

## 7 Optimization potential of ramp metering systems

The last two chapters have revealed the strong influence of onramps on the overall traffic state of a highway because of the synchronization of the lanes. However, empirical observations and theoretical studies indicate that the overall travel-time of vehicles in a traffic network can be optimized by means of ramp metering control systems. Such systems [111] allow to control the onramp flow and thus to stabilize the traffic on the highway. In particular, empirical studies of parts of a highway network [124] have underlined the benefits of ramp metering strategies for the total mean speed and the total travel-time for both, the vehicles on the highway *and* the queuing vehicles on the onramp. These empirical findings are underscored by several theoretical investigations [1, 56, 83, 115]. Studies of the asymmetric simple exclusion process, for example, reveal the existence of a maximal current phase that obviously is the most desirable state. It can be obtained for large input and small output rates and allows to operate a highway in the optimal regime. In finite systems of more realistic models that exhibit meta-stable states, even flows larger than in the maximum current phase can be achieved by varying the input rates in a suitable way. Moreover, in [56], a simple simulation setup consisting of a two-lane highway segment with an onramp is presented. It could be shown that the travel-time of all vehicles can be optimized at a finite injection rate of the onramp in the sense that its variance is minimized.

This improvement of the system's throughput can be explained by considering fluctuations of the traffic flow. Obviously, free flow is the most desirable traffic state since large flows can be obtained. However, at increasing traffic demand, synchronized traffic forms in the vicinity of onramps, which enables a large amount of vehicles to drive with a velocity considerably larger than in a jam but smaller than in free flow, and leads to a flow comparable to free flow [73]. Unfortunately, synchronized states are not very stable so that perturbations can cause wide jams. Here control mechanisms will help to stabilize synchronized traffic and, thus, ensure large throughputs of the highway at large densities. In particular, by means of ramp metering, it is possible to trigger the injection rate of the onramp in order to affect the vehicle-vehicle interactions. Increasing the interactions will improve the vehicle coupling and help to synchronize them [59], however, strong interactions lead to perturbations of the flow and, thus, to wide jams. The variation of the onramp flow therefore helps to adjust the interactions and to stabilize the synchronized state. As a result, the perturbations are minimized, and the performance of the highway is optimized.

In this chapter an extensive analysis of a highway network is presented that helps to judge different optimization strategies and reveals in which areas they have to be applied. In contrast to former analyses that are restricted to only small parts of a highway system, here, the coverage of the network with inductive loops allows to analyze the overall traffic state on a global scale. Therefore it is possible to identify and characterize its bottlenecks. In particular, the question is raised whether bottlenecks are of topological nature

## 7.1 Network characteristics

---

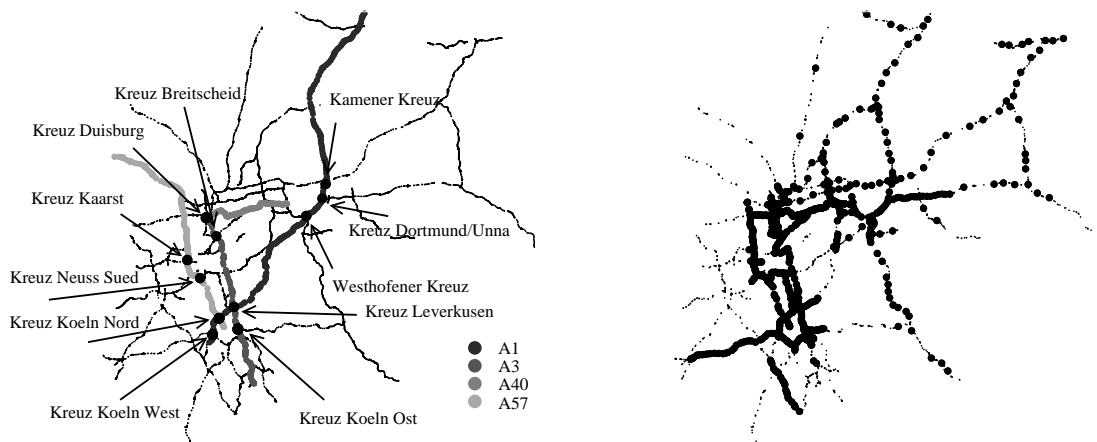


Figure 7.1: Left: Sketch of the highway network of North Rhine-Westfalia and position of the main highways, the A1, the A3, the A57 and the A40. Right: Position of the inductive loops (black circles). As one can see, the inductive loops concentrate on the inner region of the network where most of the traffic volume can be found.

or constituted by onramps with a large inflow. Topological bottlenecks are static whereas dynamical bottlenecks (like ramps) in principle can be influenced externally, e.g., by controlling their strength. Moreover, the properties of the bottlenecks may give evidence if the network's state can be optimized by local control devices or whether global traffic management strategies are necessary [14].

