual speed, location and deceleration of both vehicles.

The different deceleration functions for each regime result in a following behaviour of vehicles which comes close to real vehicle behaviour. The distance between the leading and the following vehicle varies through time as can be seen in figure 3.17. Although the regimes in figure 3.17 deviate from the regimes described above, the evolution of the distance and speed differences between both vehicles is similar.

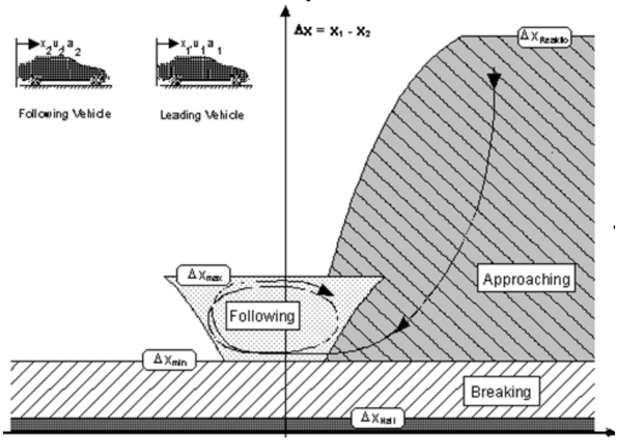


Figure 3.17: The iterating effect of speed difference and distance between a leading and a following vehicle for a psycho spacing model.

In VISSIM, two variants of the Wiedemann car-following model are implemented: Wiedemann-74 and Wiedemann-99. Both variants are very similar to each other though in the Wiedemann-99 model some thresholds have been changed in such way that it is said to model highway traffic better.

Lane-change model

The lane-change model describes the lateral movements of a vehicle between lanes, which is a discrete decision: perform a lane change, or not. Whether or not a vehicle changes lanes depends on various aspects such as safety distance (the gap between the vehicles on the target lane) and the desired speed. All those aspects are included in the lane change decision process which is part of the lane change model.

Although in reality lane change manoeuvres typically take a few seconds, many microscopic models simulate lane-changes as an instantaneous jump to the target lane. However, the representation of such lane changes are often simulated as a smooth process in such microscopic models (Treiber and Kesting 2013).

In VISSIM, the lane change model is based on a model proposed by Sparmann (VISSIM-FAQ 2013). Sparmann distinguishes between the wish to change lanes and the decision to change lanes (Nagel, Wolf et al. 1997). For a lane change from right to left these two parts are:

- *Wish* to change lanes if, on any of the two lanes, another vehicle is ahead and obstructing.
- *Decision* to actually change lanes if the gap is big enough on the other lane.

In Sparmann's model the final decision to change lanes is made by a rule-based system including both the distance towards the vehicle ahead and the gap between two vehicles on the other lane.

4

Model Environment

As mentioned in section 2.2, this study has been set up as a model study. Micro-simulation software has been used to simulate traffic and various advice systems on a network which is representative for Dutch situation. This chapter first discusses the reasons to perform a model study. Thereafter, the selection of the model software is shortly discussed. Subsequently, the design of the model environment is described. Thereafter, the model design of the advice system is extensively discussed. This is followed by a short elaboration on the model input. Finally, the number of simulations is discussed.

4.1 Model study

The aim of this research is to evaluate the potential improvements in network performance which can be achieved by the use of in-car advice system. Therefore, the effects on the network performance such advice system must be measured. These effects can be best measured if the advice system itself is the only variable in the research setting. To exclude all external impacts and create a controlled setting, this study has been performed using traffic simulation software. Furthermore, such model environment brings the possibility to test many different variants of advice systems. For the recognition of phantom jam characteristics it has been chosen to use this same traffic model. This enables the possibility to analyse these phantom jam characteristics not only for available macroscopic field data but also for microscopic variables.

4.2 Model selection

The model should not only be able to simulate phantom jams but it should also be able to simulate the implementation of various kinds of in-car advice systems. Therefore, several characteristics have been identified for selecting an appropriate software package:

The model:

- Is able to simulate a phantom jam on a two-lane highway including the lane change behaviour of drivers.

- Is able to produce actual traffic measurements (intensity, flow, velocity etc.) on any location on the network in order to identify an upcoming phantom jam.
- Is able to make adjustments to driving behaviour of individual drivers during simulation in order to simulate drivers obeying the provided advice.
- Has to be built with software which is available at Goudappel Coffeng.

4.2.1 VISSIM

First, in order to be able to have any influence on individual driving behaviour, micro-simulation is required. Several software packages to develop micro-simulation models are available on the commercial market as for example Paramics, VISSIM, Aimsum and FOSIM. However, only two of these software packages are available at Goudappel Coffeng; VISSIM and FOSIM. From these two software packages, FOSIM is lacking the functionality to make adjustments to the individual driver behaviour during simulation (property 3 respectively). The VISSIM software package on the other hand, has a COM interface included which allows the user to read and adjust specific individual driver characteristics during simulation. Therefore, VISSIM has been selected to build the model during this study.

4.3 Model development

For the model development, a procedure as proposed by Qi and Park (2005) has been used as a guideline. Qi and Park (2005) distinguish five consecutive steps within the development of a simulation model:

- Model Setup
- Initial Calibration
- Feasibility Test
- Parameter Calibration
- Model Evaluation

The goal of this research is not to exactly reproduce a specific road section of the Dutch highway network. However the modelled network should reasonably represent Dutch highway settings in order to make conclusions of this study applicable for the Dutch situation. The model developments do therefore not aim at reproducing a particular phantom jam observed in field data, but at a network in which traffic behaves reasonably similar to traffic on Dutch highways. Therefore, step 4 “Parameter Calibration” has been performed by manually varying the selected parameters of interest and selecting the “best” combination of plausible parameter values. As a result, the feasibility test and model evaluation can be performed simultaneously.

4.3.1 Model Setup

The model setup comprises the tasks which should be completed before the calibration process starts. This includes the selection of the physical network, collection of field data and traffic composition.

Physical network

A simplistic representation of a relatively small segment of the Dutch highway network is used for this study. It is chosen to use a single link network. Although this choice delimits the possibilities of evaluating the impact of the advice systems on network level, it allows the use of a small network with limited simulation times. The single link network consists of a 10 kilometre long two-lane highway section with a legal maximum speed of 120 km/h. The length of the highway section is chosen to be long enough to be able to implement measures and evaluate the effects. Although 10 km highway sections with no on or off ramp are not very common on the Dutch highway network, it is not unrealistic.

The network is equipped with detection loops which detect vehicle appearance during the simulation. Detection loops are located each 500 meter on the network, comparable to detection loop distance on the Dutch highway network.

Collection of field data

Field data have been collected in order to test the feasibility of the model to perform reasonably similar to Dutch highway traffic. For this study, the A58 (direction Tilburg - Eindhoven) has been selected for the collection of field data to use during the model development procedure. The A58 is not chosen accidentally. The trajectory Moergestel-Oirschot is known for the occurrence of phantom jams and moreover this trajectory has been chosen by the SRE (Samenwerkingsverband Regio Eindhoven) for a project to reduce the occurrence of phantom jams with the help of in-car information provision (Hendrix 2013). Furthermore, similar to the model network, this highway section is relatively long (around 8 km) with no on- or off-ramps.

Traffic composition

The first step to develop a model which represents Dutch highway settings is to get a similar traffic composition. Therefore, NDW-data (National Databank Wegverkeersgegegevens) is used. In the NDW, loop detector data from all along the Dutch road network is available. Five vehicle classes are identified in NDW data:

- Class 1: Between 1.85 m and 2.40 m
- Class 2: Between 2.40 m and 5.60 m
- Class 3: Between 5.60 m and 11.50 m
- Class 4: Between 11.50 m and 12.20 m
- Class 5: Larger than 12.20 m

From this classification, class 1 includes mostly motorcycles, class 2 and 3 include cars and small trucks and class 4 and 5 represent trucks. However, not only vehicle length is an important difference between these classes. Also legal maximum speed is a characteristic of these classes which is included in the model environment. For the model environment it is chosen to use two different vehicle classes. On the one hand trucks with a maximum speed of 80 km/h and cars with a maximum speed of 120 km/h. For this study, motorcycles have been included in the cars class as less than 1% of all traffic has been identified as NDW class 1. Based on A58 data the percentage of trucks on the network has been determined to be 9%. This is slightly above the national average of 8% (Emissieregistratie & Planbureau voor de Leefomgeving 2010).

Within both the truck as the car class, various vehicle types are included in the model. These vehicle classes differ in length and weight. For the variation in desired speed, a speed distribution for the desired speed is used with a minimum and maximum speed of 75 km/h and 90 km/h for trucks and 100 km/h and 140 km/h for cars.

4.3.2 Calibration and evaluation

Besides traffic composition, traffic behaviour is crucial in order to set up a realistic micro-simulation model. The car-following model is of great influence on this behaviour. VISSIM has included the Wiedemann 74 and the Wiedemann 99 car following model. For this study the Wiedemann 74 model has been used, as this resulted in a better representation of the capacity drop of the traffic system. Furthermore, the model was much more easy to interpret as it has a limited number of parameters in comparison to the Wiedemann 99 model.

In the Wiedemann 74 car following model, the desired distance between two vehicles is calculated using formula ***(4.1)***. The desired distance is the sum of the standstill distance ax and de safety distance bx. Moreover, the safety distance is also of influence on the lane change behaviour of vehicles in the model. Unfortunately, due to the fact that the lane change model in VISSIM is kind of a “black box”, the exact effect of the safety distance on lane change behaviour cannot be determined.

$$Dist = ax + bx \tag{4.1}$$

with ax being the standstill distance (with accepted ranges between 1 and 5 m (Qi and Park 2005) with a default of 2m in VISSIM) and bx *(safety distance):*

$$bx = \sqrt{v} \cdot (bx\_add + bx\_Multi \cdot z) \tag{4.2}$$

With:

v is the vehicle speed [m/s]

z is a value of range [0,1] which is normal distributed around 0.5 with a standard deviation of 0.15.

bx_add has a default value of 2,5 in VISSIM and has accepted ranges between 2 and 2,5 (Qi and Park 2005).

bx_Multi has a default value of 3,5 in VISSIM and has accepted ranges between 3 and 3,7 (Qi and Park 2005).

From this formula can be derived that, especially for higher speeds (as is common on highways), *bx* has the largest contribution to the desired distance between two vehicles and, as a result, on the saturation flow rate. Therefore *bx_add* and *bx_Multi* are most appropriate parameters to use for the calibration process.

By manually varying these parameter values, the model has been calibrated to meet four important traffic characteristics observed in field data (A58). Each of these characteristics is easily derivable from the speed-flow and speed density diagram. Appendix I shows a visualisation of this process for both the field data as the model data. From the traffic characteristics, listed below, the capacity drop, although it is still within the range Leclercq (2011) observed, is relatively high with 23%. However, it must be acknowledged that the determination of the capacity drop for this study is arbitrary. The outflow rate has been identified manually using the flow-density diagram and not by analysing single capacity drop occasions such as for example has been performed by Chung et al. (2006).

- Free flow capacity: 5200 veh/h
- Speed at capacity: 87 km/h
- Density at capacity: 60 veh/km
- Queue discharge: 4000 veh/h

The calibration parameters have been manually varied within the ranges determined by Qi and Park (2005). For each combination of calibration parameters, all four parameter values have been determined. Once model parameter values did reasonably match field data observations (appendix I), the calibration parameters were selected. This resulted in the following calibration parameter values:

- bx_add : 2,00
- bx_Multi : 3,40

4.4 Advice system

The developed micro-simulation environment has been used to simulate in-car speed advice systems. This section discusses the design of these advice systems and the classification of such systems. The advice systems, as simulated during this study, consist of three autonomous design variables (figure 4.1):

- Penetration rate
- Speed advice
- The triggering mechanism

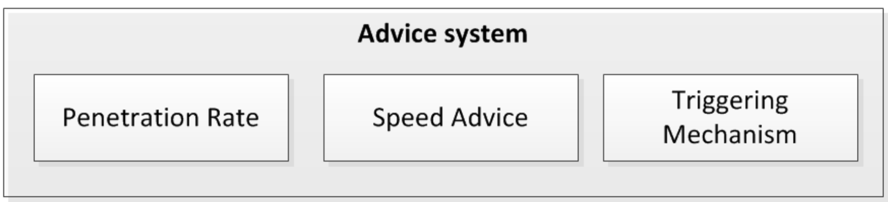


Figure 4.1: Design variables advice system

4.4.1 Penetration rate

The first design variable, the penetration rate, is the share of vehicles which is equipped with an in-car advice device. For this study it is assumed that all equipped vehicles follow the speed advice which they receive. Therefore, the penetration rate should be more seen as a follow-up rate. The penetration rate is operationalized for simulation purpose by listing a predefined share of vehicles (equal to the penetration rate for the particular simulation) by their vehicle ID. Consequently, these listed vehicle ID's can be used to give speed advice only to the equipped vehicles. This results in a perfectly equally distribution of equipped and non-equipped vehicles. By vehicle interaction, this distribution gets somewhat more mixed downstream on the network.

For this study seven penetration rates have been simulated, knowing: 0%; 1%; 2%; 5%; 10%; 20%; 50% and 100%. The lower penetration rates are over represented in this set as these are most interesting for practical implementation. A penetration rate of zero is equal to no advice system active and forms the reference scenario. The reference scenario is used to compare the results of all advice system variants and to analyse the effect of these systems.

4.4.2 Speed advice

The second design variable, the speed advice, is straightforward in its expression. It is the speed which is advised to the driver in an equipped vehicle. For this study, five different speed advices have been simulated: 80, 85, 90, 95 and 100 km/h. In order to achieve a realistic application of such speed advices, the advice is not fixed to these values but has been implemented as a multiplication factor to their desired speed. For example: a speed advice of 80 km/h is processed as a multiplication of 0,67 * 120 = 80 km/h. Note that a distribution over the initial desired speed of 120 km/h is provided by the input generator of VISSIM. The use of such multiplication factor results in the fact that the distribution in speed is remained after vehicles received a speed advice. As the speed advice is implemented by means of adjusting the desired speed in VISSIM, the change in speed of the vehicles elapses smoothly. Another implication of this assumption is that vehicles with an original desired speed below the maximum speed of 120 km/h, will also have a desired speed below the advice speed. It needs to be remarked that this might result in a minor overestimation of vehicles driving below the advice speed. Note that it is less likely to have a desired speed below an advice speed than having a desired speed below a legal maximum speed. For practical application this would mean that lower speed advices must be provided in practice to achieve similar results as in this study. Note, that

4.4.3 Triggering mechanism

The third design variable is the triggering mechanism. The triggering mechanism determines every minute interval whether or not advice should be given and where on the network this advice should be given. Therefore, the network has been subdivided in sections of 500 meter. For each section the traffic states are estimated using loop detector measurements. An algorithm has been developed to process these measurements into traffic state identification (this is explained more detailed in section 5.3.1). Using these traffic measurements, the triggering mechanism determines when and where on the network advice should be provided. The triggering mechanism can be classified within two main classes: Prevention based and dissolving based mechanisms. Both classes are discussed in the following sections within their theoretical background.

Prevention-based triggering mechanisms

Kerner's three phase theory suggests that free flow traffic with an intensity above the queue discharge capacity is metastable (Kerner 2003). Metastable traffic is sensitive for disturbances and traffic can easily fall into congestion. By preventing the traffic from achieving such high intensities, it is theoretically possible to prevent the traffic from spontaneous decay into congestion. Note that if traffic flow never exceeds the queue discharge capacity, traffic is always stable and is able to overcome any disturbance. Not only is the intensity locally reduced using this methodology, also the traffic becomes more homogeneous. Smulders (1990) describes that homogenization by speed limits can result in a decrease of up to 50% of serious speed drops. This could contribute significantly to a more stable traffic flow.

In line with this theory, advice can be given to vehicles in two ways: Non-controlled and controlled ("smart"). Non-controlled advice is given no matter what the traffic situation on the road is. All equipped vehicles receive the same pre-determined speed advice and are assumed to follow this advice. This way, the ambition is to achieve a more stable and homogeneous traffic situation over the whole network.

On the other hand, the controlled "smart" advice is more advanced and takes actual traffic measurements into account. For this study, the controlled prevention based triggering mechanism is focussed on reducing the peaks in the intensity pattern. This way, it is strived for to stabilize and homogenize only there where it is really necessary according to Kerner's theory.

To do so, high intensity waves are identified in traffic flow to specify the selectiveness of the system. The presence of such intensity waves in traffic flow is discussed on in section 5.1.2. An algorithm processes traffic measurements in order to identify such intensity waves. Furthermore, the algorithm classifies the intensity wave into various danger levels which is a surrogate measure for the metastability of the traffic flow. The development of the algorithm is described in section 5.4.1. If an intensity wave with a certain minimum danger level is detected on the network, the advice system is locally activated. If activated, speed advice is given only to equipped vehicles located within the detected high intensity wave. Note that these section need to be stabilized. This speed advice is typically lower than the actual vehicle speed. Consequently this results in a reduced speed within the high intensity wave. Together with the density, which does not change when speed drops on a longer stretch (no vehicles can appear or disappear), this results in a reduced intensity on the affected sections. This leads to a locally adjusted free flow branch of the fundamental diagram. The advised road sections are still in a free flow traffic state but at a lower speed. This way, the traffic flow is stabilized and it is able to recover from perturbation from itself. Figure 4.2 illustrates the effect of the speed advice in the fundamental diagram. Note that the red dotted free flow branch only holds for the advised traffic.

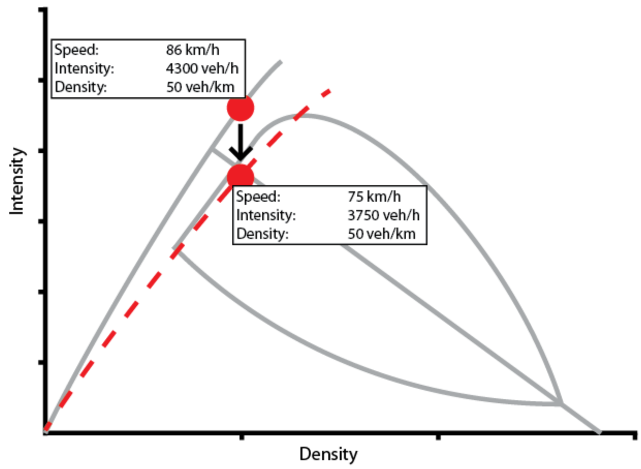


Figure 4.2: The effect of the intensity wave based preventing advice system. The red dotted free flow branch represents the adjusted traffic states of the advised platoon of vehicles.

For this study, three variants of the intensity wave based triggering mechanism have been simulated. Each variant uses the danger level provided by the algorithm which identifies the intensity waves. However, each variant uses a different threshold for the danger level from which advice should be given. This way, each system differs in it selectiveness to provide advice. In the overview below all three variants are presented. In principal a higher danger level indicates a higher average intensity (a more metastable traffic flow) within the intensity wave.

Give advice if:

- Variant 1: Danger level >=1
- Variant 2: Danger level >1,5
- Variant 3: Danger level >2,5

To provide the control mechanism from flip flopping (switching on and off the advice every minute), speed advice remains active for the rest of the simulation once a vehicle received advice. This might have as a result that vehicles remain their advised speed while the local network conditions allow higher speeds (or even their original desired speed). For the results this would mean that the average network speed can be slightly underestimated in case of intensity wave based advise.

Dissolving based triggering mechanisms

Once congestion has already been originated, there is no need to apply advices which focus on prevention, but there is need in dissolving the congestion. Studies by Hegyi et al (2005; 2008) and Popov (2008) have proved (variable) speed advice, communicated by roadside systems, to be effective in dissolving phantom jams. These methodologies are based on creating space on the network upstream of a jammed area. This is achieved by decreasing the speed on the upstream stretch. Although this mechanism can be very effective, the active upstream intensity is crucial for the success of this approach.

Two variants of dissolving triggering mechanisms have been applied. These two variants differ from each other for the required traffic measurement to activate the advice system. The first mechanism only activates the advice system if a phantom jam is detected. This detection takes place using a developed algorithm which processes traffic measurements into phantom jam detections. This algorithm takes into account the spatial temporal characteristics of a phantom jam and is discussed more detailed in section 5.3.2. The second mechanism does already trigger the advice system if only a single jam detection is done. This is the case if only one section has been identified as jammed without recognition of the spatial-temporal characteristics of a phantom jam yet.

For both variants, only vehicles within a range of 2 km upstream of the section, detected as jammed, are advised. In contrary to the prevention based triggering mechanism, the provided advice for the dissolving based algorithm is reset after a while. The location of this reset is the first section downstream of the initial jam detection. It is chosen not to include the propagation of the front of this jammed section in the reset scheme. This is done as the propagation distance is limited within the duration of the speed advice and the aggregated traffic state identification is too rough to determine exact location of the head of the jam.

4.4.4 Schematization of design variables

For more clarity and better understanding of the design variables and its classification, they have been visualized in the schematization of figure 4.3.

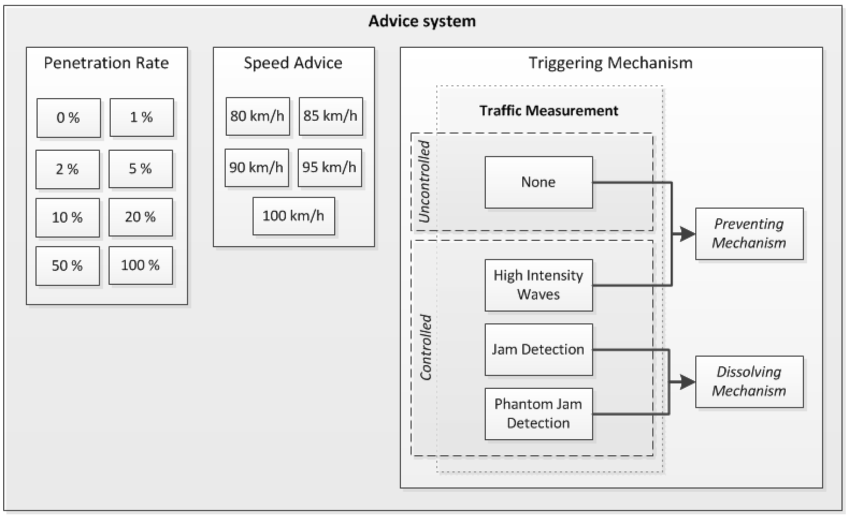


Figure 4.3: Schematization of the design variables and its classification.

4.5 Model input

The model input is the number of vehicles generated by the simulation software at the upstream end of the network. Model input basically consists of two elements: Demand and composition of traffic. From these elements, the composition of traffic has already been determined in section 4.3.1. Therefore, this section only elaborates on the demand.

4.5.1 Demand

The demand is the actual number of vehicles generated by the simulation software and put on the network. In VISSIM, this is expressed by the number of vehicles per hour. VISSIM distributes this demand on the network during simulation. It has been chosen, not to use a uniform distribution of demand. In practice, traffic never represents a uniform distribution during morning or evening peak hour. Therefore, a simple peak demand has been simulated during simulation (figure 4.4). The simulation starts with only 90% of the maximum demand. This is increased in fixed time steps of 12 minutes up to the maximum demand after 36 minutes. The last time step, the demand is again reduced a bit. Besides the fact, that such demand distribution represents real traffic flows better, it avoids problems with any capacity restrictions early in the simulation.

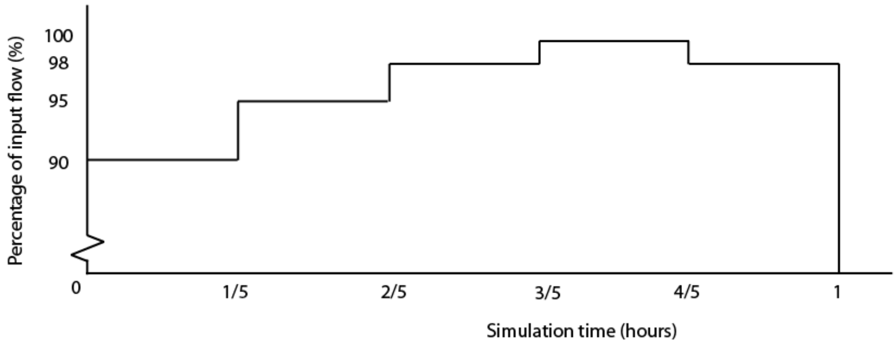


Figure 4.4: Demand distribution model.

Besides the distribution of the demand, also the absolute number of the demand is of great influence on simulation results. For this report, the reported demand is the maximum demand which is generated during simulation (demand between time =3/5 and time=4/5). If demand is too low, no phantom jams exist on the network. Consequently, no effects of in-car advice systems could be evaluated. If demand is too high, the VISSIM generator gets obstructed and not all vehicles are released on the network. Therefore, for this study, three demands profiles have been selected for simulation purposes (table 4.1).

Table 4.1: Demand profiles selected for this study.

Demand Profile:	***1***	***2***	***3***
Number of cars (veh/h)	3600	3700	3800
Number of trucks (9%) (veh/h)	356	365	376
Total (veh/h)	**3956**	**4065**	**4176**

Demand profile 1, with a total maximum demand of 3956 veh/h, has been selected as bottom-variant. For lower demand profiles, phantom jams rarely occurred on the modelled single-link network. On the other hand, demand profile 3 has been chosen in such way that a maximum amount of phantom jams occurred on the network without obstructing the generator. For higher demand, the number of phantom jams did not increase as the input generator got obstructed. The second demand profile, at last, is chosen in between as the regular phantom jam scenario. It needs to be remarked that these demands are average values and that the demand generated by the VISSIM generated is not uniformly distributed. This, together with the effect of interaction between vehicles, leads to the phenomenon that higher or lower intensities can be measured on the network. This can be recognized in figure 4.5 in which local intensity measurements on the network are presented for the full simulation period for demand profile 2. It can be observed that for the one-minute averages intensity clearly shows large differences between minutes. For the ten-minute average however, it can be seen that intensity is gradually built up to an intensity of around 4100 veh/h.

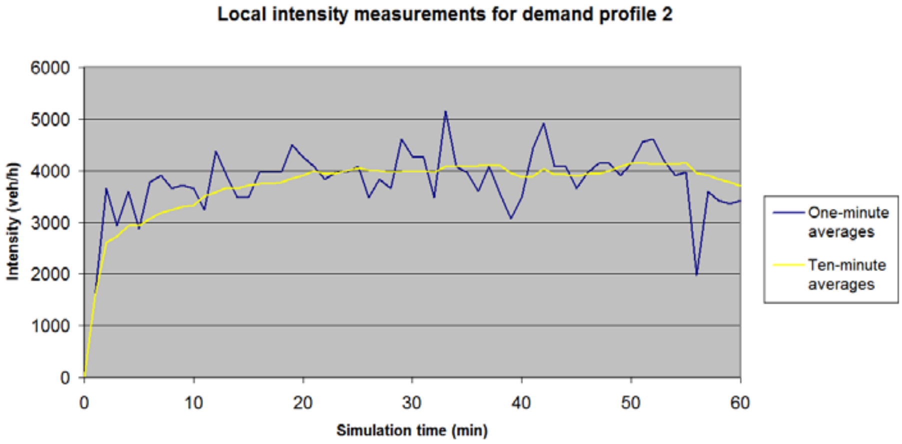


Figure 4.5: Local intensity measurements for demand profile 2.

4.6 Number of simulations

For any combination of advice system and demand profile, fifty simulations have been performed. Besides, fifty simulations have been performed for the reference scenario with no advice system on for each demand profile. The decision to perform fifty simulations per advice system is mainly due to time restrictions and limited availability of the simulation software. Each of these fifty simulations has its own unique vehicles distribution (seed). The same fifty seeds have been used for the simulation of any of the systems. As the same vehicle distributions have been used as input for all scenarios, the results of the scenarios are paired. Therefore, the results of the simulation of an advice system for, for example, seed one, are directly comparable to the results of the reference scenario with the same seed. Note that if the only difference between two runs is the setting of the advice system, the differences between these two runs in the results are directly caused by the setting of the system. The fact that simulations of all combinations of advice systems and demand profiles are paired is used for the statistical analysis in chapter 7.

It needs to be remarked that in the VISSIM simulation software all random vehicle parameters are determined once the vehicle is generated. The provision of speed advice has no implications for other vehicle depended decision parameters. This is illustrated in Appendix II.

5

Phantom jam Characteristics

Simulation data is processed and analysed to identify characteristics of phantom jams. The analysis has been twofold. On the one hand traffic states can be recognized which can help to identify the phantom jam once it already originated. On the other hand traffic patterns have been recognized which are typical for the pre-phantom jam phase. For both the phantom jam as the pre-phantom jam phase an algorithm has been developed which identifies the specific traffic characteristics corresponding to each of these phases. Both algorithms are “live” applicable, which means that data is processed during simulation and directly operable by the triggering mechanisms of the advice systems.

The chapter is introduced by a discussion of macroscopic traffic patterns on the network. Subsequently, it elaborates on the identification of the phantom jam itself and the pre-phantom jam phase. The analysis, described in this chapter, is based on the fifty simulations of the reference scenario for demand profile 3. Demand profile 3 has been chosen for this analysis, as most phantom jams occur using this demand profile.

5.1 Macroscopic traffic patterns

Macroscopic detection loop data is used to identify traffic patterns on the network. Therefore, individual vehicle data has been aggregated for one-minute intervals for each detection loop. For speed, the arithmetic average has been used as arithmetic data is usually directly available from loop detection.

As detection loops are separated 500 meter from each other, the macroscopic variables *speed* and *intensity* are available for this same interval. However, for the representation of the traffic patterns each detection loop is seen as being representative for the traffic state of a full 500 meter interval. Note that this representation is not completely correct as point measurements has been used instead of continues segment measurements.

5.1.1 Phantom jams

In figure 5.1 the time-space diagrams for speed as well as intensity are shown. In these diagrams clearly two phantom jams can be identified. Both phantom jams fulfil the definition as stated in section 3.1. They are not caused by any physical bottle-neck and have two sharp fronts bounding a plateau of slow moving traffic of which the downstream front is moving in an upstream direction. Both in the speed- as in the intensity- diagram, the upstream movement is clearly identifiable. Furthermore, a clear reduction of respectively speed and intensity can be seen within the phantom jam.

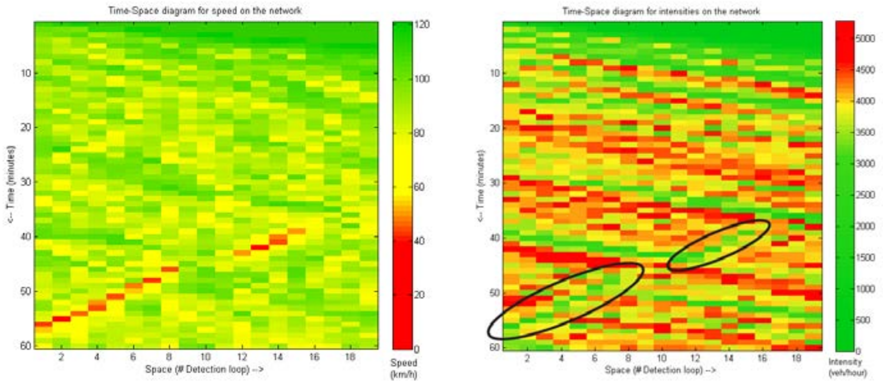


Figure 5.1: Time-Space diagram for speed (left) and intensity (right) on the network during simulation. Phantom jams are encircled.

Not only can the presence of the phantom be deduced from the analysis of the speed- and intensity diagrams, also the movement speed of the phantom jam can be deduced from the diagrams. For these model conditions, the movement speed of the phantom jams appeared to be constant over various simulations with a speed of around 22 km/h in opposite direction of the traffic. This movement speed is slightly above the movement speed of roughly 20 km/h observed by other researchers based on real traffic observations (Kerner, Rehborn et al. 2004; Sugiyama, Fukui et al. 2008).

5.1.2 Intensity shockwaves

Besides the phantom jam, no exceptional speed patterns can be observed within the speed-diagram in figure 5.1. However, the intensity-diagram shows a clear pattern of alternating high and low intensity shockwaves (figure 5.2). Both phantom jams find their origin in such high intensity wave as pointed out in the right diagram. Further analysis showed that most phantom jams are originated in such high intensity shockwaves (This is discussed on more extensive in 5.4.2). However, this finding does not hold the other way around. Not every high intensity shockwave turned out to result in a phantom jam.

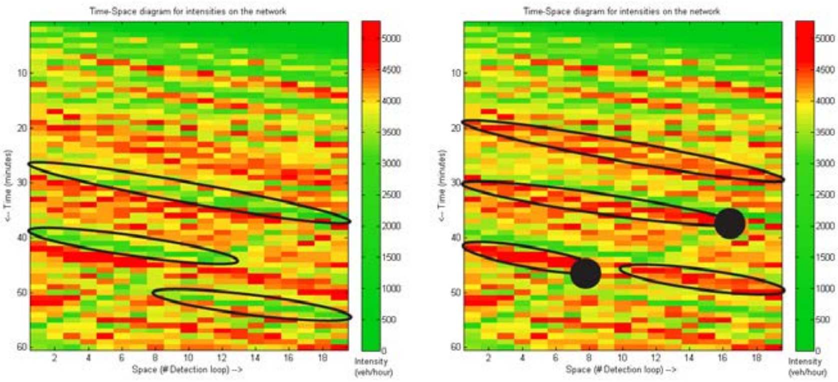


Figure 5.2: Space-time diagram for intensities on the network with low (left) and high (right) intensity shockwaves encircled.

This pattern of alternating high and low intensity waves is not only observed in model data, but can also be observed in field data. In figure 5.3, the intensity measurements for a small section of the A58 are presented for an early Friday morning peak. Just as in the model data, clear high and low intensity waves are seen.

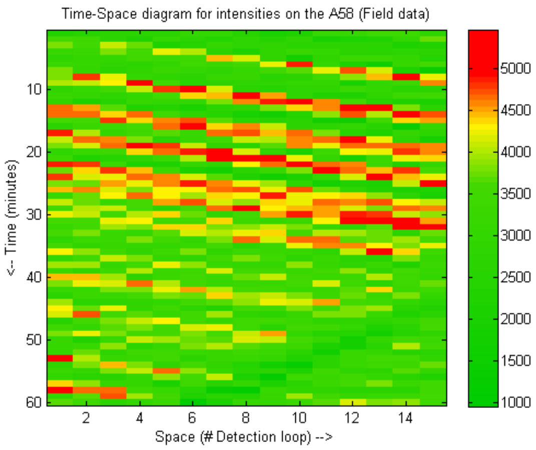


Figure 5.3: Space-time diagram for intensities on the A58 (Friday, April 13th 2013, 6.40-7.40 am).

5.1.3 Traffic patterns in secondary microscopic variables

Besides a visualization of the macroscopic variables *speed* and *intensity*, also the secondary microscopic variable *headway* has been analysed during this research. However, although one might expect smaller headways and a more homogeneous distribution of the headways in the pre-phantom jam phase, no such clear pattern has been recognized for headways as was done for intensity. This is most likely to be caused by the fact that aggregated minute data is used. However, declaring variables for phantom jams are much more likely to be found in the relation of microscopic data between single vehicles (i.e. time-to-collision in combination with significant decelerations). A short elaboration and visualization of the relation between headways and phantom jams can be found in Appendix III.

5.2 Algorithm development

Using the macroscopic traffic patterns discussed in section 5.1, various algorithms have been developed. First, two “live” algorithms have been developed which process loop data during simulation. The first “live” algorithm processes loop detection data into a traffic state per section. With knowledge of the traffic state for each section on the network, jammed and free flow sections can be recognized. The second “live” algorithm processes loop detection data in such way, that high intensity waves are identified. These algorithms provide input data for the triggering mechanism of the advice system as previously described in section 4.4.3.

Besides these two “live” algorithms, two offline algorithms have been developed. These algorithms process the output of the “live” algorithm into more aggregated data which forms input for the jam indicators in the evaluation framework (discussed more detailed in chapter 6). Furthermore, the offline algorithms help to clarify the relation between phantom jams and intensity waves. Figure 5.4 offers an overview of the “live” and offline algorithms and their relations.

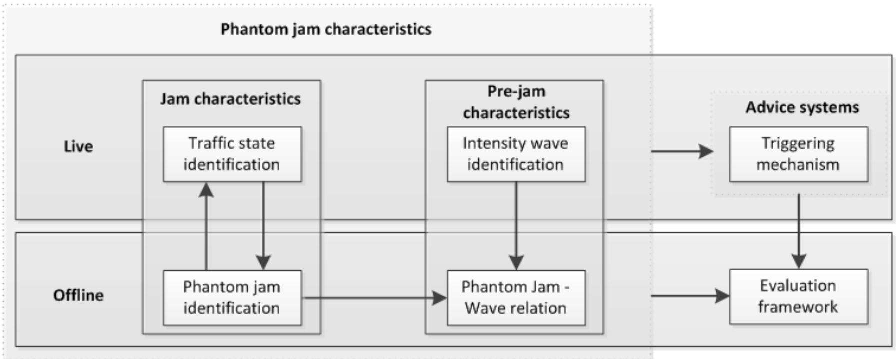


Figure 5.4: Live and offline algorithms and their relations.

The following sections, first describe the development of the “live” and “offline” algorithm belonging to the jam characteristics. Subsequently, the algorithms belonging to the pre-phantom jam phase are described.

5.3 Jam characteristics

Section 5.2 showed that phantom jams can be recognized by their macroscopic characteristics through space and time. First step in the identification process, is to identify traffic state for each network section. This is performed using a “live” algorithm which identifies traffic states based on the speed-intensity relation during simulation. Thereafter, an “offline” application is used which processes the traffic state detection further into phantom jam identification. Both these algorithms have been used for the dissolving based triggering mechanism. The “live” algorithm produces single jam detections which trigger the jam detection based triggering mechanism whereas the “offline” algorithm produces phantom jam identifications which are used for the phantom jam based triggering mechanism. The following section elaborates extensively on the design of both algorithms.

5.3.1 Live algorithm – Traffic state identification

To determine the traffic state for each 500 meter interval every minute, a fuzzy logic framework is used. Such system has proved to be successful in traffic state recognition in previous research by Kerner, Rehborn et al. (2004) (see section 3.6.1).

Fuzzy logic

Each traffic measurement *v(t)* and *q(t)* is considered in a set of fuzzy rules. Empirical features such as the fact that vehicles speed is low in congested traffic are included in this set of rules. Besides congested and free flow traffic a third traffic state is identified by the algorithm: synchronized flow. Synchronized flow is a traffic state identified by Kerner (2003) in his three phase theory. It differs from congested traffic (or wide-moving jam as Kerner calls it) by its spatial temporal characteristic (see section 3.4).

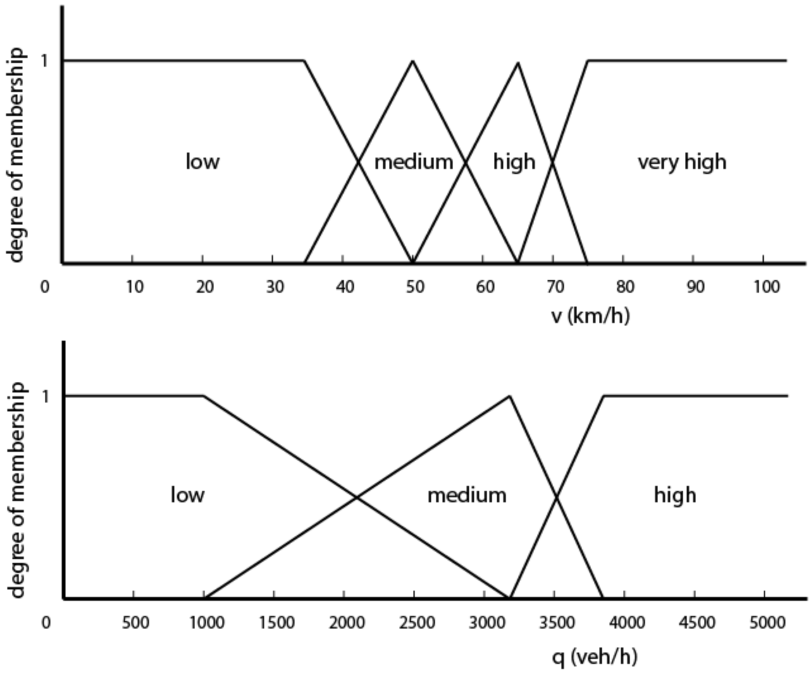


Figure 5.5: Illustration of fuzzification of speed and intensity measurements.

The measured speed and intensity are fuzzified into the values “low” to “very high” as is illustrated in figure 5.5. The numerical values of the membership functions are based on various distinguishable regions in the speed-flow diagram. The determination of the numerical values can be seen a trade-off between early identification and false identification. For this study, the numerical values used by Kerner, Rehborn et al. (2004) have been used as a starting point. The determination of the final numerical values which has been used during this study is discussed later on.

In order to identify the traffic state of network segments, the fuzzified speed and intensity are processed using the following set of rules:

- **Rule 1:** If vehicle speed is “very high”, the traffic phase is “free flow”.
- **Rule 2:** If vehicle speed is “low”, the traffic phase is “congested”.
- **Rule 3:** If vehicle speed is “medium” and traffic flow is <u>not</u> “high”, the traffic phase is “congested”.
- **Rule 4:** If vehicles speed is “high” and traffic flow is <u>not</u> “low”, the traffic phase is “synchronized”.

Table 5.1: Example for the use of the fuzzification rules.

#	v	q	Speed				Flow			Rule 1	Rule 2	Rule 3	Rule 4	Phase
			Low	Medium	High	V. High	Low	Medium	High	“free”	“jam”	“jam”	“sync”	
1	30	2400	1	0	0	0	0.37	0.63	0	0	1	0	0	Jam
2	72	4000	0	0	0.3	0.7	0	0	1	0.7	0	0	0.3	Free
3	58	3450	0	0.47	0.53	0	0	0.58	0.42	0	0	0.47	0.53	Sync

In table 5.1, an example is shown of the use of these fuzzified values for three hypothetical measurement locations. The first step is to fuzzify the measured values for speed and intensity using the distribution shown in figure 5.5. Thereafter, each rule is scored using these fuzzified values. If both a speed as an intensity condition is part of the rule, the lowest value for both conditions becomes the score for that rule (see example measurement 3 in table 5.1). Finally, the rule with the highest score determines the traffic state at the measurement location. The result is a discrete value (free flow, synchronized flow or traffic) for each measurement section.

Each minute, the live algorithm processes speed and intensity data into a traffic states using the fuzzification. In figure 5.6 the result of this process is presented for all 19 sections on the network for the full simulation length of one hour. Clearly, two phantom jams can be recognized in this time-space diagram. Furthermore, some temporary occasions of synchronized flow are identified. Although Kerner’s three phase theory (section 3.4.2) states that no transition from free flow to congested traffic or vice versa is possible, such transitions are visible in figure 5.6. A plausible explanation for this phenomenon is the use of aggregated minute data which wipes out the presence of the temporary presence of synchronized flow in between free flow and congested traffic.

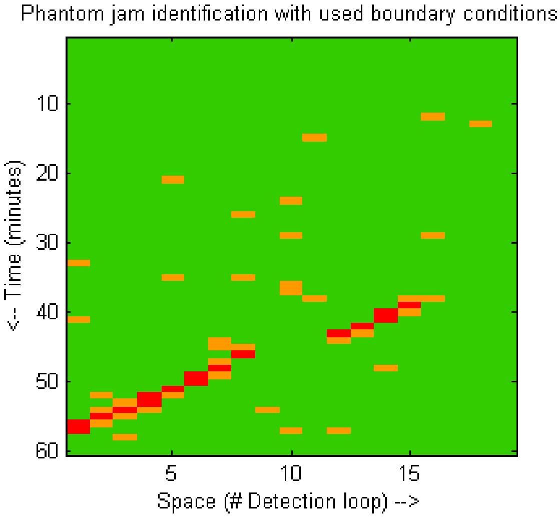


Figure 5.6: Traffic state identification (green=free flow, orange=synchronized flow, red=congested traffic).

Determination of the numerical values of the membership functions

Road sections, identified as jammed, can either be part of a phantom jam or it can just be a temporary disturbance of the traffic flow. In case traffic flow is stable enough, it is able to resolve automatically without propagating to be a phantom jam. For this study, such detections are called single jam detections.

The numerical values of the membership functions (figure 5.5) between synchronized flow and jam are a trade-off between the amount of (collateral) single jam detections and early phantom jam identification. By expanding the boundary conditions of jammed traffic the number of single jam detections will increase. On the other hand, reducing the boundary conditions of jammed traffic, results in less accurate phantom jam identification. Figure 5.7 illustrates an example of this trade-off by presenting the results of the phantom jam identification algorithm for expanded boundary conditions (left figure), actual boundary conditions (middle figure) and reduced boundary conditions (right figure).

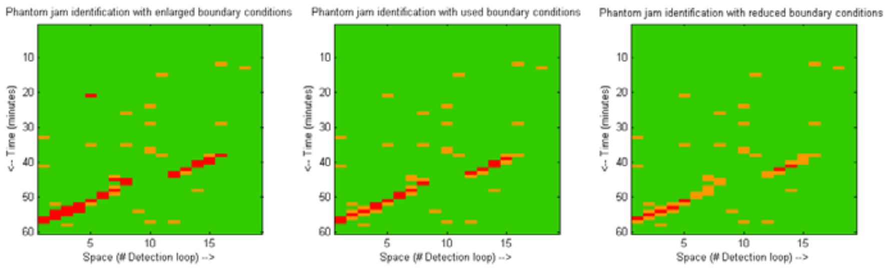


Figure 5.7: Phantom jam identification for enlarged (left), used (middle) and reduced (right) boundary conditions for jam with respect to synchronized flow. Red is jam detection, orange is synchronized flow and green is free flow.

In the middle figure, it can be seen that the phantom jam is fully detected by the algorithm and that none of the jam-detected locations are false detections. In the left figure, with the enlarged jam boundaries, it is seen that in and around the phantom jam more jam detections have taken place. However, also a single jam detection has been observed at detection loop 5 after 20 minutes. In the right figure, with reduced jam boundaries, it can be clearly seen that the phantom jam is only observed after it developed itself some time (around 3-4 minutes).

To determine the numerical values for this study, Kerner's research (2004) has been taken for the initial values. These values have been adapted using a visualisation of the fuzzification process. This visualization is presented in figure 5.8. In this visualization can clearly be observed that the numerical values for the membership functions (figure 5.5) are chosen in such way that free flow, synchronized flow and jam are in accordance with Kerner's theory. The measurements in figure 5.8 are taken from field model observations.

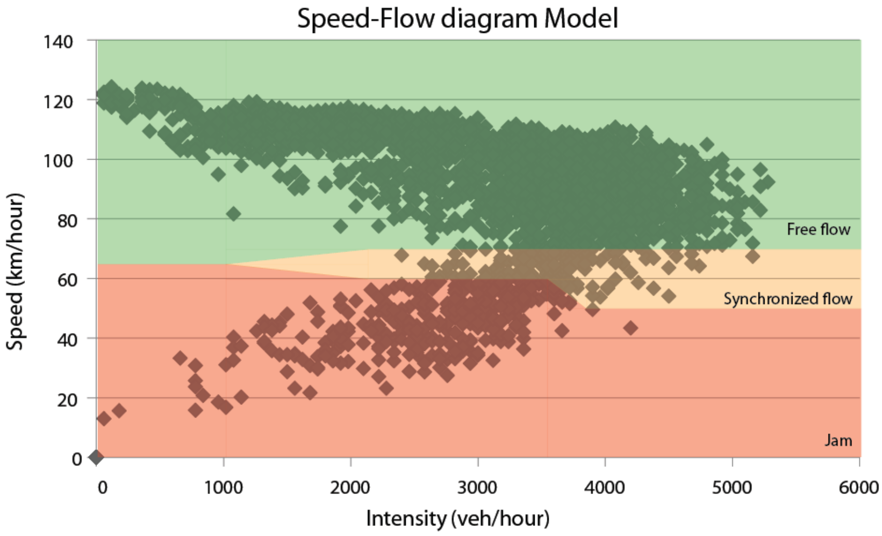


Figure 5.8: The fuzzification process visualized in the speed-flow diagram.

5.3.2 Offline algorithm – Phantom jam identification

To identify whether or not a jammed section is part of a phantom jam, an offline algorithm has been developed. This algorithm is able to analyse traffic states through space and time and recognize the spatial temporal pattern of a phantom jam. Therefore, the algorithm makes use of a simple clustering technique.

Phantom jam clustering

The output of the "live" algorithm consists of traffic states through space and time which distinguishes between free flow, synchronized and jammed traffic. Comparable to the "Adaptive Smoothing" methodology of Treiber and Helbing (2002), as described in section 3.6.3, this data is processed using a filter to identify the phantom jam. This filter is operationalized by a clustering process.

The phantom jam clustering processes the jammed sections in order to identify phantom jams on the network. Therefore, the jammed data is clustered if they fulfil the spatial temporal pattern of a phantom jam. This spatial temporal pattern is described by the two rules (supported by Figure 5.9). The rules are based on the spatial temporal characteristic that a phantom jam moves upstream with a speed of around 20 km/h (visualised by the red hatched area).

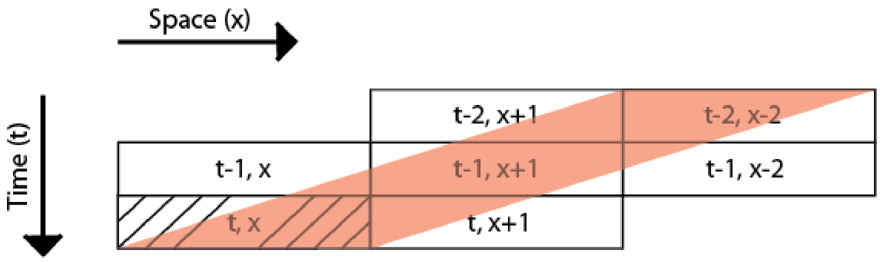


Figure 5.9: Supporting illustration for phantom jam clustering rules.

- **Rule 1:** If traffic state *t,x* is jammed and traffic state *t-2,x+1* or *t-1,x+1* or *t,x+1* or *t-2,x+2* or *t-1,x+2* is jammed, than both measurement section are part of a phantom jam.
- **Rule 2:** If traffic state *t,x* is jammed and measurement section *t-1,x* or *t-2,x+1* or *t-1,x+1* or *t,x+1* or *t-2,x+2* or *t-1,x+2* is part of a phantom jam, than measurement section *t,x* is part of a phantom jam.