## 7.1 Network characteristics

In this chapter, the highway network of North Rhine-Westfalia (see Fig. 7.1 for a sketch of the network) will be examined. It has a total length of about 2 250 km and includes 67 highway intersections and 830 on- and offramps. The data set is provided by about 3 500 inductive loops that send minute aggregated data of the flow, the occupancy and the velocity online (that is every minute) via permanent lines from the traffic control centers in Recklinghausen and in Leverkusen. For the sake of simple data handling, the driving directions are classified into south/west and north/east. As one can see in Fig. 7.1, most of the detectors are concentrated on the inner network. This is justified by the distribution of the traffic volume, as it will be shown later. The recording of the data started on 10-10-2000. For the analysis of the network, a period of 265 days from 10-10-2000 to 07-01-2001 was considered.

The highway network of North Rhine-Westfalia has an average traffic load of about 30 000 veh/24 h per measurement section for one driving direction. Note that the traffic volume is calculated per measurement section, and thus sums the flow of two or three lanes. However, there are large differences between the highways (Fig. 7.2). Obviously, only a few sections with very large traffic volumes exist which concentrate on the main urban areas. In detail, the Kölner Ring, especially the section between the highway intersections Kreuz Leverkusen and Kreuz Köln Ost, large parts of the A3 and the A40, the A57 near

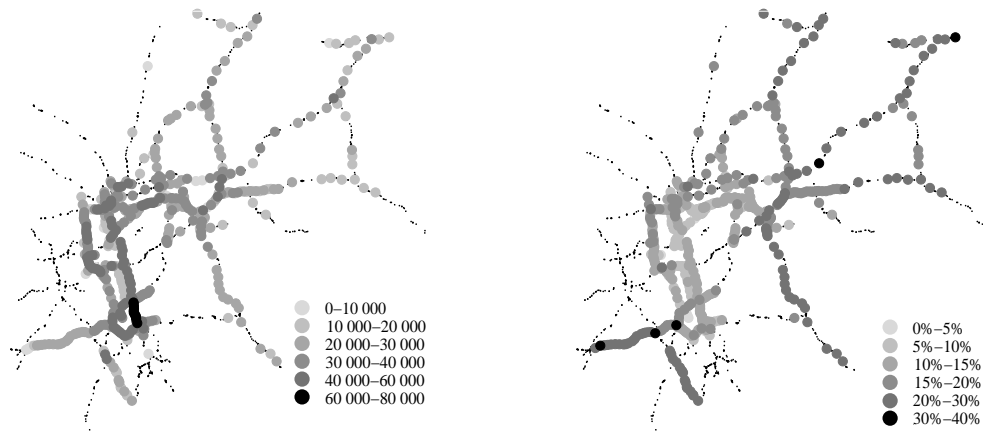


Figure 7.2: Left: Number of vehicles per measurement location per 24 hours and driving direction. Right: Relative number of trucks per measurement section.

Neuss and the A2 near the highway intersection Kreuz Duisburg have an average load of 40 000 – 80 000 veh/24 h. The more the highways leave these conurbations, the less is the traffic volume that can be measured. In addition, nearly the same values of the traffic volumes can be found for both, the driving directions south/west and north/east. About 15% of the vehicles are trucks. Fig. 7.2 shows the distribution of the relative number of trucks per measurement section. Obviously, the share of trucks on the traffic volume increases with the distance to the conurbations. Indeed, this fact can be traced back to the decrease of the overall traffic volume. On the other hand, the absolute number of trucks does not change significantly on the main highways. Thus, the long-distance traffic is mainly dominated by trucks, while at short distances commuter traffic leads to large traffic loads of the network.