If a jammed section fulfils the spatial temporal characteristics of a phantom jam, the section is marked as part of a phantom jam. For the analysed fifty simulations, the live algorithm has detected 517 sections as jammed. This included a total of 64 phantom jams with an average of 6.78 jammed sections. Converted to jam weight, this means an average jam weight of 3.89 km*min per phantom jam. A total of 83 jammed sections (16%) were not part of a phantom jams and were only single jam detections. If full phantom jams are included for this analysis as one single detection (note that various jam detections are clustered into one phantom jam detection), this ratio is 64 phantom jams against 83 single jam detections. Hence, it can be concluded that from all single jam detections done by the live algorithm, 44% develops into a real phantom jam.

5.3.3 Validation

It would be desirable to compare the results of the developed algorithms with the results of comparable algorithms. Note that the detection of phantom jams, using these algorithms, is all depending on the parameter setting of the algorithm. Unfortunately, no such algorithms are available. Therefore, the dependency of the correct determination of the algorithm parameters on the reliability of the algorithm results should be taken in mind carefully. On the other hand, the theoretical principals on base of which the algorithms are developed are clear and straightforward. Therefore, it is likely that the results for traffic state and phantom jam clustering form a solid and trustworthy representation of the actual traffic situation.

5.4 Pre-phantom jam conditions

The ability to identify a phantom jam once it already occurred is used in the dissolving based triggering mechanism. However, for the prevention based mechanism, the pre-phantom characteristics have been used in the triggering mechanism. As mentioned in section 5.1.2 high intensity waves can be identified on the network. Such intensity waves seem to be closely related to the occurrence of phantom jams. As intensity is high, traffic become more metastable in such waves. Following Kerner's theory, this means that traffic is more likely to fall into congestion.

This section, first describes the "live" algorithm which identifies and classifies high intensity waves on the network. Therefore, the algorithm uses both intensity and spatial-temporal characteristics of such waves. This algorithm and its classification system are used for the prevention based triggering mechanism. Furthermore this section contains the description of an additional "offline" algorithm which gives more insight in the actual relation between phantom and intensity waves (and its classification).

5.4.1 Live algorithm – High intensity waves identification

As already shown in section 5.1.2, traffic is not homogeneous through time. Relatively high intensities are alternating with relatively low intensities. A live algorithm has been developed which identifies such high intensity waves during simulation. Although it sounds straightforward that phantom jams are more likely to occur during higher intensities (and the fact that this is in line with Kerner's theory), this phenomenon has not been used with respect to "smart" in-car information before.

The live algorithm contains of three consecutive steps. First, the algorithm detects high intensities. Subsequently, sections identified with high intensity, are clustered into high intensity waves. Thereafter, each wave is classified to indicate the heaviness of the wave. For each of these steps, not only intensity is used as an indicator but also the length of the wave (the number of subsequent detection loops satisfying the intensity boundary) is taken into account.

High intensity identification

For the identification of a high intensity the algorithm simply checks if boundary intensity is measured at *two* subsequent detection loops over the last minute interval. This intensity is chosen in such way that it is clearly above the lower boundary of the capacity drop. This way, only intensity waves are detected which are reasonably metastable and therefore potentially risky for phantom jam origination. In figure 5.10 a visualization of Kerner's theory about the flow-density relation is shown. The line, which connects the outflow of the jam and $k_{max,}$ separates stable from metastable traffic flow. Traffic states located above this line are metastable and perturbations in these traffic states can easily result in decay from free flow to synchronised flow.

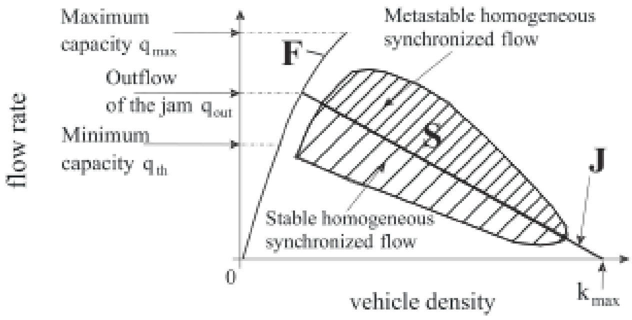


Figure 5.10: Kerner (2004) suggests the existence of metastable and stable .traffic

As has been described in chapter 4, the network has a maximum flow rate of 5200 veh/h and an outflow rate of around 4000 veh/h. As achieved outflow rate is widely scattered around this value, the boundary intensity has been chosen to be 4200 veh/h. It should be remarked that the exact value of this boundary intensity is a design variable which is not by definition good or wrong. However, a boundary intensity which is set too low could result in non-reliable intensity wave identification as almost all sections would be detected as part of such wave. On the other hand, a boundary condition which is set too high would result in no intensity waves or only single fragments of waves.

High intensity wave clustering

The identified high intensity segments are clustered into high intensity waves by a clustering algorithm similar to the phantom jam clustering algorithm. This clustering process is similar to the free flow filter Treiber and Helbing (2002) developed in order to identify free flow traffic. The high intensity wave clustering process is described by only one rule (supported by figure 5.11) which is based on the spatial temporal characteristic that high intensity waves propagate downstream with approximately the speed of traffic (illustrated by the red line).

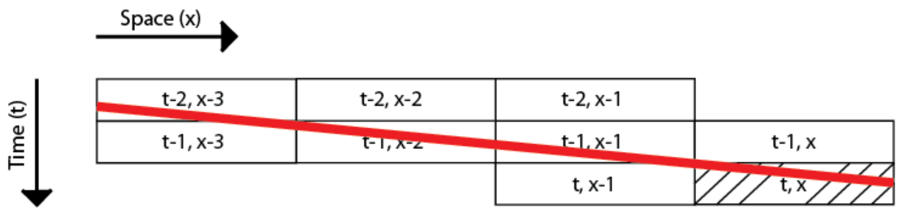


Figure 5.11: Supporting illustration for high intensity wave clustering rules.

- **Rule 1:** If section *t,x* has been identified as high intensity and section *t-1,x* or *t,x-1* or *t-1,x-1* or *t-2,x-1* or *t-1,x-2 or t-2,x-2 or t-1,x-3 or t-2,x-3* is identified as high intensity both measurement sections are part of the same high intensity wave.

Figure 5.12 visualizes the results of this identification process. It can be seen that besides several fragments of high intensity identifications at least four waves are sufficiently “heavy” that they can stand time.

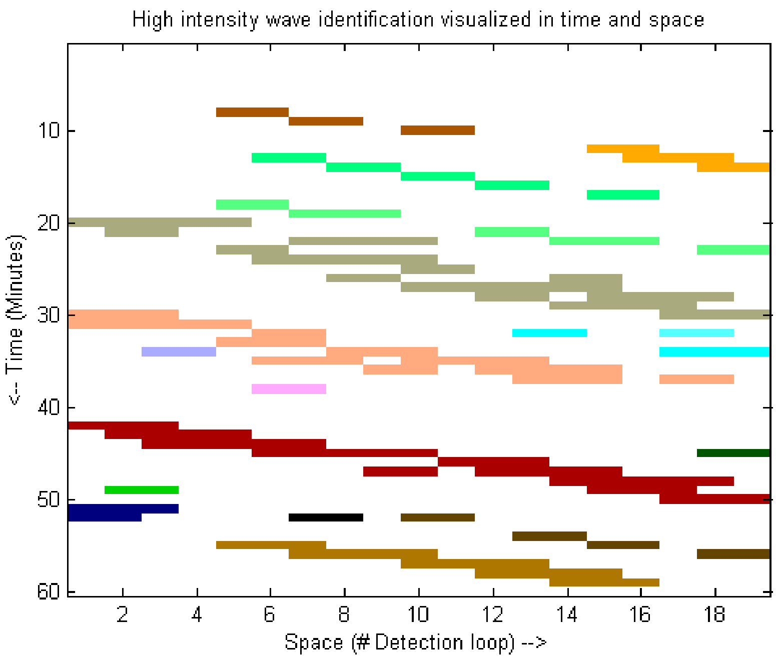


Figure 5.12: High intensity wave identification in time and space (each colour represents an identified wave)

Danger level label

The algorithm classifies the identified high intensity wave by giving a so-called danger level to each intensity wave. The danger level of a shockwave is determined every minute with the use of a fuzzification methodology equal to that of the phantom jam identification. The danger level of the intensity wave is only updated if it exceeds its danger level of the previous time step. Within this fuzzification both the length as the average intensity of the wave are taken into account (figure 5.13). The numerical values for this fuzzification process are chosen in such way that intensity waves are reasonable distributed over each danger level with a high danger level occurring the least and a low danger level occurring far most. This is chosen for to ensure that with each danger level the selectiveness of the algorithm is clearly different to be able to assess the effect of this selectiveness. As in the application of the fuzzification, the danger level remains a continuous value, the exact determination of the numerical values plays a minor role. However, the actual danger level to be used in the application of the advice system is affected by this design variable.

For each intensity wave the average intensity (over the various detection loops during the particular minute interval) and the length are fuzzified into the values “low” to “high”. Subsequently, the following rules are implemented on these fuzzified values:

Rules:

- **Rule 1:** If shockwave intensity is “high” and shockwave length is <u>not</u> “low”, the phantom jam danger level is “high”.
- **Rule 2:** If shockwave intensity is <u>not</u> “low” and shockwave length is “high” , the phantom jam danger level is “high”.

- **Rule 3:** If shockwave intensity is <u>not</u> “high” and shockwave length is “low”, the phantom jam danger level is “low”.
- **Rule 4:** If shockwave intensity is “low” and shockwave length is <u>not</u> “high”, the phantom jam danger level is “low”.
- **Rule 5:** If shockwave intensity is “high” and shockwave length is “low”, the phantom jam danger level is “medium”.
- **Rule 6:** If shockwave intensity is “low” and shockwave length is “high”, the phantom jam danger level is “medium”.
- **Rule 7:** If shockwave intensity is “medium” and shockwave length is “medium”, the phantom jam danger level is “medium”.

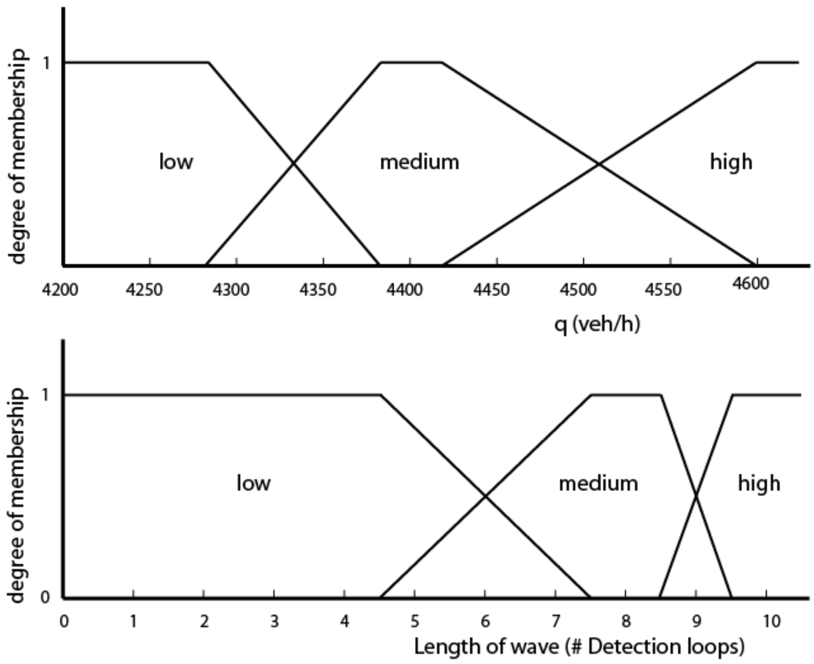


Figure 5.13: Illustration of fuzzification of average wave intensity and length of wave.

In contrast with the fuzzification process of the jam identification (section 5.3.1), the score of the “winning” rule is not converted to a discrete value, but remains continuous. This way, it offers the possibility to distinguish intensity waves not only in three discrete danger labels, but in a more continuous rating. A low danger level is ranked with score “1”, medium danger level with score “2” and high danger level with score “3”. Intensity waves which do only partly fulfil the conditions of one these danger levels receive a score which is weighted in between. This results in a more or less continuous range of danger levels between 1 and 3. In figure 5.14 the results for the intensity wave identification algorithm is presented.

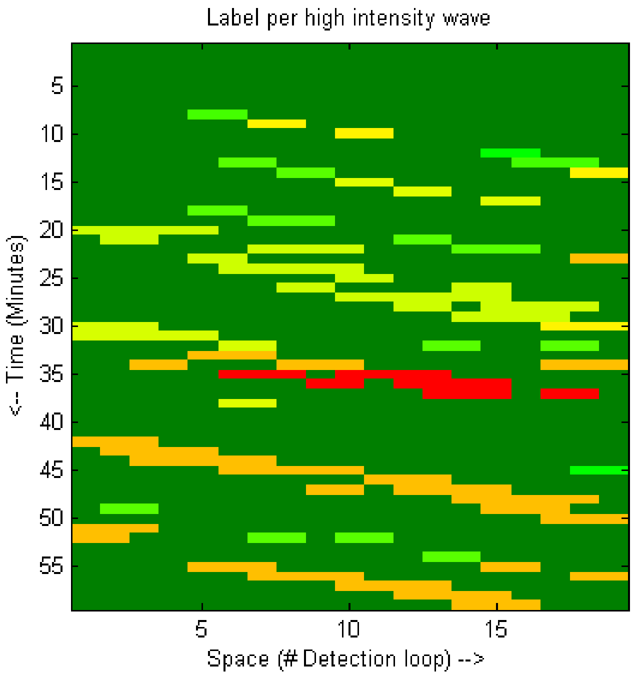


Figure 5.14: The determined danger label per intensity wave. Dark green=free flow, light green= low danger, orange = medium danger and red = high danger.

5.4.2 Offline algorithm – Relation between high intensity waves and phantom jams

Using an offline algorithm, the relation between high intensity waves and phantom jams has been analysed. This analysis has been performed in both directions. On the one hand it is useful to know the chance of a phantom jam to originate from a high intensity wave and respectively from what danger level of the intensity wave. On the other hand, in order to examine the usefulness of this relation for preventing measures, the chance of a high intensity wave to result in a phantom jam is worth knowing. A description of the algorithm and an extensive analysis, are presented in appendix IV.

Table 5.2 presents the relation from phantom jams with intensity waves. A total of 81% of all phantom jams (52 out of 64) seemed to be originated during a high intensity wave. The majority originated from an intensity wave with a danger level of in between 1.5 and 2.5. From the 19% of the phantom jams for which no direct relation with an intensity wave is detected by the algorithm, additional visual analysis has proved that for many of these jams an indirect relation with an intensity wave is present though. Therefore, it can be concluded that high intensity waves are a preconditions for the origination of phantom jams.

Table 5.2 : The distribution of phantom jam origins.

Origin source	Number of Phantom Jams	Percentage (%)
High danger (score: 2,5 or higher)	16	25
Medium danger (score: 1.5-2.5)	32	50
Low danger intensity wave	4	6
Other	12	19
Total:	**64**	**100**

Table 5.3 presents the results for the analysis of the relation between intensity waves and phantom jams in the other direction. Although table 5.2 showed that intensity waves seem to be a precondition for phantom jams to originate, this does not say that intensity waves are a useful declaring variable. From all intensity waves, only 5% resulted in the occurrence of a phantom jam. However, it is clearly seen that as the danger level of high intensity waves increases, the chance of a phantom jam to originate from it is increasing too. For the highest danger level, over 50% of all waves resulted in a phantom jam. However, only 8 out of 52 phantom jams originated during an intensity wave with the highest danger level. If only measures would be taken in case of danger level 3, only 8 out of 52 phantom jams are potentially affected. On the other hand, for intensity waves with a danger level of 2 or higher, the chance of a phantom jam to originate is 9%. However, in this case over 75% of all phantom jams could be affected if measures would be taken.

Table 5.3: Number of high intensity waves versus number of phantom jams.

Danger level	Number of waves	Number of phantom jams	Percentage (%)
=3	14	8	57
>=2,5	43	16	37
>=2	433	40	9
>=1,5	643	48	7
>=1	1063	52	5

This analysis shows that although intensity waves seem to be a clear precondition of phantom jams, such waves are not an accurate declaring variable for phantom. Only in a small minority of all intensity waves phantom jam originates. More accurate declaring variables are expected to be seen in detailed microscopic data for single vehicles or small platoons of vehicles (i.e. hard deceleration or lane changes with small gaps between vehicles). However, for this study it is chosen to make use of loop detection data aggregated over minute intervals for the practical application of the research results. Therefore, it is hardly possible to identify or measure where such declaring microscopic behaviour takes place. However, it sure is possible to identify the condition under which such actions are most likely to lead to a phantom jam: the high intensity wave. Therefore, it is chosen to make use of this preconditions and it is aimed for the prevent vehicle behaviour leading to phantom jams under these conditions.

For the prevention based triggering mechanism this analysis has some important implications. For the triggering mechanism based on high intensity waves variant one (see section 4.4.3), any section part of an intensity wave is provided with information. This analysis however shows that this means that advice is given many times while no phantom jam would actually originate from this intensity wave. Therefore, the advice should have a “no cure no pain” nature. On the other hand, using a higher danger level as threshold in the triggering mechanism, only a small share of all phantom jams is actually affected by the system.

5.5 Conclusion

From the previously described traffic state analysis several conclusions can be drawn. First, the speed and intensity has proven to be the appropriate variables to use for phantom jam identification. Both macroscopic variables are easy to extract from detection loops and show a clear relation towards the phenomenon of phantom jams. Using these variables an algorithm can identify traffic states on the network using fuzzy logic. An additional offline phantom jam clustering algorithm processes this traffic state data into phantom jam identification. Each of these algorithms is used for the dissolving based triggering mechanisms.

Intensity waves can be identified using only the macroscopic quantity intensity. By combining this quantity with both spatial as temporal characteristics, intensity waves are identified. High intensity waves have been seen as a precondition of phantom jams. A fuzzy logic approach is used to classify intensity waves. This algorithm is used for the prevention based triggering mechanisms. The higher the danger level set as threshold to give advice, the higher the chance of only providing advice to intensity wave which would actually result in a phantom jam. On the other hand, the lower the threshold of the advice system, the more potential phantom jams could be prevented but advice is many times given to vehicles which would actually never end up in a phantom jam.

6

Evaluation Framework

Research objective of this study is to improve the network performance with respect to phantom jams. In order to be able to analyse this performance, an evaluation framework has been developed. The framework helps to evaluate the network performance before and after implementation of the advice systems. For this study, it is chosen to make use of aggregated indicators, which represent the performance of the network as a whole. Such indicators suit the research objective of evaluating the effect of in-car advice systems on the network performance. Note that this decision to use more aggregated indicators for the evaluation, excludes the possibility to evaluate the exact microscopic effect of each advice system.

The network performance has been divided into two components for this study: The jam component and the network component. The jam component consists of jam indicators which help to analyse the performance of the network with respect to phantom jams and contains surrogate measures for traffic safety. On the other hand, the network component consists of network indicators which evaluate the macroscopic performance of the network. For traffic management studies, normally, mainly the network component is aimed to improve. For example, a measure like ramp metering is mostly used in order to improve the network performance in terms of network speed and intensities. However, for this study, the main goal is to improve network performance with respect to phantom jams. Therefore, the focus of the evaluation is on the jam component. However, as a precondition the network indicators should preferably never worsen.

Table 6.1 presents the indicators which are part of the jam and network component in the evaluation framework. The following sections consecutively discuss each indicator.

Table 6.1: Jam and network indicators part of the evaluation framework.

Jam indicators	Network indicators
Number of phantom jams	Average network speed
Jam weight	Network outflow
Number of jam detections	

6.1 Jam indicators

Using the three jam indicators the network performance can be evaluated with respect to phantom jams. From these jam indicators, also surrogate measures for traffic safety can be deduced. Note that congestion deems to be an important source for head-tail congestions (Marchesini and Weijermars 2010). Furthermore, speed variation or large speed differences between vehicles (whether or not caused by phantom jams) is closely related to traffic safety (and other externalities) (Beek, Derriks et al. 2007).

To calculate indicator values, the algorithms as discussed in chapter 5 are implemented in the evaluation framework. Although, the jam indicators are closely interrelated, each indicator has its own specific power for analysis. This is discussed more closely in the following sections.

6.1.1 Number of phantom jams

As mentioned before (section 5.1.1), the speed and flow during a phantom jam are temporary reduced in comparison with a free flow traffic state. This means that vehicles which are confronted with this phantom jam experience an increased travel time. Reducing the number of phantom jams on the network would result in less temporary speed and flow reductions. As a consequence it reduces the number of vehicles which encounter local speed reductions.

Besides, a sudden drop of speed during phantom jams might result in dangerous situations as drivers do not expect such speed deduction on a highway setting. Head-tail collisions at the rear end of a congested road section are a common phenomenon. A decreased number of phantom jams reduces the frequency of such sudden speed drops. This is likely to have a positive impact on traffic safety.

Finally, the propagation of phantom jams towards fixed bottlenecks on the road network (i.e. onramps) can result in a stationary jam at such locations while maximum capacity has not been reached at that location yet. Also phantom jams might propagate on arterial roads. Although phantom jams itself are not likely to have a large impact on travel time (note that vehicles only experience a very temporary speed reduction), such stationary jams on bottlenecks and arterial roads can however have a significant effect on travel times. However, using a single-link network, these effects cannot be measured as it lacks of bottlenecks. Only a qualitative assessment of the potential effect on the total travel time on a full network scale can be performed based on the observed change in number of phantom jams.

The indicator number of phantom jams is implemented in the evaluation framework using the phantom jam clustering algorithm (section 5.3.2). The total number of clusters is counted over all fifty simulations per advice system. The total sum of clusters is a measure for the number of phantom jams occurring on the highway network.

6.1.2 Jam weight

The jam weight is the number of jam kilometres times the duration of the jam. This indicator is of use in the analysis of how a network performs in "solving" phantom jams. In case of an equal number of phantom jams in the before and after scenario, but a reduced average jam weight, the network is better able to solve phantom jams. Consequently, such phenomenon would reduce the chance of the phantom jam to induce stationary traffic jams at fixed bottlenecks. For this study, especially the dissolving based advice systems are expected to have an effect on this indicator.

The jam weight is operationalized by counting the total number of sections (in km), part of phantom jam clusters over all fifty simulation. Although this indicator is strongly related to the number of phantom jams, it also includes the length of phantom jams.

6.1.3 Number of jam detections

As mentioned in section 5.3.1, single jam detections are sections of which the traffic state has been identified as jammed by the traffic state identification algorithm. A single jam detection can either be part of a phantom jam or a local traffic condition which resolves automatically in short time. Even though not all of these jam detections are part of a phantom jam (as follows from the clustering algorithm), speed and flow are clearly reduced for such sections. Therefore, they can be seen as mini-phantom jams. Just as during phantom jams, the sudden drop of speed can result in an unsafe situation and, although to a lesser extent, induce congestion on arterial roads.

The number of single jam detections is an indicator for the amount of significant speed drops on the network. Although aggregated, this makes the indicator useful to measure the variation in speed on the network. Once the number of significant speed drops is reduced, it can be reasonably assumed that the speed variance decreases as well. Speed variation have been proved to have a negative effect on traffic safety (Beek, Derriks et al. 2007). An increasing number of jam detections indicates a less safe traffic network. Therefore, the speed variance should be seen as a surrogate measure for traffic safety. Once the number of jam detections is reduced due to the advice system, speed variance decreases and traffic safety increases.

The number of jam detections has been simply operationalized using the output of the traffic state identification algorithm. First, all jam detections are summed over the fifty simulations. Thereafter, the number of sections which were part of a phantom jam is subtracted from this amount. The result is the number of single jam detections which are all not identified as part of a phantom jam.

6.2 Network indicators

Using the network indicators, the network performance is examined in terms of average network speed and network outflow. As mentioned in section 5.4.2, advice is not always given based on the actual identification of such jam, but also precautionary. As, in such precautionary cases, it is not desired to decrease the network performance, two network indicators are included in the evaluation framework. It however would be a very welcome bonus if an increase is measured for these indicators.

6.2.1 Average network speed

On a network, drivers always tend to get to their destination as fast as possible. The higher the average speed on a section of the network, the faster a driver is able to pass this section on average. Therefore, the average network speed is desirably as high as possible. Also, the average network speed can be used to compare a before and after scenario in case of measure implementation. If, after implementation, the average network speed has fallen, the network performs less well.

By taking the average speed of all vehicles over the whole length of the simulation, the average network speed can be calculated. On the single-link network used during this study, there are only two sources which can affect the average network speed. At first, the presence of phantom jams. However, the effect of a phantom jam on the average network (link) speed is likely to be limited over the full simulation length. This is caused by the fact that a phantom jam only causes a very temporary speed reduction for a limited share of vehicles. A second source which can affect the average link speed is the provided speed advice. Depending on the nature and the penetration rate of the advice system, this is likely to have significant effects on the average network speed as reduced speed is maintained over a longer stretch and by a larger share of vehicles.

It needs to be remarked that the average speed of vehicles is only calculated for vehicles once they are on the network. In case that a phantom jam is obstructing the generator, this results in a delayed enter time of vehicles. The delay of the vehicle in the generator itself is not included in the average network speed. If no vehicles are delayed in the generator (no phantom jam hits back in the generator) this will have no effect on the average network speed. However, if vehicles are delayed in the generator, the calculated average network speed is slightly overestimated as this delay is not included. The more vehicles are delayed in the generator, the more the average network speed is overestimated. This is more discussed on in chapter 8.

The average network speed is both measured for equipped as for non-equipped vehicles. This way, not only insight in how the measure influences both vehicle categories, but also an idea of the acceptability of the measure can be obtained. If average speed of equipped vehicles drops while vehicle speed of non-equipped vehicles increases, it is doubtful whether or not drivers, provided with speed advice, will follow up this advice as they will be harmed by following up the advice.