## 7.2 Bottleneck localization

Since the traffic volumes are simple integrated quantities, it is possible that a large traffic volume can indicate that a two-lane road is often jammed, while the capacity of a three-lane road is still not reached. Therefore, in order to allow an evaluation of the traffic load, the probability to find a jam is calculated. This has the advantage that traffic volumes that are larger than the highway capacity can be related directly to a large jam probability, and thus bottlenecks of the highway network can clearly be identified. In order to calculate the jam probability, the time-series of the density of each inductive loop for each day of the observation period is analyzed. If the density of at least one minute is larger than 50% (the density is given as occupancy which is the percentage of time a detector is covered by a vehicle), a jam this day is supposed<sup>1</sup>. Increasing the time interval, the density has to exceed 50% only reduces the overall jam probability but does not change the results

<sup>1</sup>Indeed, this threshold value is relatively arbitrary. The empirical observations of chapter 3, however, show that very large densities can only be found in a wide jam. Increasing the value will not change the results significantly.

## 7.2 Bottleneck localization

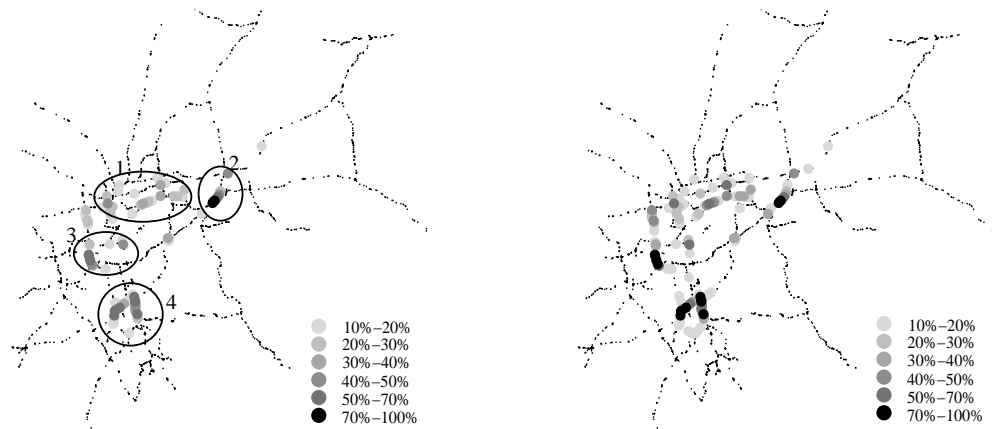


Figure 7.3: Left: Jam probability for the driving direction south/west. The encircled regions are the Ruhrgebiet (region 1), the area of Dortmund (region 2), the area of Krefeld and Düsseldorf (region 3) and the area of Köln (region 4). Right: Jam probability on Wednesday for the driving direction south/west.

significantly. However, if the time interval is getting large, the threshold density has to be reduced.

The usage of the density as an indicator for a jam has some advantages compared to the mean velocity and the flow. First, the flow as well as the velocity depend on speed limits that vary in the network. Therefore, it is not possible to distinguish whether a small velocity is due to a large density or a speed limit. Moreover, the detection of the velocity has a lower limit at about 10 km/h. Nevertheless, slower vehicles are taken into account in the determination of the occupancy (see chapter 3). Second, a small flow can refer to both a jam or just free flow with only a few cars. The jam probability is therefore calculated as the relation of the number of days a jam was found to the total number of days of the observation period (265 days).

Fig. 7.3 represents the jam probability of the network for the driving direction south/west. Obviously, large jam probabilities can be found in a region of the inner network, where the conurbations of the Ruhrgebiet (region 1), the areas of Dortmund (region 2), Düsseldorf and Krefeld (region 3) and Köln (region 4) are located. As one can see in Fig. 7.1, most of the inductive loops are concentrated in this regions, which indeed is a fact based on the experience to find there snarl-ups very often. In contrast, in regions that are less equipped with counting devices, only few jams can be found.

Large differences of the jam probability between the areas can be observed. Only 10% – 30% of the observation days were jammed in the area of the Ruhrgebiet (region 1), that is every third day a jam occurred. In contrast, in the areas of Dortmund (region 2), Krefeld and Düsseldorf (region 3) and Köln (region 4), more than 50% of the days showed jams. Especially in the area of Dortmund, between the Westhofener Kreuz and the Kreuz Dortmund/Unna, nearly 5 days a weak jams can be measured.

In order to specify these results, the jam probability for each day is calculated since it can be supposed that on weekends jams occur only rarely, and the prior results may be misleading.

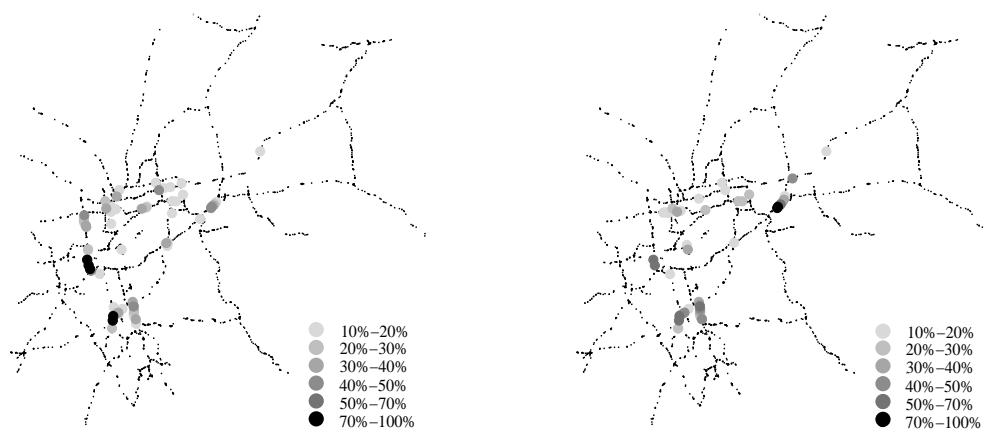


Figure 7.4: Jam probability for the driving direction south/west averaged over the whole observation period for the time interval 6-11 a.m. (left) and 1-8 p.m. (right).

Indeed, the exclusion of weekends leads to an increased jam probability on weekdays compared to the probability averaged over the whole observation period. During the week from monday to friday, there exist only small differences between the days (Fig. 7.3). As expected, on Saturdays and Sundays, only a few jams are measured. However, remarkable is that on Sundays these jams concentrate on the region of Dortmund between the Westhofener Kreuz and the Kreuz Dortmund/Unna, leading to a very large jam probability. This classification of the days into Monday to Thursday, Friday, Saturday and Sunday is qualitatively confirmed in [20, 21] by the analysis of city data.

Up to now, only the daily occurrence of jams was measured, while the exact time a jam emerges was not considered. In order to allow for the daily variations of the traffic volume, the time-series is further divided into five time intervals, in order to capture the main rush-hours. The first interval covers the time from 0 to 6 a.m., the second interval from 6 to 11 a.m., the third interval from 11 a.m. to 1 p.m., the fourth interval from 1 to 8 p.m. and the fifth interval from 8 to 12 p.m. Indeed, the division of a day is somehow arbitrary, but a finer discretization of a day will not change the results significantly. Moreover, analyses of city data revealed the existence of basically two rush-hour peaks in the time-series of the traffic volume at about 8 a.m. and 4 p.m. [20, 21].

Figure 7.4 shows the jam probability of the whole data set in driving direction south/west for two time intervals. The main traffic volume occurs in the second and in the fourth interval, that include the rush-hours. In the first time interval, that is 0 to 6 a.m., no jams could be measured. In the time from 11 a.m. to 1 p.m. only a few jams are visible, while from 8 p.m. to 12 p.m. just one region shows jams, namely the region between the Westhofener Kreuz and the Kreuz Dortmund/Unna. The jams therefore occur mainly in the morning and afternoon rush-hours, but for the areas of Köln and Dortmund the probability to find a jam is large even throughout the whole day.

The same picture can be drawn from the analysis of the data set classified in single days that are divided into the five time intervals. Due to the exclusion of the weekends, the values of the jam probability increase significantly. The main disturbances of the network can be measured in the rush-hours, while the regions 2 and 4 show continuously a large

### 7.3 Spatial extension of jams

---

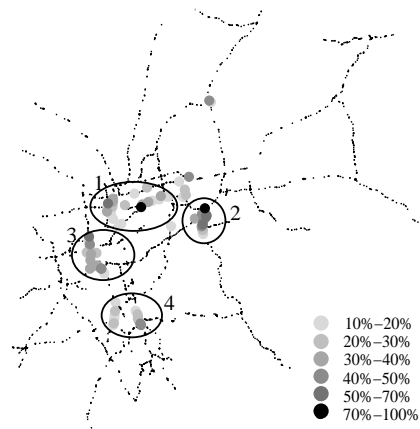


Figure 7.5: Jam probability for the driving direction north/east averaged over the whole data set. The encircled regions are the Ruhrgebiet (region 1), the area of Dortmund (region 2), the area of Krefeld and Düsseldorf (region 3) and the area of Köln (region 4).

traffic load. Again, there are only small differences between the weekdays. On Fridays on the one hand, the load of the network in the time between 6 and 11 a.m. is smaller, but, on the other hand, is increased significantly between 1 and 8 p.m. compared to Monday to Thursday. Moreover, on Sundays, the large jam probability in the area of Dortmund can be traced back to congestions between 1 to 8 p.m.