Similar to the average network speed, the total number of vehicle loss hours is frequently used in research. However, for this study, the average network speed suits better as during measure implementation desired speed of vehicles is varied. This variation in desired speed affects the automatic calculation of the number of vehicle loss hours by the simulation software.

6.2.2 Network outflow

Network performance is not only about speed, but also about flow. The more vehicles the network can handle, the more drivers can make use of the road. Therefore, the network outflow is selected as the second network indicator. The outflow is measured downstream of the road network. As for the pre- and after scenario traffic input remains constant, this measurement is appropriate to assess the number of vehicles the network is able to handle during simulation.

Due to phantom jams hitting back in the generator, it might be that vehicles experience some delay in the generator. As a result these vehicles enter the network later than their desired enter time. If less phantom jams occur on the network, vehicles, which were delayed in the reference scenario, can enter the network earlier. Therefore, they are more likely to reach the end of the network within simulation duration.

7

Results

This chapter offers a presentation of the research results. First, the data processing is explained. Thereafter, the results for the reference scenario are presented for each of the three demand profiles. Subsequently, the results for the prevention based advice system are presented in section 7.3. The results for the dissolving based advice systems are presented in section 7.4. The results are presented for each of the five indicators part of the evaluation framework. For both the preventing as the dissolving advice systems only the results for demand profile 2 are presented in the main section of this report. The result for the other two demand profiles can be found in Appendix V-XI. Off course, in chapter 8, the results of all three demand profiles are part of the analysis

7.1 Data processing

Each advice system has been simulated for the same fifty seeds. For every simulation each of the five indicators, part of the evaluation framework, has been calculated. In order to determine the results per advice system the sample mean has been calculated over these separate indicator values using formula ***(7.1)***.

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{7.1}$$

These sample means can be compared with the results of the reference scenario (or with other variant of the advice system). However, it should also be known if apparent differences are really significantly different. Therefore a paired t-test has been performed between the reference scenario and all advice system variants. The t-test is assumed to be paired as the same fifty seeds (with exactly the same input distribution) are used for every simulation. The differences in the resulted indicator values can therefore only be caused by the nature of the advice system. The theory behind the paired t-test is described in appendix XII.

It needs to remarked that the fact that only fifty simulations are performed per advice system has a clear impact on the evaluation process of the systems. Fifty simulations have been enough to prove the significance of results. However, stochastic still play major role in the interpretation of the results. This limits a more quantitative examination of the effects. For more exact estimations of the effects on the network performance of specific advice systems cannot be made based on this study though.

7.2 Reference scenario

Each advice system has been simulated for three different demand profiles (as explained in section 4.5.1). Table 7.1 presents the results for the reference-scenarios with no advice system active for each demand profile.

Table 7.1: Reference scenario results per demand profile.

Demand Profile:	1	2	3
Network Speed (km/h)	85,97	83,81	82,75
Outflow (vehs)	3335	3382	3416
# Phantom Jams	0,52	1,14	1,3
Jam Weight (km*min)	1,66	4,17	4,34
# Jam Detections	1,16	1,72	1,66

From the values alone, presented in table 7.1, no conclusions can be drawn besides the fact that the average network speed drops with an increasing demand profile. Furthermore it can be clearly seen that jam weight increases such as the number of phantom jams and jam detections per run.

It is important to ensure that phantom jams originate on the network due to vehicle interaction and not due to biased model functioning. Therefore, an additional analysis on the location of phantom jam originations has been performed for one of the reference scenarios. It is expected that, due to the increasing traffic demand through time, a majority of phantom jam originate during the second half of the simulation. Through space, it is expected that phantom jam originations are relatively equally divided over the network with a small majority of the originations located in the upstream half of the network. Figure 7.1 illustrates the distribution of phantom jam originations for both time as space. This visualization largely matches these expectations indicates a correct operation of the model. Fact that no phantom jam originations have been observed in the first kilometre of the network is due to the implemented clustering algorithm. Jammed sections in this first kilometre which might have resulted in phantom jams if the network would continue, could not be clustered by the algorithm and are therefore not identified by the clustering algorithm yet.

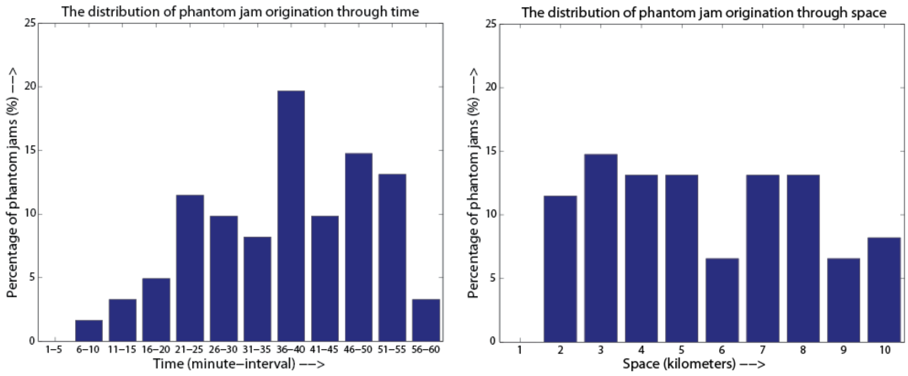


Figure 7.1: The distribution of phantom jam originations through time (left figure) and space (right figure) for demand profile 3.

7.3 Prevention based advice

The results for the both prevention based advice systems are discussed in the following sections. First the results for the non-controlled system are presented. Thereafter, the results for each of the three variants of the intensity wave based systems are shown.

7.3.1 Non-controlled advice

As described in section 4.4, non-controlled advice has been simulated by reducing the desired speed of any equipped vehicle in the network no matter what the actual traffic situation is. This means 100% of the equipped vehicles is provided with speed advice. The results of these simulations are presented in figure 7.2. For each indicator, the indicator value is drawn against the penetration rate for all five speed advices. Note that the penetration rate is not plotted on a linear but on an adjusted logarithmic scale in order to have a better visualization of the lower penetration rates. As a reference, the results for the reference scenario have been added to the plot. These can be recognized as the horizontal black line (Note that there is only one reference scenario per demand profile). The plotted dots visualize results which significantly differ from the reference scenario using a 95% confidence interval. As mentioned before, the calculation of this significant difference is explained in appendix XII.

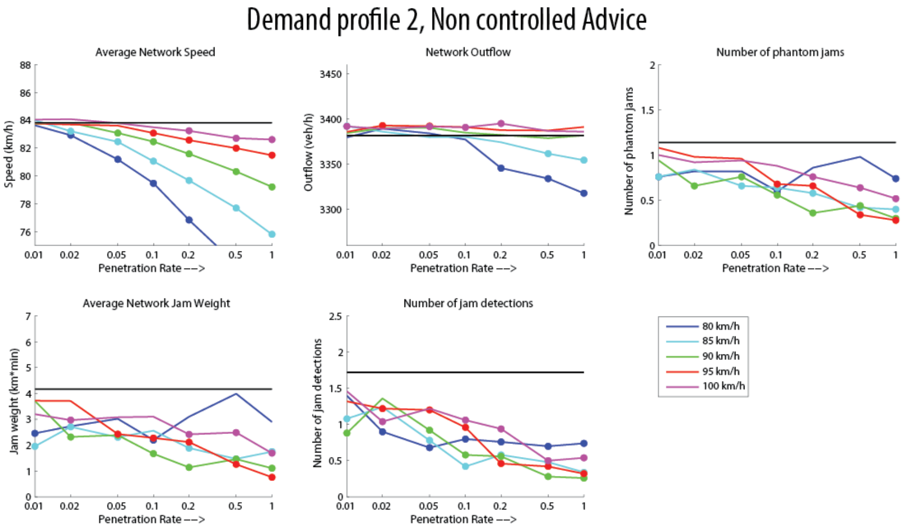


Figure 7.2: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

As can be seen in figure 7.2, independent of the given speed advice or penetration rate, the average network speed decreases if speed advice is given. With exception of the two "low" speed advices, the network outflow is not negatively affected by non-controlled speed advices. For the lower speed advice of 80 and 85 km/h a negative effect on the network outflow is seen from around penetration rates of 10 %.

Looking at the average number of phantom jams per simulation, a clear trend can be recognized that the number of phantom jams decreases as a result of providing speed advice. The same trend can be recognized for the average network jam weight and the number of jam detections. For each of these three indicators a decrease of up to 50%-75% is achieved for a penetration rate of 100%. As the visualization of the penetration rate axis is on a logarithmic scale it should be remarked that this decrease is not linear as it might seem, but that the largest share of this decrease is achieved with only a relatively low penetration rate.

The results for demand profile 1 and 3, as presented in appendix V, show similar trends as described above. However, for demand profile 3, significant decreases for all jam indicators are only seen from around penetration rates of around 10%. In chapter 8, the differences in results between the various demand profiles are discussed more closely.

7.3.2 High intensity waves

As described in chapter 4, besides the non-controlled advice system, the high intensity wave based advice system is a second prevention based mechanism. In contrary to the non-controlled system, the intensity wave based system is strictly controlled. This system aims at stabilizing and homogenizing the traffic flow in high intensity waves in order to reduce the "chance" of a phantom jam to occur due to small disturbances. Three variants of this advice system have been simulated, each varying in the boundary condition for the danger level which triggers the system. The results of each of these variant are presented in figure 7.3 - figure 7.5 (again, only the results for demand profile 2 are presented in the main text, the results for demand profile 1 and 3 can be found in appendix VI).

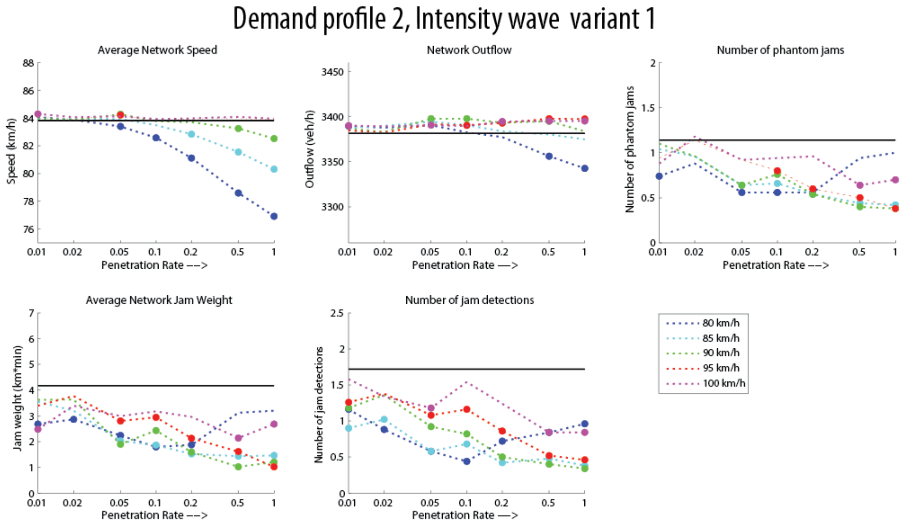


Figure 7.3: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

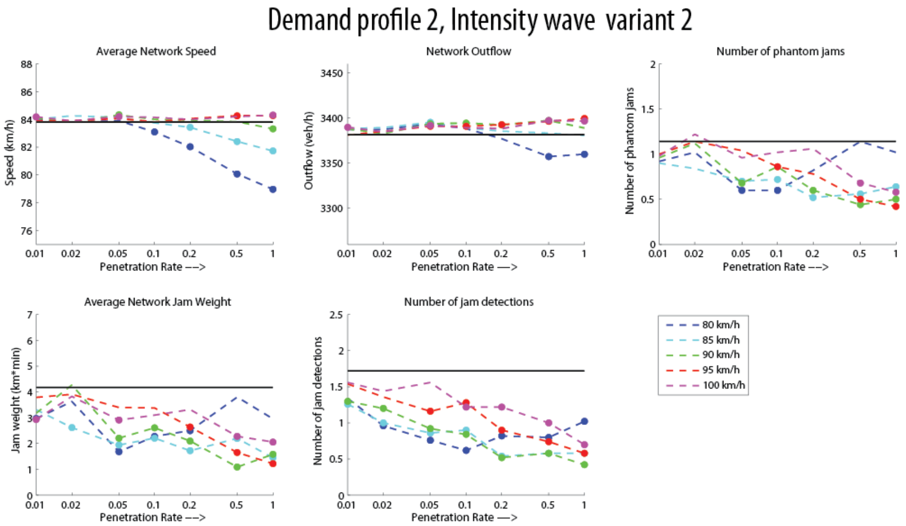


Figure 7.4: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

As can be seen in figure 7.3 and figure 7.4, the results for variant 1 and 2 are very similar to the results of the non-controlled advice system (figure 7.2) for the jam indicators: number of phantom jams, average network jam weight and number of jam detections. A reduction is measured for all three indicators and the positive effect seems to increase with an increasing penetration rate except for the 80 km/h speed advice.

For the network indicators average network speed and network outflow also a similar effect for variant 1 and 2 is measured compared to the non-controlled advice system. However, the negative effects seem to be reduced. Note that the results for both indicators are less negative for variant 1 than for variant 2.

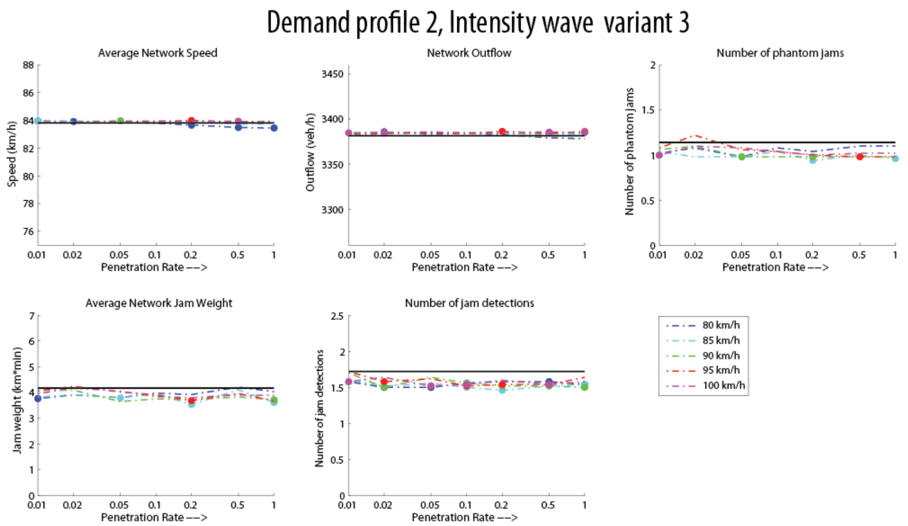


Figure 7.5: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

The results for variant 3 are very different from those of variant 1 and 2 and the non-controlled advice system. Only for the 80 km/h speed advice a significant decrease in average network speed has been measured. However, this decrease is still very small compared to the decreases for the previously described systems. Furthermore, no negative effects are measured for the network outflow. For the indicators number of phantom jams, average network jam weight and number of jam detections a small improvement is measured although most of these measurements do not significantly differ from the reference scenario. Interesting to mention is the fact that the penetration rate seems to have no effect on the positive or negative effect of the advice system.

7.4 Dissolving based

The results for the both dissolving based advice systems are discussed in the following sections. First the results for the single jam detection based system are presented. Thereafter, the results for the phantom jam based system are given.

7.4.1 Single jam detection

The results for demand profile 2 for the single jam detection based advice system are presented in figure 7.6. The results show hardly any significant effects on any of the indicators. No negative effects on both network indicators are measured, but simultaneously no real significant improvements are measured for all three jam indicators.

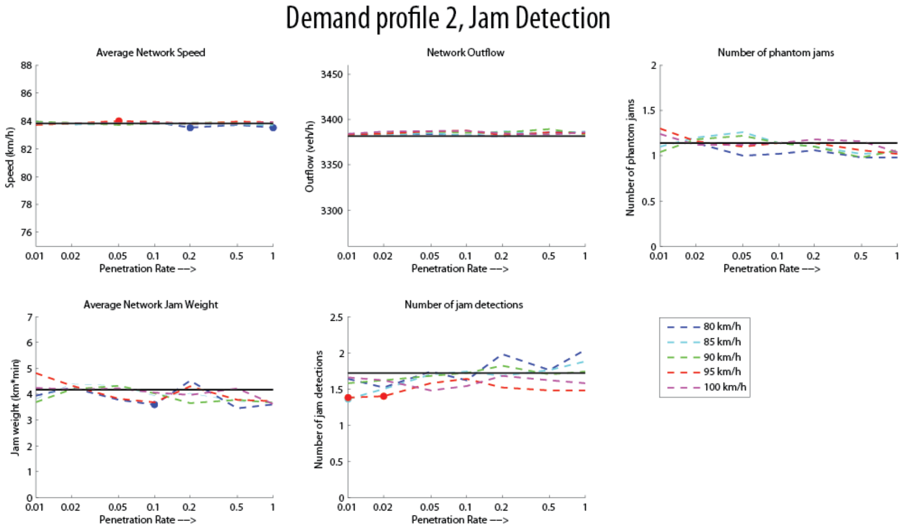


Figure 7.6: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

The results for demand profile 2 are very similar to the results for demand profile 1 which are presented in appendix VII. However, the results for demand profile 3 show remarkable deviations. Therefore, the results for demand profile 3 are presented in figure 7.7. It can be clearly seen that for none of the indicators any significant improvement is measured. This difference with the results for demand profile 1 and 2 might be explained by the fact that a dissolving control mechanism needs some “space” (low intensity areas) on the network which can be used to dissolve jammed areas. With demand profile 3, the demand is that high that such low intensity areas do not happen to be present on the network. Therefore, the advice given to vehicles upstream of a jammed section causes disturbances in a metastable traffic flow. This results in more congestion than in the reference scenario.

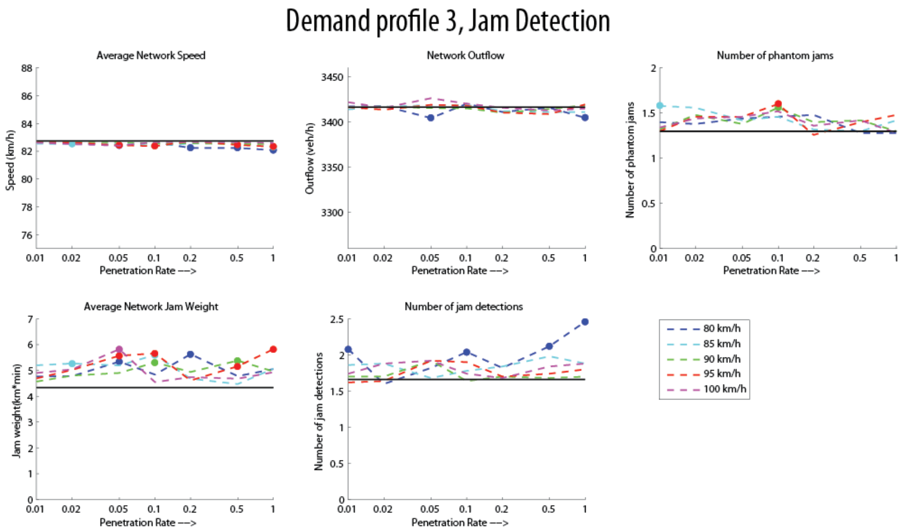


Figure 7.7: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

7.4.2 Phantom Jam Detection

The second dissolving advice system is triggered by the measurement of a phantom jam on the network. Figure 7.8 shows the results for this advice system. Similar to the results of the advice system triggered by single jam detections, no spectacular effects of the system are measured. Only for the indicator number of jam detections there seems to be a weak trend of decreased number of detections. However, this decrease is not significantly different from the reference scenario for most measurements.

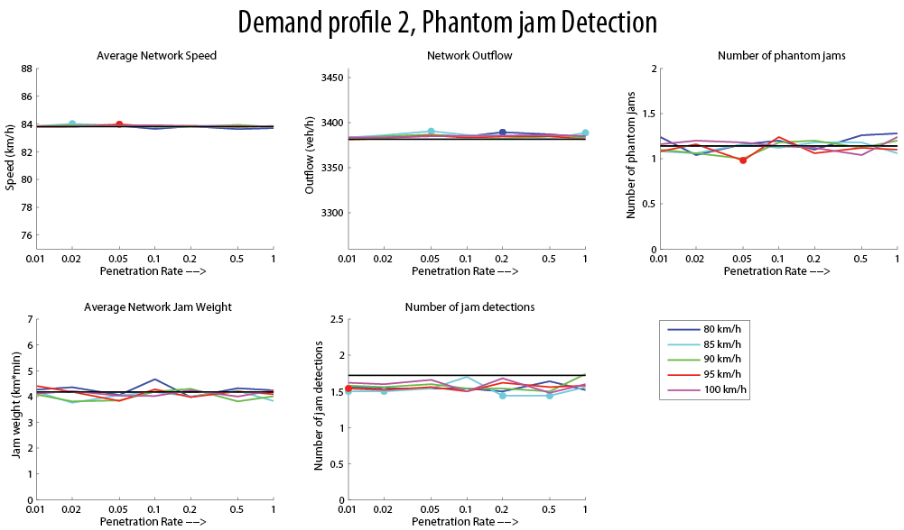


Figure 7.8: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

8

Analysis

This chapter contains the analysis of the results, presented in chapter 7. First, each indicator from the evaluation framework is extensively discussed. Subsequently, an analysis is performed in order to select the most successful advice systems. Thereafter, some analysis on speed difference between equipped and non-equipped vehicles is presented, which can help to examine the acceptability of the advice system. Finally, most important findings are highlighted in the concluding section.

8.1 Evaluation framework

In this section the results are analysed per indicator from the evaluation framework. The results for all advice systems are compared for demand profile 2 first. Similarities and differences in the results are mentioned and explained. Thereafter, the results for demand profile 2 are compared to the results for demand profile 1 and 3. Again, similarities and differences in the results are mentioned and explained. Additionally, some specific features of the indicators are highlighted and the effects of design choices in the modelled environment are elaborated on. As already mentioned during the presentation of the results in chapter 7, the dissolving based advice systems have hardly any significant effect on the network performance. Therefore, the focus in this chapter is mainly on the prevention based advice systems.

8.1.1 Average Network Speed

In section 6.2.1 it has already been mentioned that for this study, there are two main sources which affect the average network speed on the link itself: the presence of phantom jams and the provided speed advice. From these two sources, the provided speed advice is likely to have the most significant effect as it affects, depending on the nature and the penetration rate of the system, more vehicles on a longer stretch.

Decreasing average network speed

As seen in the results, the effect of the advice system on the average network speed differs for the various advice systems. Though, before the differences between the systems are discussed, one important conclusion should be made: None of the advice systems is able to improve the average network speed significantly on the used single-link network. As the results have shown that most of the advice systems reduce the number of phantom jams, the presence of phantom jams is not likely to be the cause of this decreasing network speed in this case. Therefore, the provided speed advice must be the source.

This might be seen as remarkable as some of the provided speed advices are above the average network speed, but this does not necessarily have to be so. If the speed advice is active on a section with an actual speed above the advice speed, the advice speed reduces the average speed on this section. Simultaneously, the traffic on this section is stabilized, but this is at the expense of the average speed. On sections with an actual speed below the speed advice, vehicles are not able to drive faster although they get a higher speed advice. However, their acceleration and deceleration behaviour within this flow is weakened as desired speed is closer to the actual speed. Combining these two phenomena, can only result in a decreasing average network speed as a result of speed advice. The fact that for none of the advice systems an increase in average network speed is measured, makes clear that the profit gained by preventing phantom jams does not compensate the disadvantages of some advice systems on link-level.

The effect on the average network speed of the simulated advice systems is clearly related to the speed advice given. The lower the speed advice, the higher the decrease in average network speed. This is best seen for the prevention based advice systems (except variant 3).

Number of advised vehicles

Furthermore, for the intensity wave based systems, it is clearly seen that the higher the selectiveness (the danger level) to trigger the advice, the less the decrease in average network speed is. This is not remarkable in itself. The higher the danger level used as threshold, the less road sections (and so vehicles) are provided with speed advice. As mentioned before, the speed advice is likely to result in some decrease of the average network speed.

Appendix IX includes an analysis in which the nature of the system (the danger level which is used for triggering) is compared with the actual number of provided vehicles per penetration rate. To check if the decrease in network speed is only caused by the number of vehicles provided with advice or that in fact the nature of the system also plays a major role, figure 8.1 is included. In this figure, the average network speed is not visualized against the penetration rate but against the actual share of provided vehicles per advice system (only prevention based systems are shown).

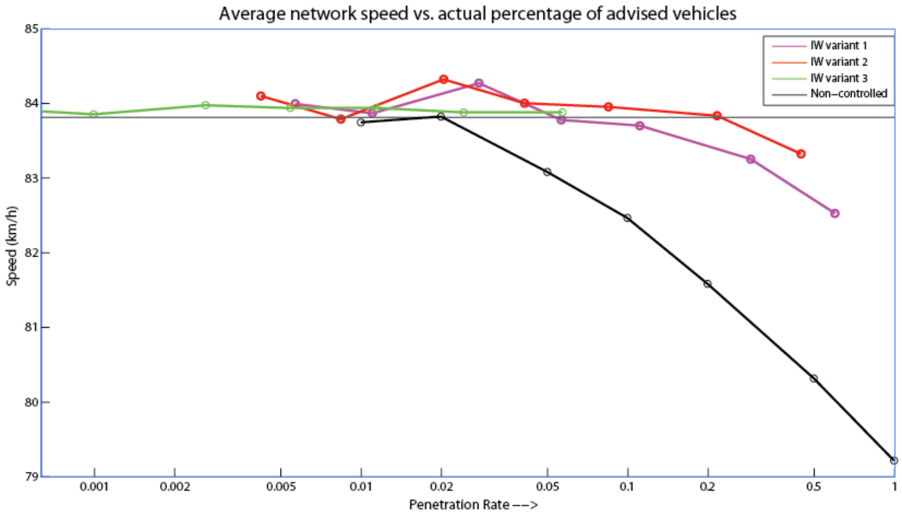


Figure 8.1: Average network speed versus the actual share of vehicles provided with information on a logarithmic scale. Visualised for non-controlled advice and three variant of the Intensity Wave (IW) based advice systems.

Variant 3 of the intensity wave based advice system does not result in a decrease of the average network speed. This is in line with the results in chapter 7. However, for the same share of advised vehicles, also variant 1 and 2 do not result in a decreasing average network speed. On the other hand, the non-controlled advice system does already result in a decrease of the average network speed if only 2 % of all vehicles are provided with information. For variant 1, decrease in average network speed is observed from 10 % and for variant 2 from around 30%. From this analysis can be concluded that the relation from the penetration rate and the decrease in average network speed is not only caused by the actual number of vehicles informed, but also by the nature (the moment and location of triggering the system) of the advice system. Providing “smart” advice in high intensity waves does affect the average network speed to a lesser extent than randomly providing advice.

Demand profiles

Between the three demand profiles which have been simulated for each advice system, no remarkable differences can be reported. For each of the demand profiles any speed advice results in decreasing average network speeds (especially for high penetration rates). The absolute decrease of the average network speed in comparison with the reference scenario for demand profile 1 and 3 speed is in proportion with the decreases seen for demand profile 2.

Effects of design choices

The presence of phantom jams and the height of the speed advice are the two variables which affect the average network speed once vehicles are on the network. However, due the use of micro simulation software and the spillback effect of phantom jams on the generator, vehicles can also get delay on their desired entering time to the network. This delay is not taken into account in the determination of the average network speed. This results in an overestimation of the network speed when vehicles are delayed in the generator. Note that a delayed vehicle is released later on the network with a speed according to the queue discharge capacity instead of a speed according to a phantom jam.

The more phantom jams obstruct the generator, the more vehicles encounter delay before they enter the network and the higher the overestimation will be. In the reference scenario, relatively a lot of phantom jams originate and hit back in the generator. This means that the average network speed in the reference scenario is likely to be slightly overestimated in comparison with the after scenarios with reduced number of phantom jams. Compared with model results, the actual decrease in average network speed is expected to be somewhat limited.

Another design variable which affects the results for the average network speed is the choice of the distribution of the speed advice. As discussed in 4.4.2, the speed advice is operationalized by multiplying the desired speed of vehicles with a predefined factor. This, however, results in the fact that approximately half of the vehicles on the network receives a new desired speed which is even lower than the provided speed advice. From field observation (Burgmeijer, Eisses et al. 2010) it can be seen that road users are not likely to adjust their speed in such way. In reality, road users can be expected to adjust their speed to a speed somewhere in between the advice speed and their original desired speed. The decrease in average network speed is likely to be overestimated compared to a more realistic simulation of the speed advice. However, the effects on other indicators are overestimated as well due to this design choice. Hence, the effect of the speed advice is not so much biased but the presentation of the exact height of the speed advice is overestimated. In reality a lower speed advice should be provided in order to achieve the same speed distribution and the same effects as for this study.

For this study it is chosen to make use of a single link. As discussed before, on this link no significant improvement of the average network speed has been measured with an advice system active. However, as the number of phantom jams might reduce, the spillback effect of phantom jams on bottlenecks can be reduced. This can prevent or delay the origination of a structural jam on a bottleneck which can have a significant contribution to the average network speed on a full network scale.

Conclusions

From the analysis of the average network speed can be concluded that none of the advice systems result in an increase of the average network speed. In order to avoid a decrease of the average network speed low speed advices and high penetration rates should be applied carefully as they easily result in such decrease. This is likely to be caused mainly by the provided speed advice which is below the original desired speed of vehicles on affected sections. On link level, the potential gain in average network speed due to prevented phantom jams does not compensate this decrease due to the speed advice.

It however needs to be remarked that the determination of the average network speed does not include delays due to obstruction of the generator in the model resulting in some overestimation. As the reference scenario encounters relatively a lot of phantom jams, the average network speed is likely to be most overestimated for the reference scenario. Therefore, the actual decrease in average network speed is likely to be slightly limited compared to the model results. Furthermore, on a full scale network with bottlenecks and arterial roads possible benefits on average network speed can be achieved due to reduced spillback effects. This depends on the number of phantom jams originated on link-level. This is discussed more detailed in section 8.1.3. Therefore, it needs to be remarked that due to these two design choices the negative effects on the average network speed is likely to be limited in reality compared to these model results.

The various advice systems can be ranked as in table 8.1, based on their performance for the average network speed. Remarks in the table are general remarks and might not hold for any penetration rate.

Table 8.1: Ranking the advice systems based on the results for average network speed.

Rank	Advice System	Remark
1	Jam Detection based	No significant effect
1	Phantom Jam Detection based	No significant effect
3	IW variant 3	Only negative for 80km/h advice
4	IW variant 2	Negative for 80 and 85 km/h advice
5	IW variant 1	Negative for 80,85 and 90 km/h advice
6	Non-controlled	Negative with any speed advice

8.1.2 Network outflow

The results for the network outflow are quite similar to the results of the average network speed, however the relative decrease is limited. Again, the dissolving based advice systems do not really show results which significantly differ from the reference scenario. Therefore, also for this analysis, the focus is on the prevention based advice system. Furthermore, the lower speed advices (80km/h and 85 km/h), again, result much worse than the higher (>90 km/h) speed advices.

Where for a low speed advice significant negative effects on the network outflow are measured, high speed advices generally result in a (significant) increase of the network outflow. However, although this increase is statistically significant, it is only an increase of 0.6% at max. Such as for the average network speed, the network outflow decreases most for higher penetration rates for the non-controlled advice system, followed by variant 1 and 2 of the intensity wave based systems.

Demand profiles

A comparison from the results of demand profile 2 with demand profile 1 and 3 shows that with lower network intensity (demand profile 1) no significant increase in network outflow is measured. Furthermore, decrease in network outflow starts from lower penetration rates. On the other hand, for higher network intensity (demand profile 3) less negative effects are measured.

Decreasing speed vs. Increasing flow
It is remarkable that increases in network outflow have been observed while section 8.1.1 showed that the average network speed does not increase (or even decrease for many systems). This is most likely to be caused by a combination of two factors. First, due to the reduced number of phantom jams, vehicles can be loaded onto the network earlier than in the reference scenario for some simulations as the generator is not obstructed. These vehicles do not encounter delay if in the after scenario no phantom jam has originated. If they are loaded on the network earlier, they can have a lower average speed and still reach the end of the network. Note that the delay in the generator is not taken into account in the average network speed. Second, the final state of the network is crucial. This is caused by the fact that the network is not fully released after sixty minutes and the effects of the final network conditions on the calculated average network speed is limited.

This second cause is illustrated in figure 8.2 in which two scenarios are visualised. In both scenario's a vehicle with a constant speed is released on the network every minute. In scenario one, each next vehicle receives a speed which is 1 km/h below the speed of the previous vehicle (starting at 120 km/h in the first minute). This scenario illustrates a network which worsens in the second half hour (similar to the simulations for this study with higher intensities in the second half of the simulation hour). In the second scenario, every vehicle receives the same speed of 86 km/h (similar to more homogeneous network conditions). It can be seen that although the average network speed of the homogeneous scenario is lower, the network outflow at the end of the simulation is higher. A similar phenomenon to the one presented in figure 8.2 is likely to have occurred in the few cases in which vehicle outflow increased with a decreasing average network speed.

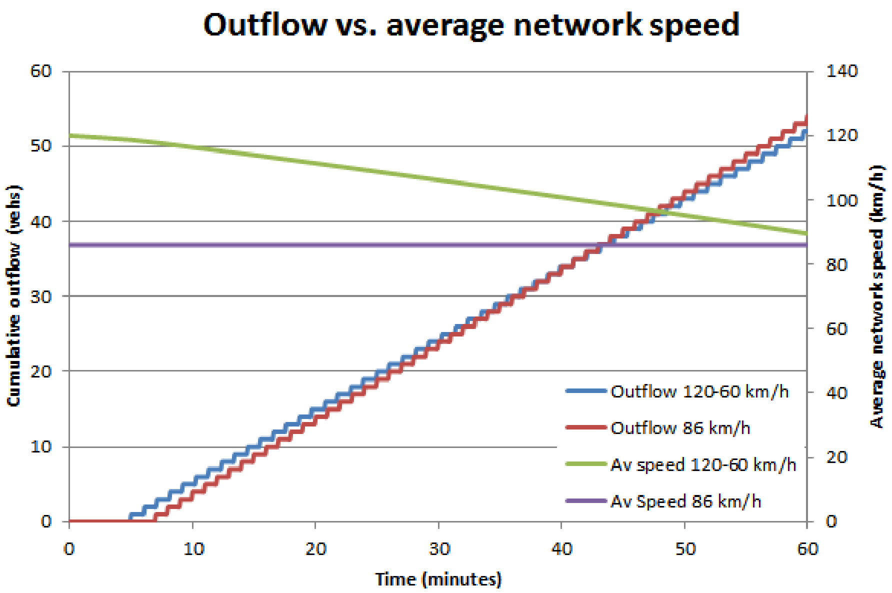


Figure 8.2: Outflow versus average network speed for two different scenarios.

Conclusions

Prevention based advice systems can have a limited positive impact on the network outflow. For speed advices which are below the average network speed a decrease in network outflow has been measured. For any speed advice equal or higher than the average network speed, no decrease is measured and even small increases can be observed. The observations of these minor increases in the network outflow are accompanied by a decrease in average network speed. This is most likely to be caused by the worse final traffic state after simulation duration in the reference scenario and the reduced delay of vehicles in the input generator.

The various advice systems can be ranked as in table 8.2, based on their performance for the network outflow. Remarks in the table are general remarks and might not hold for any penetration rate.

Table 8.2: Ranking the advice systems based on the results for network outflow.

Rank	Advice System	Remark
1	IW variant 1	Mostly positive effects
1	IW variant 2	Mostly positive effects
3	Non-controlled	Both positive as negative effects
4	IW variant 3	No effect
4	Jam Detection based	No effect
4	Phantom Jam Detection based	No effect

8.1.3 Number of phantom jams

The prevention based advice systems result in a significant decrease of the number of phantom jams on the network of up to 74%. Both the non-controlled as intensity wave variant 1 and 2 result in large improvements on this indicator.

Prevention based systems

Figure 8.3 presents the improvements on the number of phantom jams for three of the prevention based advice systems. Where the effects of these variants on the average network speed and outflow were clearly different from each other, the effects on the number of phantom jams are very close. In section 8.1.1, it has already been mentioned that these different effects on the average network speed are largely dependent on the actual number of vehicles provided with information. Note that non-controlled systems provide advice to any equipped vehicle and that the intensity wave based variants are much more selective. So, the actual number of vehicles will be higher in case of a non-controlled advice systems. Now it is seen, that providing advice to a more selective part of the vehicles does not significantly affect the number of phantom jams which can be prevented. However, a very weak pattern can be recognized in these results. From visual analysis, the non-controlled advice system generally seems to result in the largest reduction of the number of phantom jams, followed by variant 1 and 2. This order is opposite to the ranking order for the average network speed in table 8.1. However, it needs to be remarked that this relation is only observed by visual analysis and that it was not possible to prove by statistical analysis. Either the sample set is too small or the suspected relation is too weak/not present.

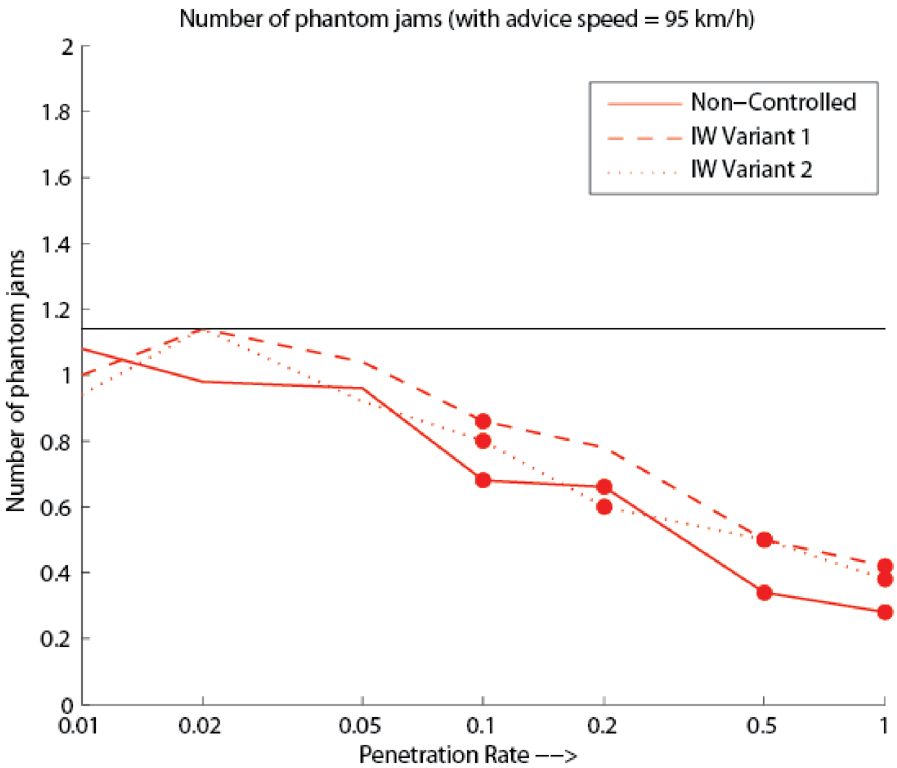


Figure 8.3: The effect of three variants of the advice system on the number of phantom jams for a speed advice of 95 km/h.

It has been discussed above that the more selective nature of variant 2 (higher danger level used for triggering) did not result in significantly different effects on the number of phantom jams compared to the less selective variant 1 and the non-selective non-controlled system. However, if advice is only provided to a too selective part of the vehicles (variant 3), the reduction in number of phantom jams is limited to maximum of around 10%. This is caused by the fact that only around 25% of all phantom jams is originated during intensity waves with a danger level >=2,5 (see appendix IV). Therefore, the range of influence of variant 3 is only 25% of all phantom jams which can be prevented in case of an effectiveness of 100%. In the results, however, a decrease of “only” 10% in the number of phantom jam is observed. This indicates that the advice system is able to prevent around 40% of all phantom jams within its range of influence. Although this percentage is not negligible, on the total number of phantom jams it is only a relatively small reduction. In comparison, the range of influence of the non-controlled system (100%), variant 1 (81%) and variant 2 (75%) is three to four times higher.

It must be remarked that the exact selectiveness for the three intensity wave based variants is clearly depending on the chosen boundaries for the danger levels. For this study, these boundaries are chosen in such way that each of the variants has a clearly different selectiveness. Now it is seen that a decrease in selectiveness from 100% to 75% does not significantly affect the results on jam indicators. However it does on for example average network speed. Another decrease from 75% to 25% affects the results in such way that only minor effects remain. For the practical application of such measure one would look for an appropriate ratio between selectiveness and its effects on network and jam indicators to achieve optimal effectiveness.

Dissolving based systems

In contrary to the prevention based systems, the dissolving based systems did not result in any improvement on the number of phantom jams. This, however, is not remarkable in itself as advice is only provided once a jam has already been observed. Dissolving based system are therefore most likely to have effect on the jam weight.

Demand profiles

Comparing the results of demand profile 2 with those of demand profile 1 and 3 gives some interesting insights. The results for demand profile 1 and 2 are quite similar, though the results for demand profile 3 do show some remarkable deviations. Still, the relations between the various systems remain the same as they are for demand profile 1 and 2. However, the magnitude of the effects of the prevention based advice systems is clearly different. For demand profile 1 and 2, the prevention based advice systems already result in a reduction of the number of phantom jams from the lowest penetration rate on (figure 8.3). For demand profile 3, however, these low penetration rates result in an increase of the number of phantom jams (figure 8.4). Apparently, the vehicles provided with information cause disturbance which are large enough to initiate new phantom jams under the prevailing traffic (in)stability. For penetration rates of above 5-10% on the other hand, still large improvements can be achieved (see Appendix V-VIII).

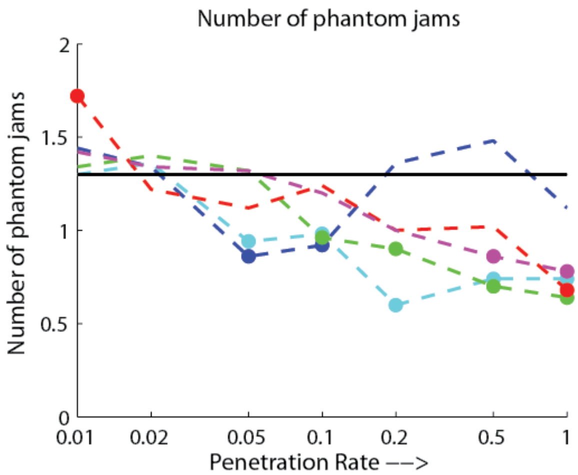


Figure 8.4: The effect on the number of phantom jams of variant 2 for demand profile 3.

In section 8.1.1 it has been discussed that significant decreases of the average network speed have been observed on link-level. The benefits of the reduced number of phantom jams do not compensate the negative effects of the speed advice. However, on network level, a reduction in number of phantom jams is likely to improve average network speed due to reduced spillback effects on bottlenecks. In order to be able to quantify this possible improvement of the average network speed, a more sophisticated network should have been used.

Traffic safety

The occurrence of a phantom jam on a highway network results in sudden speed drops at the rear-end of congested platoons. Such sudden speed drops can lead to unsafe situations. Rear-ends of congested road sections are a known source of head-tail collisions. A reduction of the number of phantom jams means a reduction of the number of sudden speed drops and results in an increased traffic safety with respect to head-tail collisions.

Conclusions

Prevention based advice systems have a clear positive effect on the number of phantom jams and so in traffic safety. For high network intensities however, low penetration rates might result in small increases. Dissolving based advice systems do not show a reduction of the number of phantom jams which is not remarkable as they are only triggered once congestion has already been observed. An increase has even been observed for the jam detection based system. This is most likely to be caused by the very metastable traffic conditions upstream of the phantom jam in which the advice is provided. This way, perturbations, caused by the advice can result in new phantom jams.

The various advice systems can be ranked as in table 8.3, based on their performance for the number of phantom jams. Remarks in the table are general remarks and might not hold for any penetration rate.

Table 8.3: Ranking the advice systems based on the results for number of phantom jams.

Rank	Advice System	Remark
1	Non-controlled	Clear positive effects
1	IW variant 1	Clear positive effects
1	IW variant 2	Clear positive effects
4	IW variant 3	Limited positive effects
5	Phantom Jam Detection based	No significant effect
6	Jam Detection based	Negative trend in effects

8.1.4 Jam Weight

The results for jam weight on the network are similar to the results for the number of phantom jams. As these two indicators are closely related, this is not remarkable.

Prevention based systems

Also the results for the prevention based advice systems are comparable to the results for the indicator number of phantom jams. As can be seen in figure 8.5, a reduction of up to 75% can be achieved. This reduction is achieved especially due to the reduction in number of phantom jams, which was relatively similar. The jam weight per phantom jam has not been decreasing so much. Again, a weak (statistically not significant) pattern in the results of the non-controlled system and IW variant 1 and 2 is seen. Such as for the number of phantom jams, low penetration rates for demand profile 3 result in an increase of the jam weight.

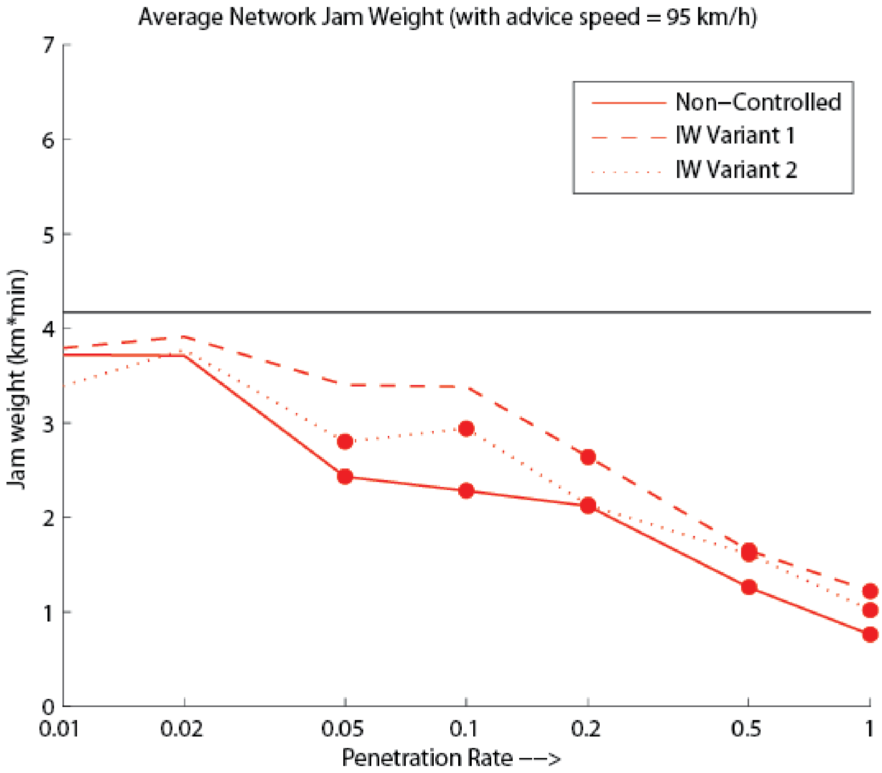


Figure 8.5: The effect of three variants of the advice system on the jam weight for a speed advice of 95 km/h.

Dissolving based system

For the dissolving based advice systems, no significant effects on the jam weight are observed for demand profile 1 and 2. For demand profile 3 however, a clear trend of increasing jam weight as result of the advice system can be determined. These observations are remarkable with respect to the nature of these systems: dissolving existing jams. One would at least expect some minor decreases in jam weight due to this dissolving nature. The following section explains the design choice to use a very dense network to be the main cause of these observations.

Effects of design choices

These observation that jam weight cannot be decreased by dissolving based advice systems is in contrast with the results of a study by Hegyi et al. (2008) in which an algorithm called "The SPECIALIST" has proved to be successful in suppressing phantom jams. This contradiction is caused by a different approach of the phenomenon of a phantom jam. As discussed in chapter 3 , for this study, the definition of a phantom jam includes the following characteristic: *The spontaneous formation of traffic congestion which is not caused by obvious reasons such as an accident or a bottleneck* (definition of a phantom jam, section 3.1). In order to produce such phantom jams, a **very** dense network has been used for simulations. Note that traffic state has to be very metastable in order to fall into congestion. On the other hand, a phenomenon, very similar to phantom jams, can be observed in real traffic data: *structural-congestion-tails ("filestaarten")*. Such tails do fulfil the spatial temporal behaviour of a phantom jam but do have an infrastructural cause, mainly capacity restrictions on bottlenecks. Such congestion tails propagate from the bottleneck onto a link on which they propagate until traffic conditions allow them to resolve automatically. Hegyi et al. have mainly focussed on such congestion tails which allows them to use a less dense network. A jam is forced in the downstream part of the network and propagates on a link with an intensity far below the intensity which is required to induce phantom jams. For road-users, both phenomena are experienced equally, but for traffic management it is crucial to identify the exact cause of observed shockwaves. Prevention based systems are most likely to be successful to prevent for real phantom jams and dissolving based systems are much more likely to be able to dissolve congestion tails.

The use of a very dense network during this study limits the ability of dissolving based advice systems to use or create "space" upstream of a phantom jam. Network intensities are that high and traffic state is that metastable that provided advice on these upstream road section rather induce new phantom jams than create space and suppress a phantom jam. For congestion tails which propagate on a less dense network however, dissolving based advice systems are much more likely to be effective in suppressing and dissolving congestion-tails. This is proved by Hegyi's research.

Conclusions

The decrease of the number of phantom jams due to the prevention based systems is seen again in the average jam weight on the network. Relatively similar decreases are observed for the jam weight. The dissolving based systems on the other hand, which were expected to have decreasing effects on the jam weight, do not result in a reduction of the average jam weight on the network. This is caused by the design choice to make use of extreme intensities on the network to be able to reproduce phantom jams. Research by Hegyi et al. (2008) has proved that such dissolving based advice systems are more successful on less dense links in case of congestion tails. The qualitative ranking of the various systems is equal to the ranking for the number of phantom jams (table 8.4).

Table 8.4: Ranking the advice systems based on the results for jam weight.

Rank	Advice System	Remark
1	Non-controlled	Clear positive effects
1	IW variant 1	Clear positive effects
1	IW variant 2	Clear positive effects
4	IW variant 3	Limited positive effects
5	Phantom Jam Detection based	No significant effect
6	Jam Detection based	Negative trend in effects

8.1.5 Number of jam detections

Also the results for the number of jam detections are somewhat similar to the results for the number of phantom jam detections.