Analogously to the analysis of the data of the driving direction south/west, the jam probability is calculated for the direction north/east (Fig. 7.5). Like for the driving direction south/west, the same regions with large jam probabilities occur which can be identified as the conurbations of the Ruhrgebiet (region 1), the areas of Dortmund (region 2), Krefeld and Düsseldorf (region 3) and Köln (region 4). In contrast, the region of the Ruhrgebiet (region 1) and the area Krefeld and Düsseldorf (region 3) have a larger jam probability in the direction north/east, while in the direction south/west the area of Köln (region 4) shows a larger traffic volume. In the area of Dortmund (region 2), a large jam probability can be found in the south of the Westhofener Kreuz. Because in the north of the Westhofener Kreuz in the driving direction south a large jam probability was measured, too, one can clearly identify the Westhofener Kreuz as a dominant bottleneck.

Again, the distinction between the days shows no difference to the analysis of the whole observation period with the exception of a larger jam probability in the single regions. In addition, the main traffic volume can be measured in the morning and afternoon rush-hours.

### 7.3 Spatial extension of jams

Calculating the jam probability in the four regions, one can observe that consecutive measurement sections are often jammed even at the same time, which may be a consequence of jams that have a large spatial extension. However, as one can see further, a sequence

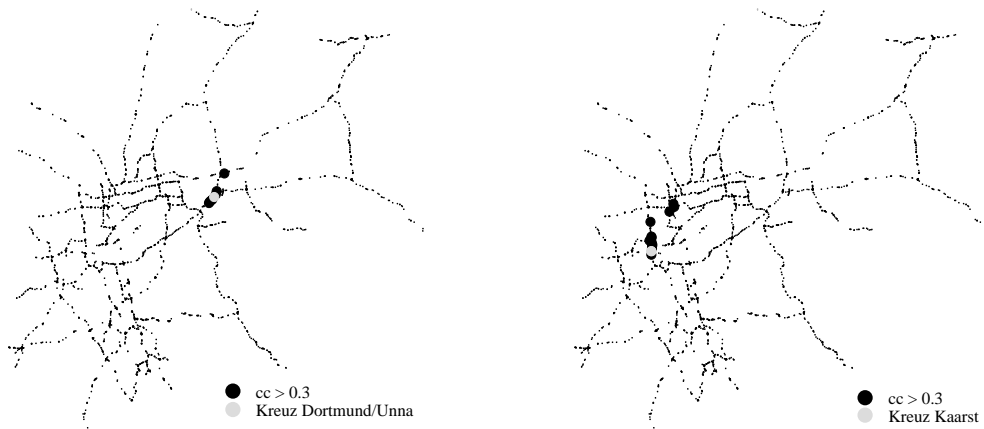


Figure 7.6: Spatial correlation of the activity in the driving direction south/west near the highway intersection Kreuz Dortmund/Unna (left) and in the driving direction north/east near the highway intersection Kreuz Kaarst (right). Correlation values larger than 0.3 are shown.

of jammed detectors is always restricted by highway intersections but not by on- and off-ramps. But more importantly a jam that branches from one highway to another highway via an intersection has been observed only in one case (see below).

In order to determine the spatial extension of a jam, it is necessary to consider its temporal occurrence. Therefore, the time-series of the activity of the measurement locations for the whole observation period have been calculated. The activity of an inductive loop on a certain day is set to one if a jam was measured on that day, otherwise to zero. This results in a binary time-series that allows the calculation of the spatial correlation between different measurement locations. The explicit calculation of the correlation of the density time-series, in contrast, has the disadvantage that the duration of jams decreases in upstream direction, which leads to vanishing correlations.