Prevention based systems

For the prevention based advice systems significant improvements for the number of jam detections are measured similar to the improvements on the indicators number of phantom jams and jam weight. As can be seen in figure 8.6, a reduction of up to 75% can be achieved. Furthermore, a weak (statistically not significant) pattern in the results of the non-controlled system and variant 1 and 2 is seen. Demand profile 3 again results in a small increase of the number of jam detections for low penetration rates. For higher penetration rates however, still significant improvement is measured.

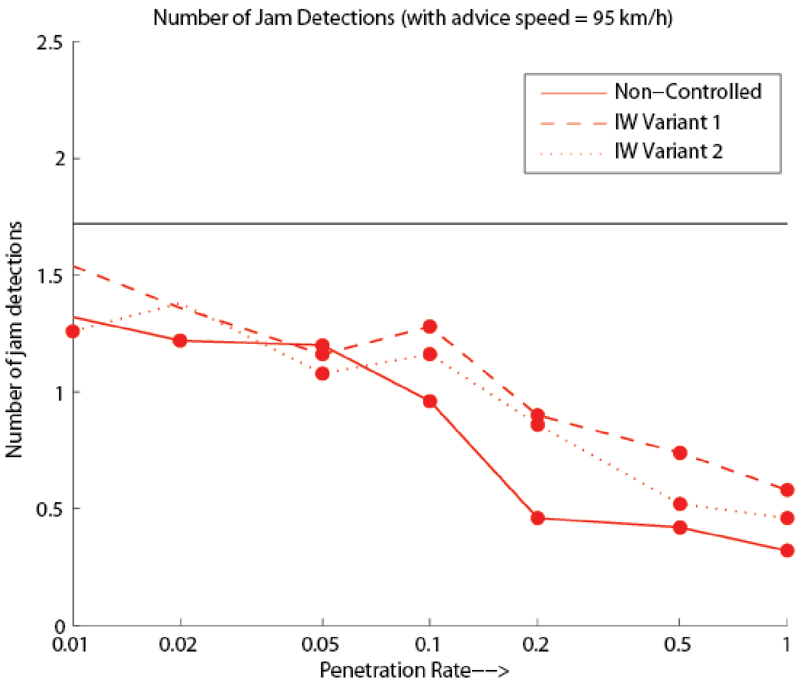


Figure 8.6: The effect of three variants of the advice system on the number of jam detections for a speed advice of 95 km/h.

Dissolving based systems

For the dissolving advice systems it is no surprise that no decrease in number of jam detections is observed as advice is only provided after such detections have been done. Small increases of the number of jam detections have been measured for both the phantom jam as the jam detection based advice system.

Traffic safety

As mentioned in chapter 6, the number of single jam detections is an aggregated representation of the speed variance on the network. A decreasing speed variance is often related to an improving traffic safety. Therefore, this indicator must be seen as a surrogate measure for safety. A reduction of the number of jam detections means a reduced speed variance on the network and an improved traffic safety. From the results for the jam detection indicator, it can be concluded that prevention based advice systems can be very successful in reducing the speed variance as the number of single jam detections significantly drops. This indicates that traffic safety is most likely to improve on the network. However, it needs to be acknowledged that aggregated data has been used for this qualitative assessment. In order to be able to make a more quantitative examination of the effect on traffic safety, more detailed microscopic indicators should have been included in the evaluation framework (i.e. number of serious decelerations or the speed variance per vehicle or the time-to-collision).

Effects of design choices

The determination of the numerical values in the fuzzification process (section 5.3.1) is crucial in the identification of traffic states. For example, if traffic speed would have been identified as “low” for speeds below 40 km/h instead of below 50 km/h, less road section would have been identified as jammed. The initial number of jam detections would have been limited. However, it is expected that these choices mainly affect the magnitude of the results and not the proportion between the various systems. Therefore, the fundamental backbone of the algorithms is expected to be strong enough. This would probably have been resulted in a limited reduction of the number of jam detections. However, still, prevention based systems would have been most likely to achieve the most improvement.

Conclusions

For the number of single jam detections on the network, similar conclusions can be drawn as for the number of phantom jams. The non-controlled and high intensity wave based systems are able to achieve the highest reduction in jam detection. Traffic is stabilised by these advice systems and speed variances are reduced. Therefore, these systems contribute to a higher traffic safety.

Table 8.5: Ranking the advice systems based on the results for the number of jam detections.

Rank	Advice System	Remark
1	Non-controlled	Clear positive effects
1	IW variant 1	Clear positive effects
1	IW variant 2	Clear positive effects
4	IW variant 3	Limited positive effects
5	Phantom Jam Detection based	No significant effect
6	Jam Detection based	Negative trend in effects

8.2 Successful advice systems for practical application

For successful practical application of an advice system, the system should fulfil some preconditions. For this study, technical elements such as achievable penetration rates or the human machine interface of the system are not taken into account. Therefore, two preconditions can be composed:

- The system should not result in a significantly reduced network performance for any of the evaluation frame indicators.
- The system should improve the network performance for at least one of the jam indicators.

Using these preconditions, the set of results for the advice systems has been analysed using pareto set analysis. For this analysis, all results which do have a significant negative effect on any of the indicators are excluded in order to fulfil the first precondition. Furthermore, as this study does not directly focus on improving the network indicators average network speed and network outflow (chapter 6), these two indicators have been excluded from the optimization process. This leaves three indicators for the pareto set analysis.

The analysis has been performed per penetration rate to exclude the relation between the penetration rate and the magnitude of the effect. This leaves five (speed advices) times six (advice systems) systems per penetration rate. Each of these systems has a result for the number of phantom jam detection, the jam weight and the number of jam detections. For these indicators, Pareto optimal sets are selected per penetration rate (table 8.6). The Pareto sets for demand profile 1 and 3 can be found in appendix XI.

Table 8.6: Pareto set of results per penetration rate for demand profile 2 (Bold percentages represent decreases which have been proven to be statistically significantly different from the reference scenario).

Penetration rate	Speed Advice (km/h)	Advice system*	Number of phantom jam detection (-)		Jam weight (km*min)		Number of jam detection (-)	
Reference	-	-	1,14		4,17		1,72	
1%	80	IW1	0,74	***-35%***	2,68	***-36%***	1,16	***-33%***
	85	IW1	1,04	*-9%*	3,55	*-15%*	0,90	***-48%***
	85	NC	0,76	***-33%***	1,96	***-53%***	1,08	***-37%***
	90	NC	0,94	*-18%*	3,71	*-11%*	0,88	***-49%***
2%	80	IW1	0,88	*-23%*	2,86	***-31%***	0,88	***-49%***
	85	IW2	0,84	*-26%*	2,62	***-37%***	1,00	***-42%***
	90	NC	0,66	***-42%***	2,32	***-44%***	1,36	*-21%*
5%	80	IW2	0,60	***-47%***	1,68	***-60%***	0,76	***-56%***
	85	IW1	0,64	***-44%***	2,02	***-52%***	0,58	***-66%***
10%	85	IW1	0,66	***-42%***	1,86	***-55%***	0,68	***-60%***
20%	90	IW1	0,54	***-53%***	1,59	***-62%***	0,50	***-71%***
50%	90	IW2	0,44	***-61%***	1,09	***-74%***	0,58	***-66%***
	95	IW1	0,50	***-56%***	1,61	***-61%***	0,52	***-70%***
100%	95	IW1	0,38	***-67%***	1,02	***-76%***	0,46	***-73%***

**Advice system: NC=non-controlled, IW1=Intensity Wave (IW) variant 1, IW2=IW variant 2, IW3=IW variant 3, J=jam detection based, PJ=phantom jam detection bases.*

Note that for demand profile 2 none of the advice systems in the Pareto sets is of dissolving nature. Therefore, it can be concluded that the prevention based advice systems perform much better than the dissolving based advice systems. This is in line with previous observations. Also the intensity wave based system variant 3 is not represented in the Pareto set for demand profile 2. This is also the case for the Pareto sets for demand profile 1. For demand profile 3 the Pareto sets for the penetration rates 1% and 2% contain advice systems of the IW variant 3 and the phantom jam detection bases classes. However, it needs to be remarked that the results of these advice systems are not significantly different from the reference scenario.

In the results of the pareto set analysis some clear trends are noticeable. Each of these trends is discussed in the following sections:

- Low demand profiles allow later provision of advice.
- Higher penetration rates require a higher speed advice.
- Higher penetration rates lead to more suppression of phantom jams.

8.2.1 Low demand profiles allow later provision of advice

By analysing the Pareto sets for each of the demand profiles it can be observed that for each demand profile a dominant advice system is present. This dominant advice system, is the advice system which is present in the Pareto set for most/all penetration rates. For demand profile 1, this is the intensity wave based system variant 1 and for demand profile 2 and 3, this is the intensity wave based system variant 2. Therefore, from each Pareto set only this dominant advice system is selected and presented in table 8.7. It needs to be remarked that for the cells which are not filled in, the dominant advice system does surely improve network performance, but that the system does not belong to the Pareto set.

Table 8.7: Dominant advice systems for each of the demand profiles.

	Demand Profile 1		**Demand Profile 2**		**Demand Profile 3**	
Penetration rate	Speed Advice (km/h)	Advice system*	Speed Advice (km/h)	Advice system*	Speed Advice (km/h)	Advice system*
1%	-	-	80	IW1	-	-
2%	80	IW2	80	IW1	85	IW1
5%	85	IW2	85	IW1	85	IW1
10%	90	IW2	85	IW1	90	IW1
20%	95	IW2	90	IW1	-	-
50%	95	IW2	95	IW1	95	IW1
100%	95	IW2	95	IW1	95	IW1

**Advice system: NC=non-controlled, IW1=Intensity Wave (IW) variant 1, IW2=IW variant 2, IW3=IW variant 3, J=jam detection based, PJ=phantom jam detection bases.*

From this table it can be concluded that a lower demand profile (less traffic demand) allows the information provision to be provided to vehicles in a more metastable traffic situation (which is operationalized by a higher danger level).

8.2.2 Higher penetration rates require a higher speed advice

From table 8.7 can furthermore be concluded that higher penetration rates require a higher speed advice. For high intensities, low speed advices do have such negative effects on network speed and network outflow that they have been excluded from this analysis. However, for low penetration rate, the pareto set analysis shows that low speed advices perform better on all jam indicators.

Looking at the theory behind the prevention based advice systems (section 4.4.3), this is not remarkable. Note that it is strived for to reduce the local metastability by reducing the average speed within a high intensity wave. With only a few cars provided with information, a low speed advice is required to achieve a significant speed reduction on average. With almost all cars provided with information, the speed advice itself can be much higher in order to achieve the same aimed speed reduction on average.

8.2.3 Higher penetration rates lead to more suppression of phantom jams

Although it might sound logical, all three demand profiles show an increasing positive effect on all three jam indicators with an increasing penetration rate. This can already be observed in table 8.6 (and similar tables in the appendix), but is made more clear in figure 8.7 in which the decreasing effect of the dominant advice system (IW variant 2) for demand profile 2 is plotted. Besides some fluctuation, a clear trend of a higher decrease for higher penetration rates can be recognized.

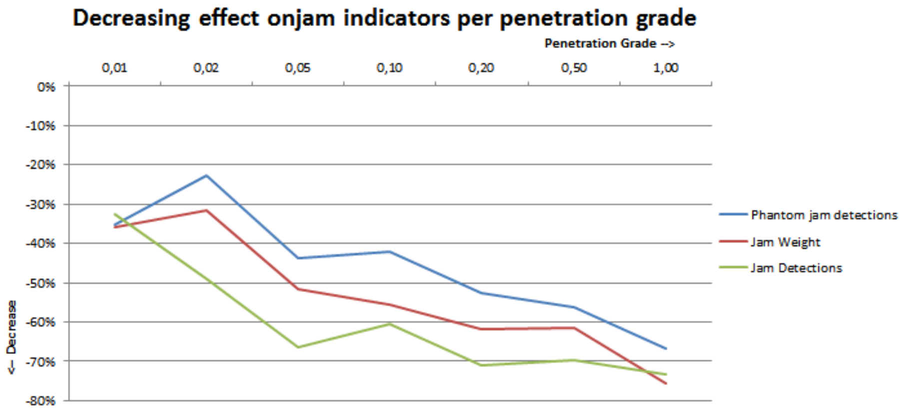


Figure 8.7: The decreasing effect on jam indicators per penetration rate for the dominant advice system for demand profile 2.

8.3 System acceptability

The results captured within the evaluation framework, form a solid basis to analyse the network performance of the advice systems with respect to phantom jams. This section presents some further analysis to help to examination of the acceptability of the advice systems.

8.3.1 Equipped and non-equipped vehicles

For the acceptability of the advice system, advised vehicles should not experience significantly lower average speeds then their non-advised co-road users. Such differences are not expressed by the indicator average network speed only.

On average, no significant difference can be found between the average speed of equipped and non-equipped vehicles. For none of the advice systems, simulated for any of the demand profiles, a speed difference of more than 0.1 km/h (which is only a difference of around 0.1%), between equipped and non-equipped vehicles has been measured. However, this is averaged over the whole network. When focussing only on the network sections on which advise is provided, a significant difference in speed between advised (equipped) and non-advised (non-equipped) vehicles is observed. These speed differences have been plotted in figure 8.8 for demand profile 2. A penetration rate of 100% has been excluded from these plots as no non-advised vehicles are present on the network in such scenario.

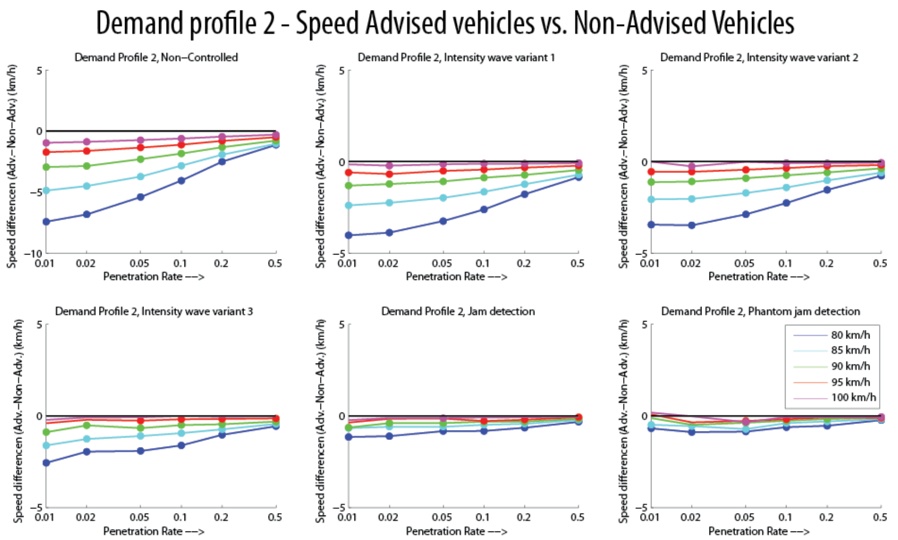


Figure 8.8: Average speed of advised vehicles – non-advised vehicles for all advice systems. Speed advice is indicated by the colour of the plot, bullets indicate a significant difference between advice and non-advised vehicle speed.

It can be clearly seen that higher penetration rates lead to lower speed differences between advised and non-advised vehicles. Section 7.3 and 7.4 already discussed that high penetration rates, in particular for the prevention based systems, have a significant negative impact on the average speed.

Besides the effect of the penetration rate, also a clear effect of the speed advice can be observed in the results. A speed advice of 80 km/h can result in a speed difference of up 7.5 km/h for the non-controlled advice system. On the other hand, a speed advice of 100 km/h results in a maximum speed difference of 1 km/h. Although this speed difference has proven to be significant, it is worth questioning if such speed difference (up to 1 km/h) is in fact really experienced by drivers.

8.4 Conclusions

The conclusions which can be drawn from the analysis are described in this section. First, the observed effects of the advice systems on the various indicators in the evaluation framework are discussed. Thereafter, the different applicability of prevention based and dissolving based advice systems is mentioned. This is followed by a short conclusion on how advice systems can help to improve traffic safety. Lastly, the relation between most important design variables in the advice systems is described.

8.4.1 Evaluation framework

Network indicators

From the analysis, it can be concluded that improvement of the network performance indicators (average network speed and network outflow) is hardly possible. None of the advice systems was able to achieve any significant improvements on the average network speed. For relatively high penetration rates and low speed advice, the average network speed easily significantly decreases. However, it needs to be remarked that these observations are done on a single-link network. The potential positive effects of a reduced number of phantom jams on the average network speed on a full scale network level have not been evaluated. Furthermore, the decrease in average network speed is expected to be slightly overestimated due to the fact that delayed vehicles in the generator of the simulation software are not taken into account. Therefore, it should be said that the negative effects on the average network speed are likely to be somewhat overestimated in this model study.

Also network outflow decreases significantly for high penetration rates and low speed advice. For the higher speed advices a small significant improvement on the network outflow is measured of up to 0.6%. This is expected to be caused by a combination of the fact that less phantom jams hit back in the generator and can therefore be released on the network earlier and an improved (final) state of the network conditions.

Jam indicators

For the jam indicators, serious improvements have been measured for some of the advice systems. Especially for prevention based advice systems significant decreases in number of jam detections, phantom jam detections and jam weight are measured. For each of these indicators improvements have been observed of up to 70-80% for the non-controlled and intensity wave based variant 1 and 2. The analysis showed that an increasing selectiveness of the prevention based systems can help to decrease the negative effects on network level without affecting the positive effects on jam indicators to some extent. However, if selectiveness is too high the positive effects on jam indicators disappear.

Dissolving based systems on the other hand, have not shown any improvements on the jam indicators. This is in contrast with a study of Hegyi et al. (2008) which has shown a similar algorithm to be successful in suppressing phantom jams/congestion tails.

8.4.2 Prevention vs. dissolving based systems

To develop a clear understanding of why dissolving based advice systems did not result in improvements of the network improvements during this study while such system actually was successful in the study of Hegyi et al. (2008), the phenomena of phantom jams and congestion tails must be distinguished. Both phenomena have the same spatial-temporal characteristics but have a different cause. Due to this different cause they can originate and persist under different traffic conditions. For this study, phantom jams have been simulated. This requires very high intensities to achieve metastable traffic states. Under such conditions no “space” is available to suppress congestion waves. In Hegyi’s research it is more focussed on congestion tails. Such congestion tails originate in structural congestion on bottlenecks and propagate upstream on a link with limited intensities. Such lower intensities allow dissolving based algorithms to create “space” and suppress the congestion. On the other hand, such congestion tails are not likely to be prevented by prevention based advice systems as the cause is not so much a perturbation under metastable traffic conditions but a structural capacity restriction at a bottleneck. However, if prevention based advice systems are embedded within the structural congestion area it might results in some positive effects. By stabilizing the congested traffic, the origination of congestion tails might be prevented.

8.4.3 Traffic safety

Prevention based advice system can be successful in reducing the number of phantom jams and the speed variance due to the stabilizing effect of these systems. Therefore, these systems are expected to have a positive impact on traffic safety. Such effects on traffic safety might even permit some minor decreases of the network indicators which can be a consideration in the decision making process.

8.4.4 Successful advice systems

From the prevention based systems, the intensity wave based variant 1 and 2 seem to perform most successful as follows from pareto set analysis. These systems outperform both the non-controlled system which decreases the average network speed to easy and the intensity wave variant 3, which nature focuses only on a narrow selection of all phantom jams. The dissolving based advice systems, on the other hand, show hardly any significant improvements on any of the jam indicators. This is most likely to be caused by the dense network used during this study. Hegyi et al. (2008) have proved to be a similar algorithm to be successful in suppressing phantom jams/congestion tails on a less dense network.

Penetration rate

For the advice systems which have turned out to be most successful (high intensity wave intensity variant 1 and 2), the network performance improves with an increasing penetration rate. For relatively low average network intensities, improvements have been measured from the lower penetration rates on. However, for a higher average network intensity (demand profile 3 for this study), penetration rates of below 5% do not evidently result in an improved network performance. For higher penetration rates though, the improvements steadily increase up to a decline of over 50% for all jam indicators.

Penetration rate vs. speed advice

For a given advice system, a relation between the penetration rate and the speed advice is recognized. For low penetration rates, most improvement on jam indicators is observed for low speed advices. With an increasing penetration rate, speed advice should be increased gradually to achieve optimal improvement in network performance. Such higher speed advice has the additional advantage of much lower speed differences between advised and non-advised vehicles. This is likely to deliver a large contribution to the acceptability of the advice system as equipped road users do not experience a disadvantage in network speed compared to their non-equipped co-road users.

9

Conclusion and Recommendations

In chapter 2 the aim of this study was stated as: *to evaluate the possibilities of in-car speed advice in order to improve the network performance with respect to phantom jams*. Three supporting research questions have been answered during this study. Therefore, a single-link network has been used in a micro-simulation environment.

9.1 Phantom jam characteristics

The first research questions concerns the traffic measurements which need to be performed in order to be able to identify the formation of phantom jams on the network. Macroscopic traffic data, collected by detection loops, have found to be successful to distinguish three different traffic states, based on Kerner's three phase theory, using a fuzzy logic framework: free flow, synchronized flow and jam. This data can be used to identify the presence of a phantom jam using its spatial-temporal property of an upstream propagating jam with a speed of around 20 km/h. The presence of high intensity waves have been found as an important precondition for phantom jams to originate. Over 80% of all identified phantom jams were directly originated during such waves. High intensity waves are characterized by its intensity, which is clearly above the queue discharge capacity, and its downstream speed of around 80 km/h. A classification can be made between high intensity waves using its heaviness (average intensity) and length: the danger level. The higher the danger level, the more likely it is that an intensity wave induces a phantom jam. Microscopic data such as headway or headway variance have showed to be less successful to identify the spatial-temporal characteristics of phantom jams or high intensity waves. Phantom jam and high intensity wave patterns are less easy to extract from this microscopic data. Furthermore, it is less easy to collect and process such data by loop detection measurement.

9.2 Network performance

Research question two concerns how the network performance can be classified with respect to phantom jams. Therefore, a framework has been built consisting of network and jam indicators. The network indicators help to examine the network performance in terms of the more traditional average network speed and network outflow.

The jam indicators, on the other hand, enable the possibility to assess the network performance with respect to phantom jams. Therefore, three aggregated jam related indicators have been used: number of phantom jams, jam weight and number of single jam detections. These jam indicators can also be used as surrogate measures for traffic safety. With a reducing number of phantom jams, the number of sudden speed drops is decreasing with a decreasing chance of head-tail collisions as a result. Furthermore, a reduction of the number of single jam detections is an indication for an improved speed variance. As speed variance and traffic safety are closely related such improvement can contribute to traffic safety as well.

9.3 Advice systems

The design of the in-car speed advice system is covered by research question three. This study has proved so-called prevention based advice systems to be most successful in improving the network performance. On the other hand, dissolving based advice systems have shown not to result in significant improvements of the network performance.

9.3.1 Prevention bases systems

Two types of prevention based systems have been simulated: non-controlled and the “smart” intensity wave based systems. These intensity wave based systems anticipate on the previously mentioned pre-phantom jam characteristic: the high intensity wave. Speed advice is provided to equipped vehicles in such intensity waves. As a consequence, the local intensity drops and traffic becomes more stable.

It has been seen that the selectivity of the intensity wave based system did not significantly affect the network improvements for the jam indicators comparing to the non-controlled system. Both non-controlled as intensity wave based systems resulted in significant improvements up to 65% on each of the three jam indicators for penetration rates of 100%. For penetration rates in between 1% and 10% improvements have been measured of about 10-40% for these indicators. On the other hand, the negative effects of the non-controlled system on the network indicators can be reduced to some extent by the selectiveness of these “smart” intensity wave based systems. It, however, needs to be remarked that being too selective (using a very high danger level as a threshold) does only result in minor significant network improvements as merely a minority of all phantom jams is within the range of influence of the system.

9.3.2 Dissolving based systems

Besides the prevention based variants, also two dissolving based advice systems have been simulated. These systems aim at dissolving identified phantom jams by creating “space” upstream of a jammed section by means of speed advice. These systems have not been proved to be successful during this study. This is in contrast with the results of a study by Hegyi et al. (2008)in which a similar algorithm, called “The SPECIALIST”, has proved to be successful in suppressing phantom jams. This contradiction is most likely to be caused by a different approach of the phenomenon of a phantom jam. An upstream moving platoon of congestion can either be caused by perturbations in metastable traffic flows (phantom jam) or by small perturbations in structural congestion (congestion tails). Where this study only included the so-called phantom jams, Hegyi's research also included congestion tails. Therefore, this study required higher network intensities to originate phantom jams. As a result, it was not able to create upstream "space" without inducing a new phantom jam. In Hegyi's research, lower intensities have been used and a phantom jam has been forced to originate downstream of the network. For such network conditions, dissolving based advice systems are more likely to be effective. On the other hand, prevention based systems are less likely to be effective in preventing congestion tails. Such systems cannot easily prevent the capacity excess on the bottleneck which is the cause for the structural congestion in which congestion tails originate.

9.4 Traffic safety

Prevention based advice systems have shown to be successful in reducing the appearance of phantom jams and seems to reduce speed variance on the network. Both of these effects are likely to have a positive impact on traffic safety. Not only are rear ends of congested areas known sources of head-tail collisions, also speed variance has shown to be positive related to traffic safety. This study has focussed on at least maintaining the network performance with respect to speed and outflow to the level in the reference scenario. However, if traffic safety is one the major pillars in the decision making process one could decide to allow some minor decline in network performance in return for more traffic safety.