Although the activity gives only a rough estimation of the jamming state at an inductive loop, the spatial extension of jams can clearly be seen. The large jam probability in region 2 in the driving direction south/west can be related to a jamming of large parts of the A1 between the Westhofener Kreuz and the Kreuz Dortmund/Unna (Fig. 7.6) since the correlation shows large values. The same picture can be drawn in the area of Köln (region 4) where a jam may cover a distance from the Kreuz Köln West and from the Kreuz Köln Ost to the Kreuz Leverkusen. The largest extension of a jam can be found on the A40 (region 1) where strong correlations between the Kreuz Duisburg and the Kreuz Bochum are measured. Obviously, there are also correlations with highways that are very far away from the reference detector, but which are not connected by a sequence of succeeding inductive loops with a large jam probability. The correlations are simply a consequence of a large traffic load of the network, which leads to many jams on various highway sections. Since the number of jams counted at the reference detector is large, correlations of a free flow signal can be excluded.

The correlation analysis of the driving direction north/east reveals strong values on the A57 near the Kreuz Kaarst (Fig. 7.6) and again on the A40 between the Kreuz Bochum

### 7.3 Spatial extension of jams

---

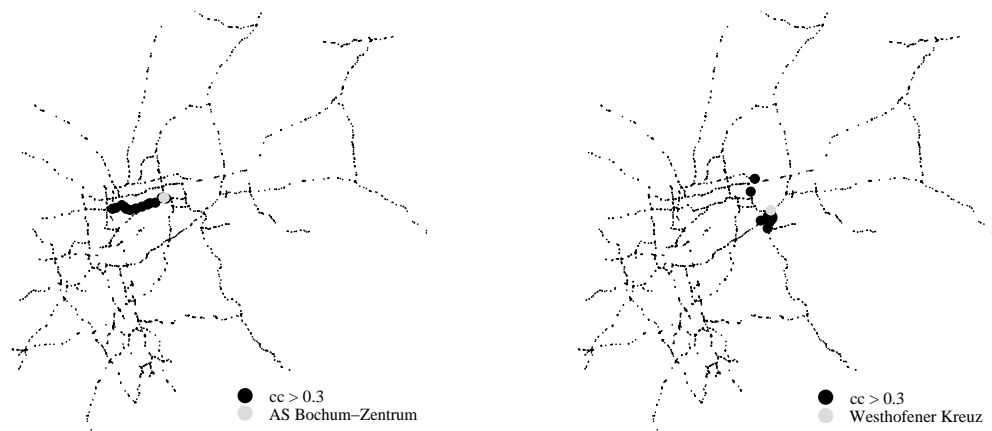


Figure 7.7: Spatial correlation of the activity in the driving direction north/east near AS Bochum-Zentrum (left) and near the highway intersection Westhofener Kreuz (right). Correlation values larger than 0.3 are shown.

and the Kreuz Duisburg (Fig.7.7). A jam measured at the Westhofener Kreuz (Fig.7.7) can branch due to the highways intersection on both, the highway A45 and the highway A1.

The analysis of the activity allows for the daily occurrence of jams, but temporal differences due to the morning or afternoon rush-hours are omitted. Therefore, the activity is classified into the five periods used for the jam probability calculation. This additional consideration of the temporal occurrence of the activity allows a better determination of the spatial correlation of the measurement locations.

The picture of large congested areas on the highways can be confirmed by the correlation analysis of the classified activity. Especially the A40 between the Kreuz Bochum and the Kreuz Duisburg in the directions east and west, the A57 in the vicinity of the Kreuz Kaarst in the direction north and the area of Köln in the direction south/west (Fig. 7.8) show strong correlations of consecutive measurement locations. Since the finer discretization of the activity time-series does not change the results significantly, the classification of the activity into five intervals is sufficient for the proper recording of the temporal occurrence of jams. Thus, although the classified activity is only a rough estimate for the density time-series of a detector, the correlation analysis nevertheless allows the determination of the spatial extension of jams.

The correlation analysis supports the results drawn from the jam probability calculation. Although jams can have a large spatial extension, branching of a jam via a highway intersection is rarely observed. As a consequence one can conclude that the bottlenecks are, except of the Westhofener Kreuz, predominantly not of topological nature, but are a result of perturbations due to on- and offramps. As one can see in Fig. 7.9, most of the sources of the network with a large injection rate are concentrated in the four regions. In addition, most of the sinks can be found there <sup>2</sup>. Therefore, traffic in these four regions

---

<sup>2</sup>The source and sink rate is calculated by summing up the average flow per hour of all lanes at a measurement section. The difference of the total flow between two succeeding sections gives the loss or gain of the number of vehicles.