9.5 Speed advice and penetration rate

The exact value of the speed advice and the penetration rate are crucial design variables of the advice system. A lower speed advice leads to worse effects on the network indicators average network speed and network outflow. Simultaneously, a higher penetration rate leads to more substantial effects (either positive or negative) on these indicators. For the jam indicators however, the tuning of the speed advice and the penetration rate is essential in order to achieve optimal effects. Low penetration rates require low speed advices whereas high penetration rates allow a higher speed advice for optimal network improvement. Finally, both the value of the speed advice as the penetration rate have a significant influence on an important acceptability issue of the advice system: the speed difference between advised and non-advised vehicles. A lower speed advice and penetration rate lead to a higher speed gap between advised and non-advised vehicles. This finding results in a duality. On the one hand, it is most desirable to equip as few vehicles as possible for economic and practical reasons. On the other hand, such low penetration rates require a low speed advice which leads to high speed differences. Such high speed differences are clearly an acceptability issue and negatively affect traffic safety.

9.6 From link to network scale

The evaluation showed that for none of the advice systems an increase in average network speed is achieved. To see this in the right perspective, it needs to be remarked that these results apply for a single-link network only. On link level the possible benefits by preventing a phantom jam are overcompensated by the reducing effect on the average speed of the speed advice. Note that a phantom jam is a very temporary and local traffic condition which is not likely to have a large impact over the full link and simulation length. However, on network level, phantom jams can have significant effects on average network speed as it can induce stationary jams at bottlenecks as a spillback effect. In contrary to phantom jams, these stationary jams can grow and have a significant effect on the average network speed. Therefore, although not measured during this study, a reduction of the number of phantom jams to originate on link level can have a significant impact on the network indicators on network level.

9.7 Final conclusion

The final conclusion of this study is that in-car speed advice can significantly improve network performance with respect to phantom jams. Prevention based systems are most successful with significant decreases for all jam indicators: number of phantom jams, the number of single jam detections and the total jam weight. Consequently, these systems are also expected to result in a serious contribution to the traffic safety on the network. The selection of the design variables speed and penetration rate lead to a duality between acceptability, effectiveness and practical implementation issues.

9.8 Recommendations

High intensity waves have been used to regulate the prevention based advice systems during this study. However, although such waves seem to be a clear precondition for phantom jams it is not so much a declaring variable as only a small minority of all high intensity waves actually results in a phantom jam. Therefore, advice is frequently provided while actually no phantom jam would originate. If a more accurate declaring variable can be identified, prevention based advice can be provided much more specific. This might diminish negative effects on network indicators. Therefore, it is recommended to proceed research on this topic as this might help the effectiveness of the advice system. It is expected that such more accurate declaring variables must be looked for in detailed microscopic data (i.e. significant speed drops under traffic conditions with small headways).

This study gave insight in the fact that the selectiveness of prevention based advice systems can help to diminish the negative effects of these systems on for example average network speed. However, the selectiveness has been chosen in such way that each of the systems used a clearly different selectivity. It has not been aimed to optimize the selectivity of the system for the results on both jam as network indicators. Further research on this topic can help to get more understanding on this topic. It is expected that a more optimized selectivity of the prevention based system can limit the negative effects on the average network speed.

As mentioned several times in this report, none of the advice systems did result in increasing average network speeds on a single-link network. For this study, such single-link network has been chosen to assure the spontaneous origination of a phantom jam and its limited simulation time. However, on a full network scale, it is expected that significant positive effects on the average network speed can be achieved due to the reduced number of phantom jams and the limited spillback effects. Therefore, it is recommended to perform further research on a full-scale network in order to quantify these expected benefits for the average network speed. This research should especially focus on prevention based advised systems. As this study showed that the limited number of fifty simulations does not allow a detailed quantitative analysis of the effects of the systems it is recommended to perform much more simulations per advice system. Furthermore, it is recommended to include the delay which vehicles might encounter in the generator of the simulation software in the calculation of the average network speed. This way, slightly overestimations in average network speeds for simulations with phantom jams hitting back in the generator are avoided.

10

Discussion

This study has shown that the provision of in-car speed advice can be helpful in preventing and suppressing phantom jams. Although this may not directly lead to major improvements with respect to average network speed, this can result in serious improvement of the traffic safety. However, for practical application of such systems, some difficulties need to be overcome. This discussion elaborates on various aspects which need to be addressed in case of a practical application of this system.

Phantom jam vs. congestion tail

As discussed, phantom jams are not always clearly distinguished from so-called congestion tails. In practice, both phenomena occur on the network with the expectation that most of such congestion waves are in fact congestion tails. Note, that especially on the Dutch road network on- and off ramps are very close to each other and long stretches without connections or interchanges are relatively rare. For a successful approach in suppressing congestion waves with the spatial-temporal characteristics of a phantom jam, an advices system should be able to handle both phenomena. As both of these phenomena require its own strategy, both strategies must be integrated in the advice system to be able to switch between both approaches depending on traffic conditions. A dissolving based strategy has been proved (Hegyi et al., 2008) to be successful in dissolving congestion tails under limited traffic density. A prevention based strategy, on the other hand, must be chosen if traffic state detection makes clear that the “danger level” of the traffic flow is near a height that phantom jams easily originate. Furthermore, a prevention based system might be used in structural congestion. The stabilizing effect which a prevention based system can have, can help to reduce the number of perturbation in such structural jam. This can prevent a congestion tail to originate from structural congestion.

Data processing time

During this study it is assumed that data is directly available after each minute interval and that the processing time is equal to zero. In reality, the time between the end of the minute-interval and the finished data processing is expected to be around two minutes. Such delays in availability of the advice would mean major implications on the effectiveness of the system. Especially the prevention based advice systems would be biased by this delay. However, expanding the data collection process with floating car data can overcome this difficulty. Recent research learned that the time to localize congested traffic on highways can be reduced with over 70% with use of floating car data of only 5% of the vehicles (Netten, Hegyi et al. 2013). Furthermore, the use of floating car data can bring more detailed information about the exact location of the head and rear end of a platoon of congested traffic, which allows more detailed advice schemes.

Flip-flopping

For the prevention based system it has been chosen to maintain the speed advice along the whole network once a vehicle was provided with information during this study. This was chosen for to prevent the unlikely event of flip-flopping (advice switching on and of every minute). However, on full network scale a regulation scheme to switch off the advice after some time must be applied to the system. Actual traffic state identification can easily be used to check whether or not an advice is still required or not. If not, the advice can be reset. Subsequently, to prevent flip-flopping a time-out (of for example 5 minutes or over a certain length) can be introduced before new advice can be provided. However, it needs to be acknowledged that the penetration rate is affected by this approach under very critical circumstances.

Penetration rate

For the effectiveness of the advice system the penetration rate plays a major role. It has been seen that for prevention based advice systems generally holds that a higher penetration rate leads to more effects on the network performance. However, in practice, only limited penetration rates of up to 5% are achievable. This study have shown that, still for such limited penetration rates, positive effects for jam indicators and traffic safety are to be expected.

Future developments

Not only can higher penetration rates help to improve the effectiveness of the advice systems presented in this study, also future developments can be an impulse to the effectiveness of such systems. Expansion of the type of information provided by the advice system is a simple example of such development. The advice can for example be expanded with keep-your-lane advice, which can reduce the number of perturbation under metastable traffic conditions. Furthermore, if technical developments allow communication between vehicles, advices can be provided on a microscopic scale which can result in a more accurate and successful system.

11

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Appendix I

Speed-flow diagrams

Figure 11.1 shows the flow-density and speed-flow diagrams for both the A58 field data as the model data. In these diagrams the characteristics *max capacity, speed at capacity, density at capacity* and *capacity drop* are visualized. The max capacity has been identified by selecting the highest capacity measured in the free flow curve during the measurement period (the two outlying measurements in the field data plot have been seen as outliers and therefore not included as part of the free flow curve). The max capacity for model data does closely match max capacity measured in the field data. The speed and density at capacity has simply been identified by taking the accessory speed and intensity for the measurement of the max capacity. Finally the capacity drop (or the outflow/queue discharge capacity) has been identified. This is not done by analysis of single capacity drop observations, but also by analysis of the speed-flow diagram. The outflow capacity is, according to Kerner's three phase theory, the intensity of the intersection of the free flow and the congested branch in the diagram. As both branches consist of a cloud of measurements no clear intersection is identifiable. Therefore, it is chosen to identify the densest part of the congested cloud and take the intersection between the upper boundary of this cloud and the density as capacity to determine the outflow capacity. This resulted in an outflow capacity of around 4000 veh/h for both field data as model data.

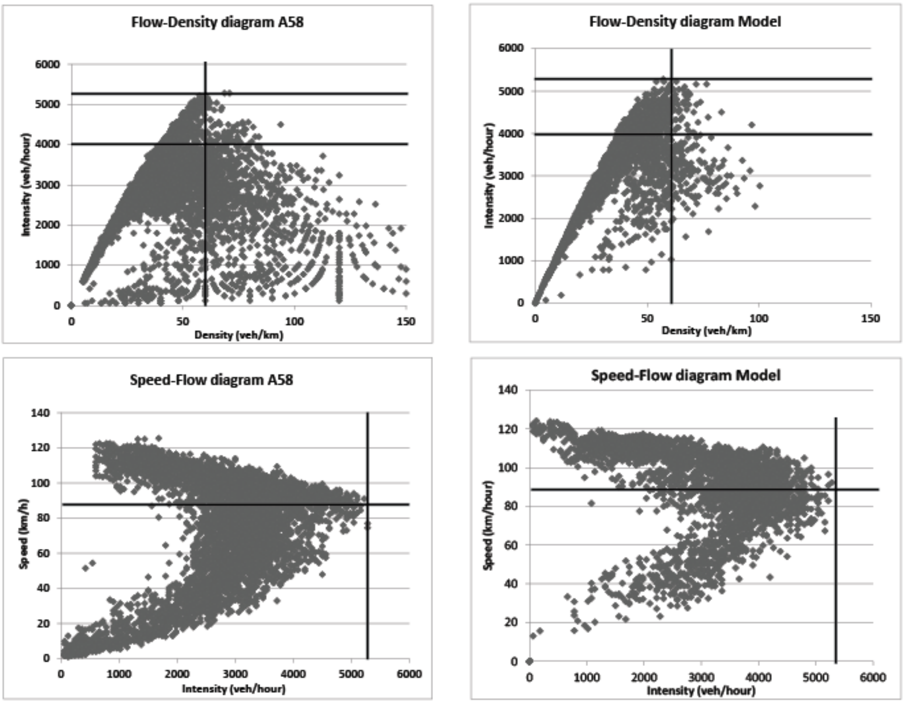

Figure 11.1: Flow-density (upper) and speed-flow (lower) diagram for A58 field data (left diagrams) and for model data (right diagrams).

As can be seen, that model outcome does largely meet field data characteristics. However, it must be acknowledged that model data lacks of low intensity data in comparison with field data. This is caused by the uniform input of 4000 vehicles per hour in the model (this can also be recognized by the fact that the density of measurements around 4000 veh/h is relatively high).

Appendix II

Illustration advice vs. non advice

For this study, the reference scenario is assumed to be paired with scenarios with an advice system active; in both scenarios the same distribution (both in time as in vehicle parameters) of vehicles is generated. Therefore, it is needed to prove that the provision of advice does not affect the random allocation of vehicle parameters for generated vehicles.

Figure 11.2 and figure 11.3 illustrate the speed on the network through space and time for two different scenarios. In figure 11.2, the time-space diagram is shown for a scenario with no advice system active. In figure 11.3, the time-space diagram is shown for a scenario in which a speed advice is provided on the downstream section 13-19. If the implementation of the advice system would affect the random allocation of vehicle parameters to new vehicles, not only the downstream section would be different between both scenarios, but also the upstream section (due to different inter vehicle behaviour). Note that upstream generated vehicles would have received different random vehicle parameters if the speed advice would effective the random allocation. This would logically result in a different inter vehicle behaviour.

It can be clearly seen that the speeds on the upstream sections are exactly equal for both scenarios. The observed phantom jam, does originate at exactly the same location for both scenarios. However, the downstream section shows another pattern of speed through space and time. The fact that only for the downstream sections differences are observed is a clear indication that vehicle distribution is not affected by the implemented advice system. Therefore, it is justified to assume that both scenarios are paired.

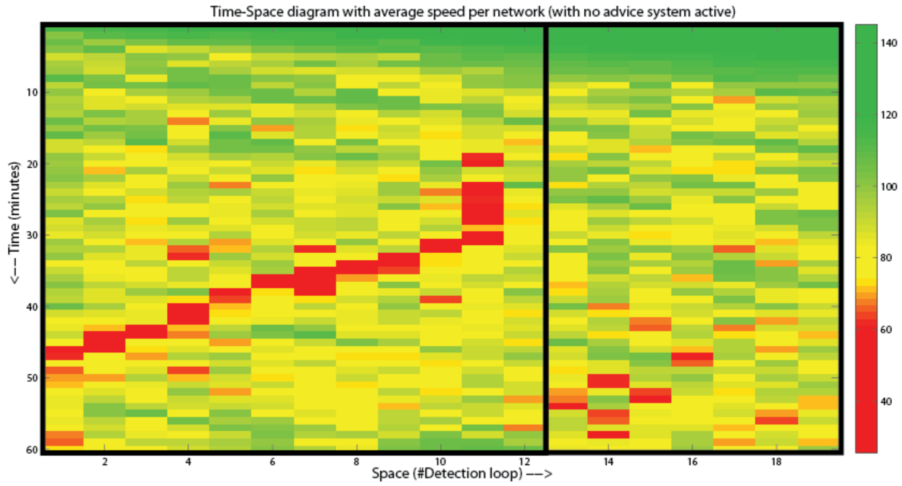

Figure 11.2: Illustration of speed on the network through space and time with no advice system active.

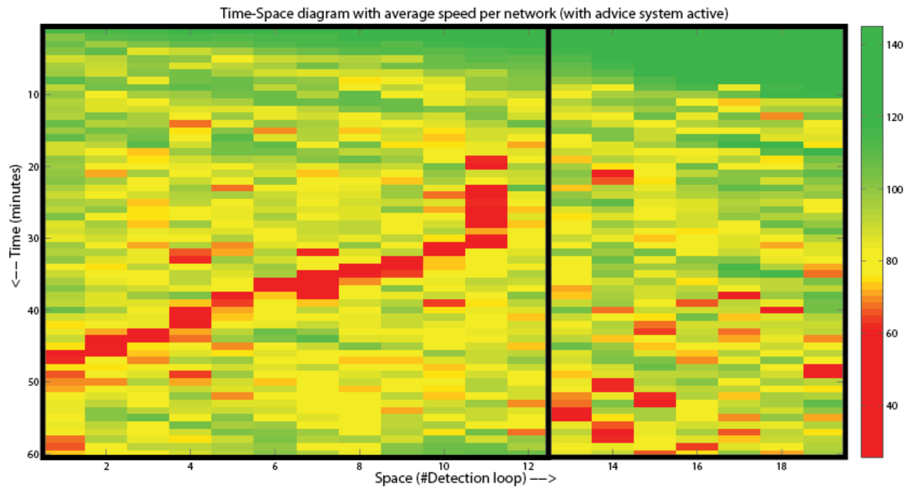

Figure 11.3: Illustration of speed on the network through space and time with advice system active for section 13-19.

Appendix III

Headway and headway variance analysis

In figure 11.4 the average headway and the headway variance are visualized for each of the two lanes per minute interval for the same simulation as in figure 5.1 and figure 5.2. Both phantom jams are drawn out in these figures. It can be seen that large differences between lanes are observed for headway. In the time-space diagram for headways, the phantom jams can only be recognized on the left lane. On the right lane, no such clear deviations in headways are seen between phantom jam and non-phantom jam sections. For the pre-phantom jam phase, it can be recognized that for both two phantom jams both headway as headway variation were small. However, this relation seems to be less strong than the relation between speed/intensity and phantom jam (origination). The relation between low headways and low headway variances is not unique for the-pre phantom jam phase only but does occur more trough space and time. Finally, for the practical application of microscopic data, the variables headway and headway variance are less easy to extract from loop data which makes the use of these variables less useful for application in a practical algorithm.

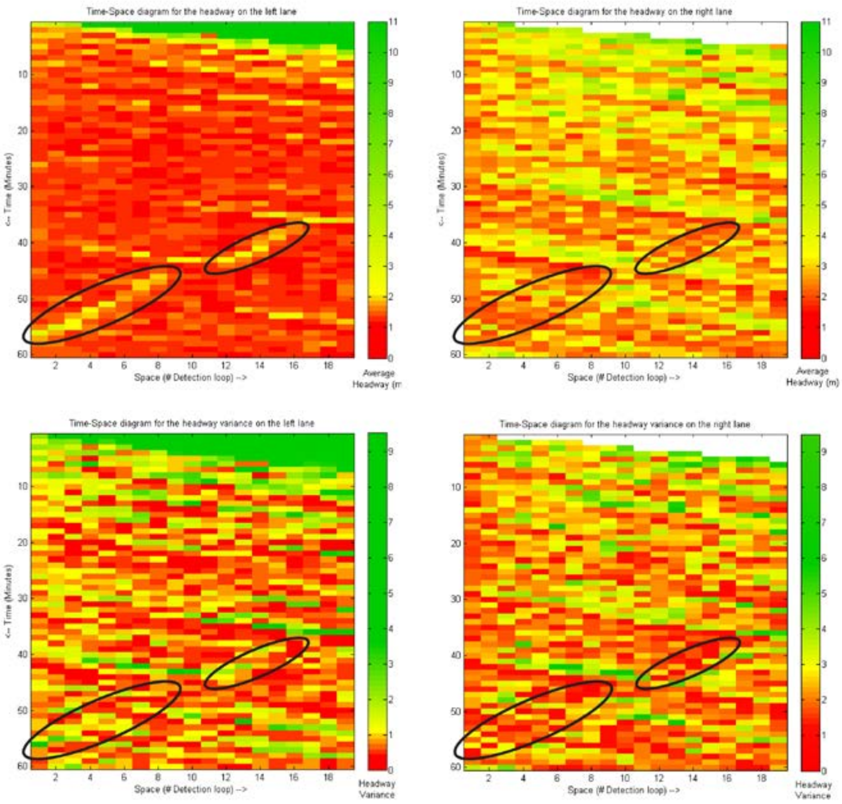

Figure 11.4: Space-time diagrams for both headway (upper two diagrams) and headway variance (bottom two diagrams) for both left (left diagrams) and right (right diagrams) lane.

Appendix IV

Phantom jam relation with intensity waves

Relation between phantom jam and high intensity waves

As mentioned before, during the fifty simulations which has been analysed for this purpose, a total of 64 phantom jams have been identified. For each of these phantom jams it has been analysed whether or not the phantom jam has been originated during a high intensity wave. Therefore, the previous three minutes at the origin of the phantom jams has been taken into account. A total of 81% of all phantom jams (52 out of 64) seemed to be originated during a high intensity wave. From this share, 16 phantom jams (25% of the total amount) originated during an intensity wave scored with a danger level of 2.5 or higher. Another 32 phantom jams originated during an intensity wave scored with a danger level in between 1.5 and 2.5, which is 50% of all phantom jams. A minority of only 4 phantom jams find their origin in intensity waves with a score below 1.5 (see table 5.2).

Table 11.1 : The distribution of phantom jam origins.

Origin source	Number of Phantom Jams	Percentage (%)
High danger (score: 2,5 or higher)	16	25
Medium danger (score: 1.5-2.5)	32	50
Low danger intensity wave	4	6
Other	12	19
Total:	**64**	**100**

Of all phantom jams, 19% does not find his origin directly in a high intensity wave. However, if these phantom jams are individually analysed, for most of them an indirect relation with a high intensity wave can be seen. Two examples of such phantom jams which are indirectly originated from high intensity waves are shown in figure 11.5 for seed 1 and seed 5. In figure 11.5, both the red as the blue sections are identified as congested by the live algorithm. The offline phantom jam identification algorithm clustered the blue section as part of a phantom jam. Both the phantom jam in seed 1 as the phantom jam in seed 5 show a pre-phase in which the live algorithm identified congested traffic. However, these congested sections are not clustered into a phantom jam by the phantom jam identification algorithm as it does not fulfil the spatial temporal characteristics of a phantom jam. Nevertheless, this pre-phase is clearly originated during a high intensity wave. Therefore, the relation between phantom jam and high intensity wave must be seen as indirect as it is separated by this specific pre-phase. The real number of phantom jams which is neither directly or indirectly originated during a high intensity wave is much lower than the presented 19% in table 11.1.

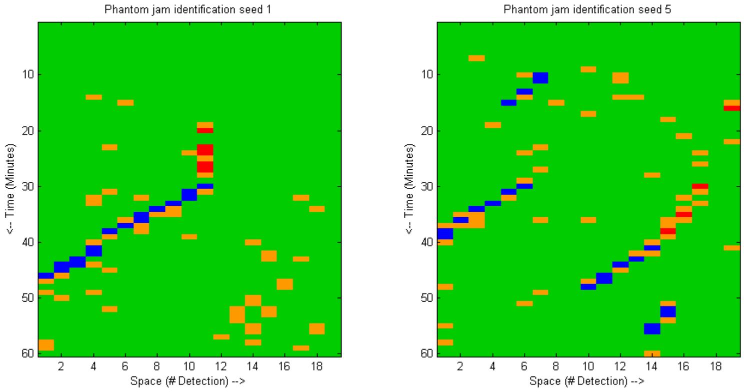

Figure 11.5: Traffic state identification for seed 1 (left) and 5 (right) (green=free flow, orange=synchronized flow, red = congested, blue = phantom jam).

Relation between high intensity waves and phantom jams

Not only has the relation from phantom jam to high intensity wave been analysed. Also the relation from high intensity wave to phantom jam has been looked into. Note that for prevention based advice systems it is not yet known whether or not the identified intensity wave will actually induce a phantom jam.

For this analysis, the total number of high intensity waves has been counted over al fifty simulations and compared to the number of phantom jams which were originated in these intensity waves. Not only has been looked at the number of intensity waves but also at the danger level. In table 11.2the results of this analysis are presented.

From all intensity waves, only 5% resulted in the occurrence of a phantom jam. However, it is clearly seen that as the danger level of high intensity waves decreases, the chance of a phantom jam to originate from it is decreasing too. For the highest danger level, over 50% of all waves resulted in a phantom jam. However, only 8 out of 52 phantom jams originated during an intensity wave with the highest danger level. If only measures would be taken in case of danger level 3, only 8 out of 52 phantom jams are potentially affected. On the other hand, for intensity waves with a danger level of 2 or higher, the chance of a phantom jam to originate is 9%. However, in this case over 75% of all phantom jams would be affected if measures would be taken.

Table 11.2: Number of high intensity waves versus number of phantom jams.

Danger level	Number of waves	Number of phantom jams	Percentage (%)
=3	14	8	57
>=2,5	43	16	37
>=2	433	40	9
>=1,5	643	48	7
>=1	1063	52	5

Appendix V

Results non-controlled advice

In addition to section 7.3, in this appendix the results for the non-controlled advice systems are presented for demand profile 1 and 3.

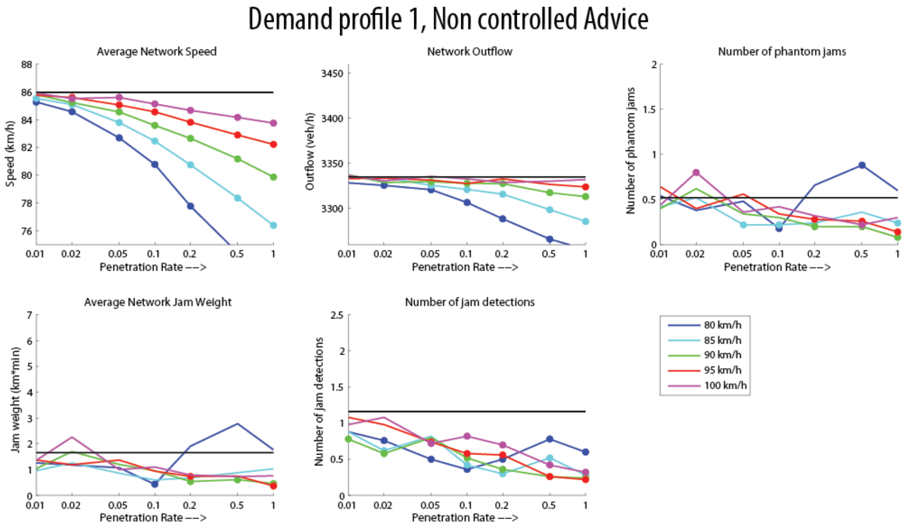

Figure 11.6: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

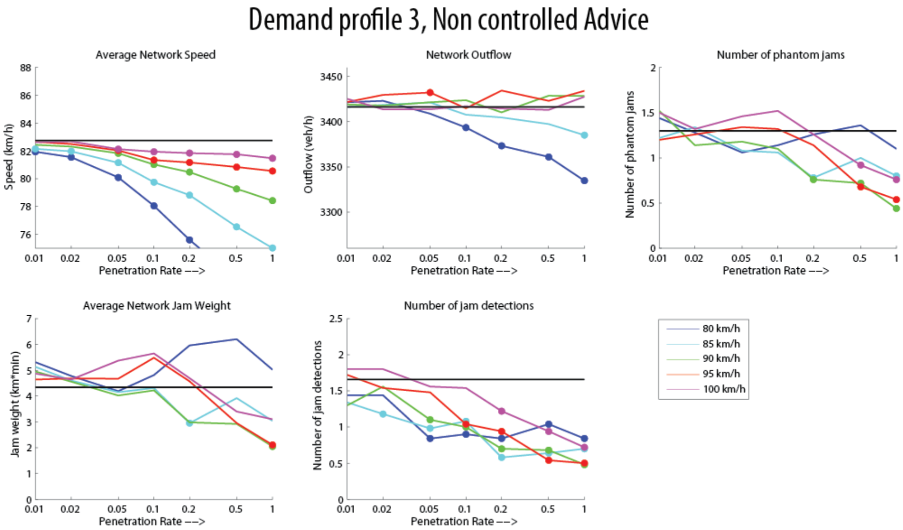

Figure 11.7: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

Appendix VI

Results intensity wave based advice system

In addition to section 7.3 in this appendix the results for the controlled, high intensity wave triggered, advice systems are presented for demand profile 1 and 3 for all three variants.

11.2 Variant 1

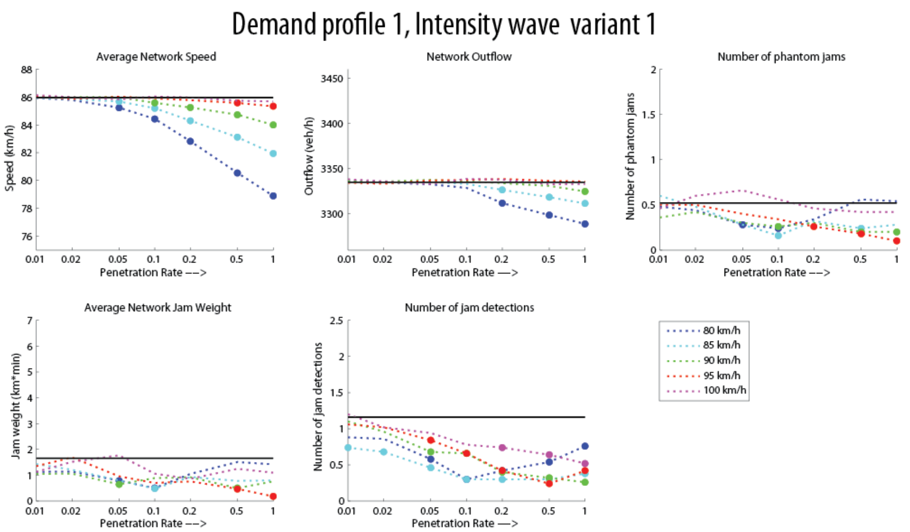

Figure 11.8: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

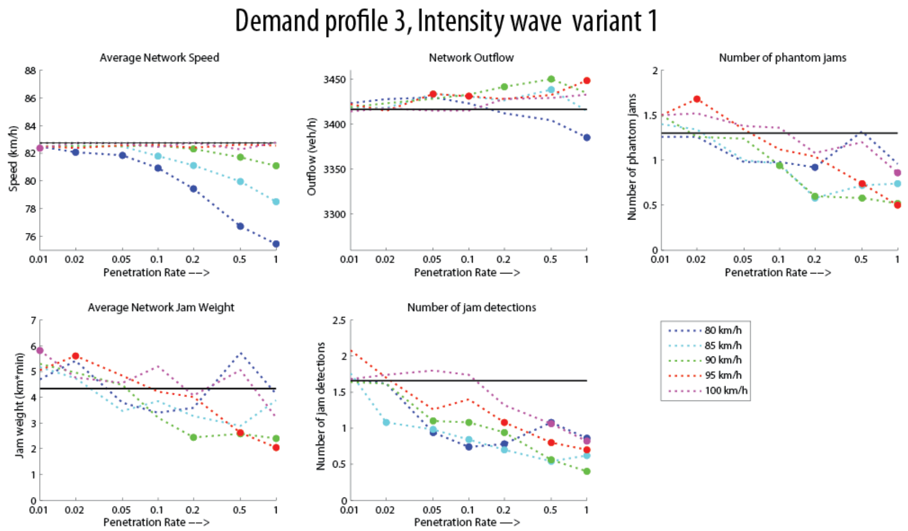

Figure 11.9: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

11.3 Variant 2

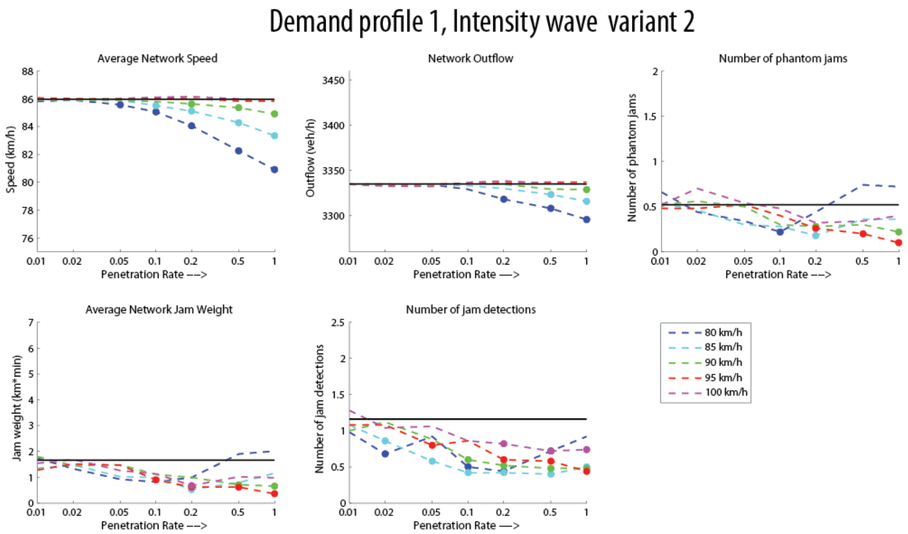

Figure 11.10: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

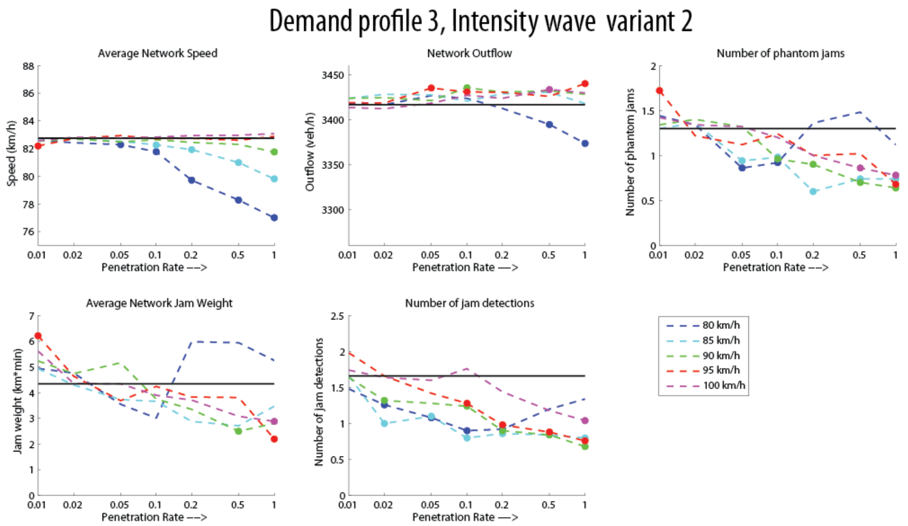

Figure 11.11: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

11.4 Variant 3

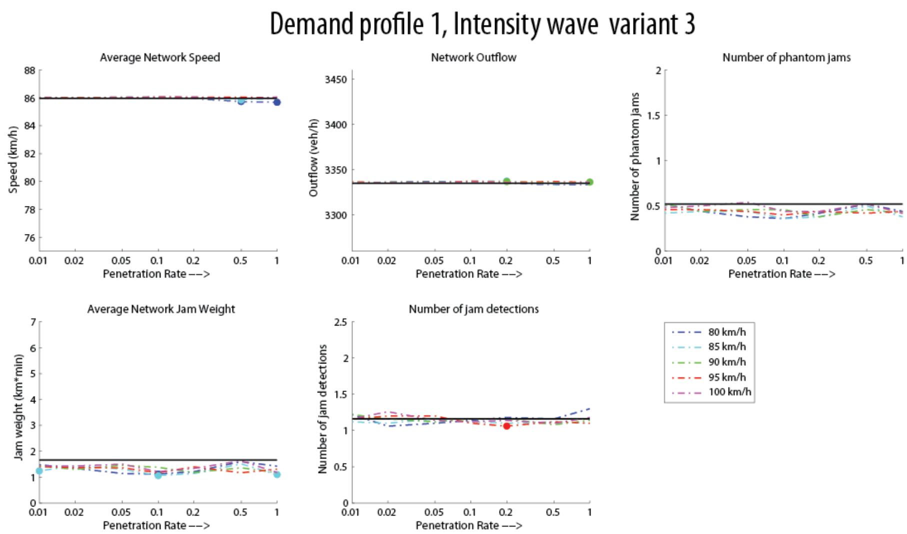

Figure 11.12: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

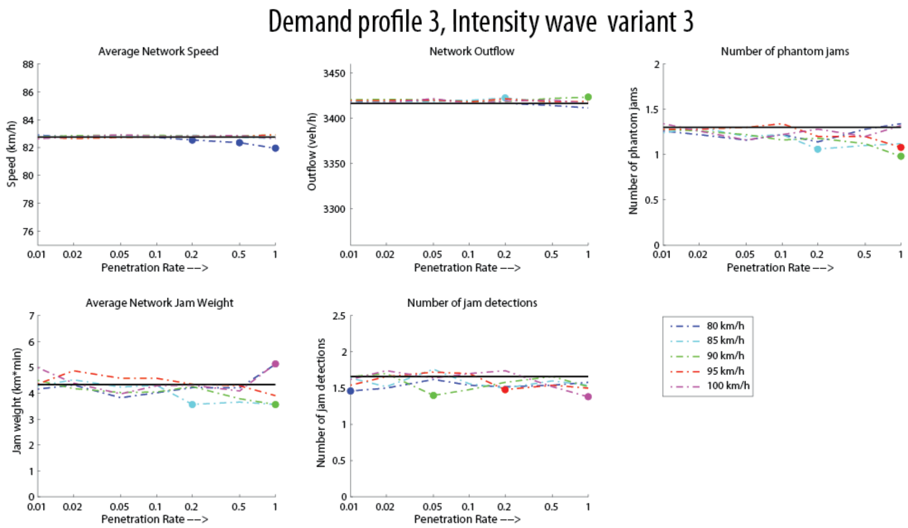

Figure 11.13: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

Appendix VII

Results jam detection based advice system

In addition to section 7.4, in this appendix the results for the controlled, jam detection triggered, advice systems are presented for demand profile 1 and 3.

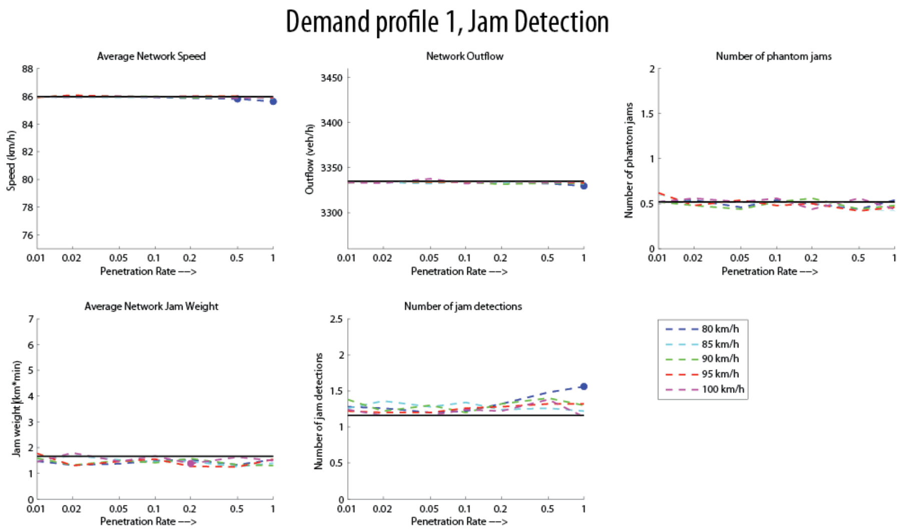

Figure 11.14: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

Appendix VIII

Results phantom jam detection based advice system

In addition to section 7.4, in this appendix the results for the controlled, phantom jam detection triggered, advice systems are presented for demand profile 1 and 3.

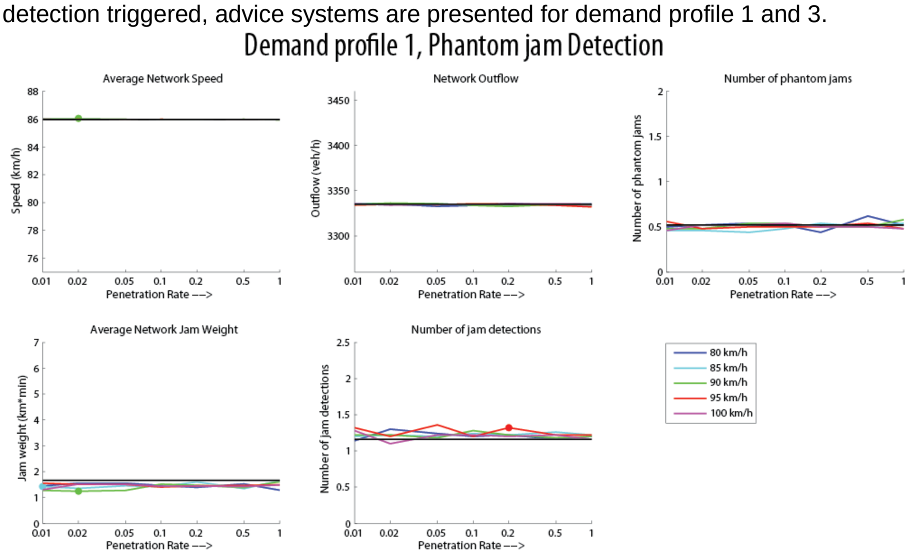

Figure 11.15: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

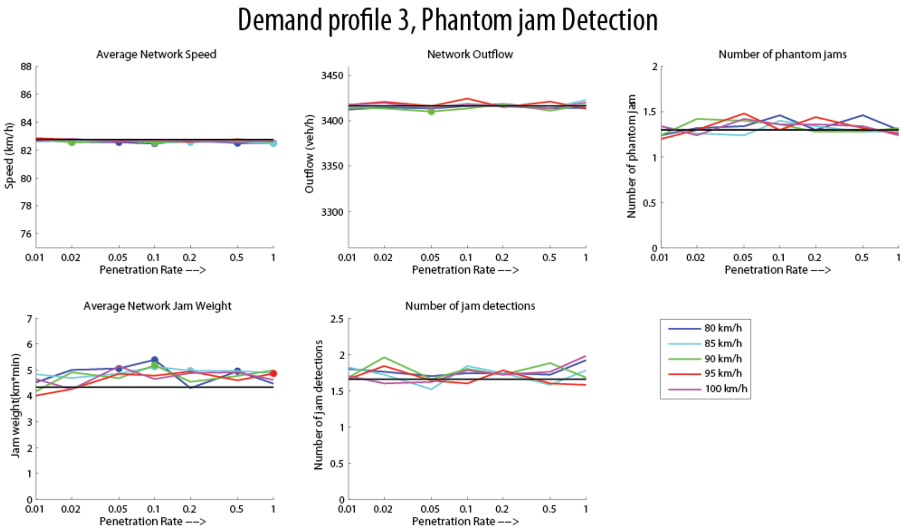

Figure 11.16: Results for various speed advices on a logarithmic penetration rate scale for each indicator visualised against the base measurement (bullets indicate measurements results which significantly differ from base situation).

Appendix IX

Penetration rate versus actual advised vehicles

Due to the various control systems, simulated during this study, the penetration rate is not always equal to the percentage of vehicles which are actually provided with speed advice. If, for example, no high intensity waves are measured during simulation, no matter what the penetration rate is, none of the vehicles on the network is provided with speed advice. Table 11.3 shows the percentage range of equipped vehicles which are provided with advice per advice system. Although these percentages can slightly vary over different penetration rates, they are relatively constant over the various speed advices. By multiplying these numbers with the penetration rate the real percentage of advised vehicles can be obtained.

Table 11.3: Percentage of equipped vehicles actually provided with information.

Control mechanism	Percentage of equipped vehicles provided with advise (%)
Non-controlled advice	100
Intensity wave variant 1	55-60
Intensity wave variant 2	40-45
Intensity wave variant 3	5-6
Jam detections	16-20
Phantom jam detection	11-13

Appendix X

Speed advised vehicles versus non-advised vehicles

In addition to section 8.3.1, in this appendix the results for the speed differences between advised and non-advised vehicles on “advised network sections” are presented for demand profile 1 and 3.

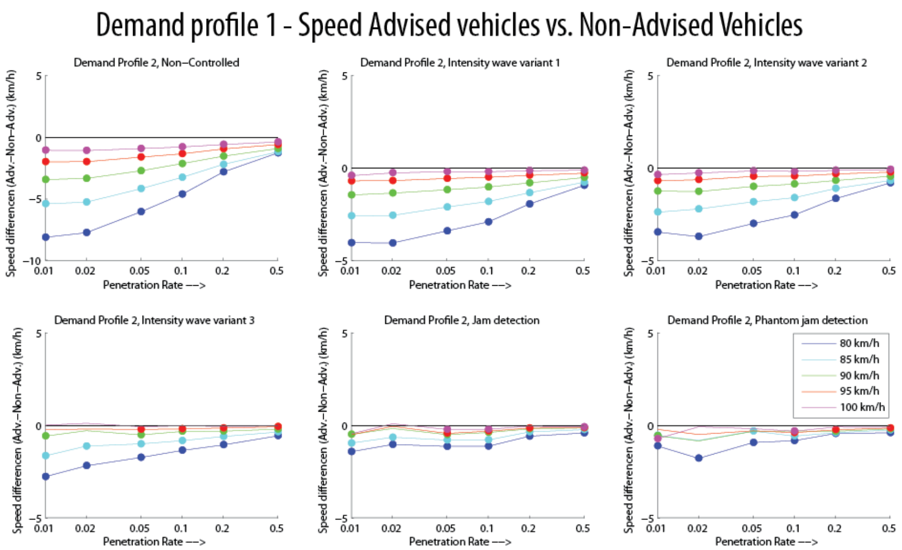

Figure 11.17: Average speed of advised vehicles – non-advised vehicles for all advice systems. Speed advice is indicated by the colour of the plot, bullets indicate a significant difference between advice and non-advised vehicle speed.

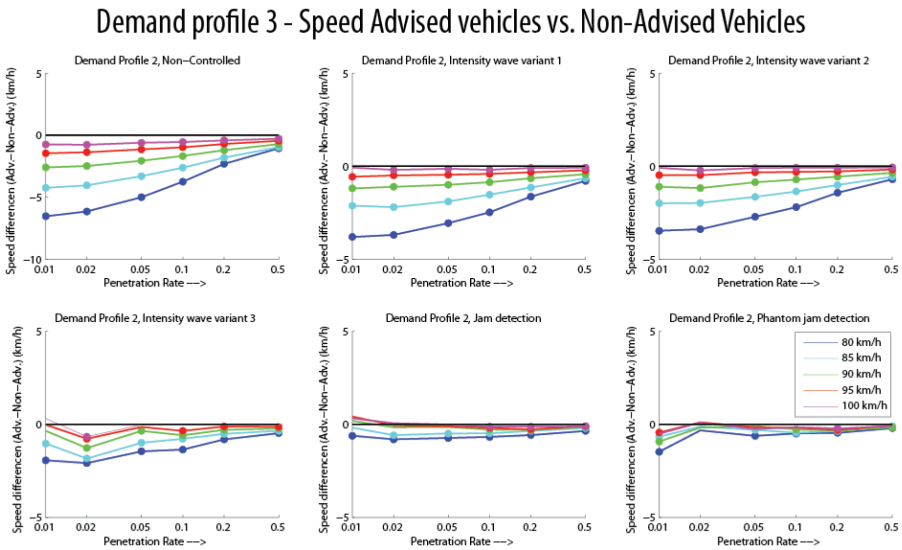

Figure 11.18: Average speed of advised vehicles – non-advised vehicles for all advice systems. Speed advice is indicated by the colour of the plot, bullets indicate a significant difference between advice and non-advised vehicle speed.

Appendix XI

Pareto sets

Table 11.4: Pareto set of results per penetration rate for demand profile 1 (Bold percentages represent decreases which have been proven to be statistically significantly different from the reference scenario).

Penetration rate	Speed Advice (km/h)	Advice system*	Number of phantom jam detection (-)		Jam weight (km*min)		Number of jam detection (-)	
Reference	-	-	0,52		1,66		1,16	
1%	85	IW1	0,60	*15%*	1,43	*-14%*	0,74	***-36%***
	90	IW1	0,36	*-31%*	1,05	*-37%*	1,10	*-5%*
	90	NC	0,40	*-23%*	1,04	*-37%*	0,78	***-33%***
2%	80	IW1	0,44	*-15%*	1,14	*-31%*	0,86	*-26%*
	80	IW2	0,44	*-15%*	1,33	*-20%*	0,68	***-41%***
	85	IW1	0,48	*-8%*	1,21	*-27%*	0,68	***-41%***
	90	IW1	0,42	*-19%*	1,06	*-36%*	0,96	*-17%*
5%	85	IW2	0,30	*-42%*	1,02	*-39%*	0,58	***-50%***
	90	IW1	0,30	*-42%*	0,65	***-61%***	0,68	***-41%***
10%	90	IW2	0,30	*-42%*	1,11	*-33%*	0,60	***-48%***
	95	IW1	0,34	*-35%*	0,70	*-58%*	0,66	***-43%***
20%	95	IW1	0,26	***-50%***	0,76	*-54%*	0,42	***-64%***
	95	IW2	0,26	***-50%***	0,62	***-63%***	0,60	***-48%***
50%	95	IW2	0,20	***-62%***	0,62	***-63%***	0,58	***-50%***
100%	95	IW2	0,10	***-81%***	0,36	***-78%***	0,44	***-62%***

**Advice system: NC=non-controlled, IW1=Intensity Wave (IW) variant 1, IW2=IW variant 2, IW3=IW variant 3, J=jam detection based, PJ=phantom jam detection bases.*

Table 11.5: Pareto set of results per penetration rate for demand profile 3(Bold percentages represent decreases which have been proven to be statistically significantly different from the reference scenario).

Penetration rate	Speed Advice (km/h)	Advice system*	Number of phantom jam detection (-)		Jam weight (km*min)		Number of jam detection (-)	
Reference	-	-	1,3		4,34		1,66	
1%	80	IW3	1,26	*-3%*	4,16	*-4%*	1,46	***-12%***
	85	IW3	1,24	*-5%*	4,28	*-1%*	1,64	*-1%*
	90	NC	1,52	*17%*	4,95	*14%*	1,30	*-22%*
	95	PJ	1,20	*-8%*	4,01	*-8%*	1,66	*0%*
2%	80	IW3	1,22	*-6%*	4,32	*0%*	1,50	***-10%***
	85	IW1	1,34	*3%*	4,74	*9%*	1,08	***-35%***
	85	IW2	1,36	*5%*	4,30	*-1%*	1,00	***-40%***
	90	IW3	1,26	*-3%*	4,18	*-4%*	1,70	*2%*
	90	NC	1,14	*-12%*	4,56	*5%*	1,56	*-6%*
	100	PJ	1,24	*-5%*	4,25	*-2%*	1,60	*-4%*
5%	85	IW1	1,00	*-23%*	3,47	*-20%*	0,98	***-41%***
	85	IW2	0,94	***-28%***	3,73	*-14%*	1,10	***-34%***
10%	90	IW1	0,94	***-28%***	3,21	*-26%*	1,08	***-35%***
20%	90	IW2	0,90	***-31%***	3,35	*-23%*	0,90	***-46%***
50%	92	IW2	0,70	***-46%***	2,50	***-42%***	0,84	***-49%***
	95	IW1	0,74	***-43%***	2,62	***-40%***	0,80	***-52%***
100%	95	IW1	0,50	***-62%***	2,05	***-53%***	0,70	***-58%***

**Advice system: NC=non-controlled, IW1=Intensity Wave (IW) variant 1, IW2=IW variant 2, IW3=IW variant 3, J=jam detection based, PJ=phantom jam detection bases.*

Appendix XII

Paired T-test

The two sets of n(=50) paired measurements (X_i, Y_i) are the starting point of the paired t-test. For the statistical analysis the null hypothesis is that both sample means are equal to each other:
$H_0 : \mu_X = \mu_Y$

From these two sets a set of differences can be calculated ***(11.1)***.

$$Z_i = X_i - Y_i \qquad (11.1)$$

Subsequently the sample mean and the standard deviation for set Z_i can be calculated using formula ***(11.2)*** and ***(11.3)***.

$$\overline{Z} = \frac{\sum_{i=1}^{n} Z_i}{n} \qquad (11.2)$$

$$S^2 = \frac{\sum_{i=1}^{n} (Z_i - \overline{Z}_n)^2}{n-1} \qquad (11.3)$$

Now the t-value can be calculated using formula ***(11.4)***.

$$T = \frac{\overline{Z}_n \sqrt{n}}{S} \qquad (11.4)$$

For this study an acceptance area has been used with an α of 0.05. This means that value T has to be in the acceptance range [-$t_{0.025}$, $t_{0,025}$] (which is [-2.001, 2,001] for 49 degrees of freedom) in order to accept the null hypothesis. In case of a t-value which falls not within the acceptance range it can be concluded that the sample means of set X_i and Y_i are significantly different from each other.

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