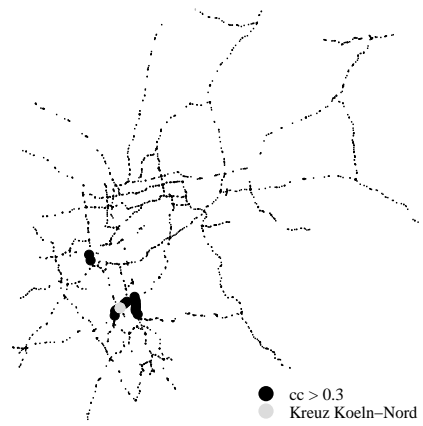


Figure 7.8: Spatial correlation of the classified activity in the driving direction south/west near the highway intersection Kreuz Köln-Nord. Correlation values larger than 0.3 are shown.

is determined by strong fluctuations of the traffic demand and, thus, the flow, resulting in jams with a large spatial extension. However, these jams are restricted to single highways and do not affect traffic in other parts of the network.

Nevertheless, an example of a topological bottleneck is given in Fig. 7.10. The bottleneck is located north of the junction Oberhausen-Lirich on the A3 and is generated by a reduction from three to two lanes in each driving direction. In September 2001 this bottleneck was eliminated by the extension to three lanes. Due to the road works, jams regularly emerged south of the bottleneck. These jams could have an extension up to the Kreuz Breitscheid, passing the Kreuz Kaiserberg undisturbed. For comparison, Fig. 7.10 shows the same part of the network after the road constructions have been finished. Obviously, the probability to find a jam on the A3 south of the junction Oberhausen-Lirich is reduced drastically. A systematical impact on other parts of the highway network, however, cannot be observed.

## 7.4 Conclusion

The analysis of the highway network of North Rhine-Westfalia leads to the following results: The main traffic load concentrates on the inner network where the conurbations of the Ruhrgebiet (region 1), the areas of Dortmund (region 2), Düsseldorf and Krefeld (region 3) and Köln (region 4) are located. In these regions, traffic is predominantly determined by commuter or local traffic. In contrast, the outer regions of the network are dominated by long-distance traffic, indicated by a large truck share on the total traffic volume. Jams can be measured very often in these regions, which leads to jam probabilities of more than 50%. This picture can be confirmed by a more detailed analysis of the traffic data that takes the daily occurrence of jams into account. Like in [20, 21], the days can be classified into monday to thursday, friday, saturday and sunday. However, the time a jam emerges is considered by the subdivision of one day into five intervals. As a result, most of the jams can be traced back on the morning and afternoon rush-hours, but for the areas of Köln (region 4) and Dortmund (region 2), the probability to find a jam is large during

## 7.4 Conclusion

---

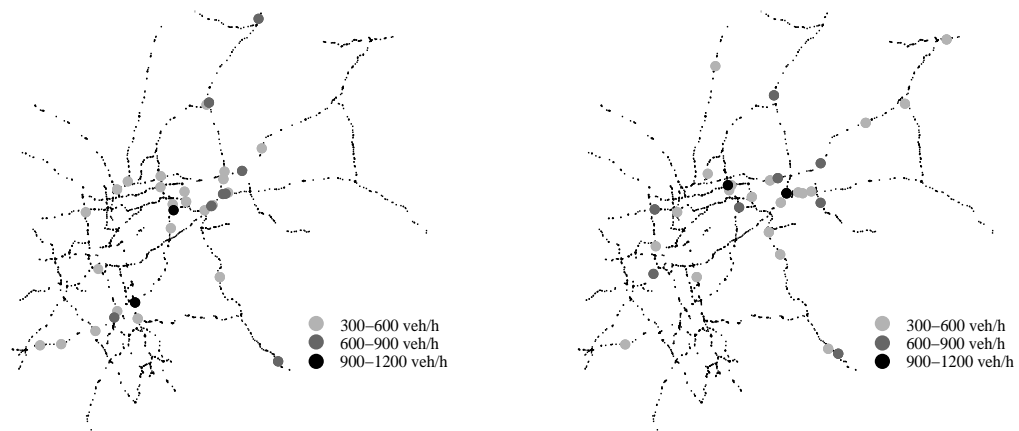


Figure 7.9: Source rate (left) and sink rate (right) in the driving direction south/west given by the difference of the average flow per hour between two succeeding measurement sections.

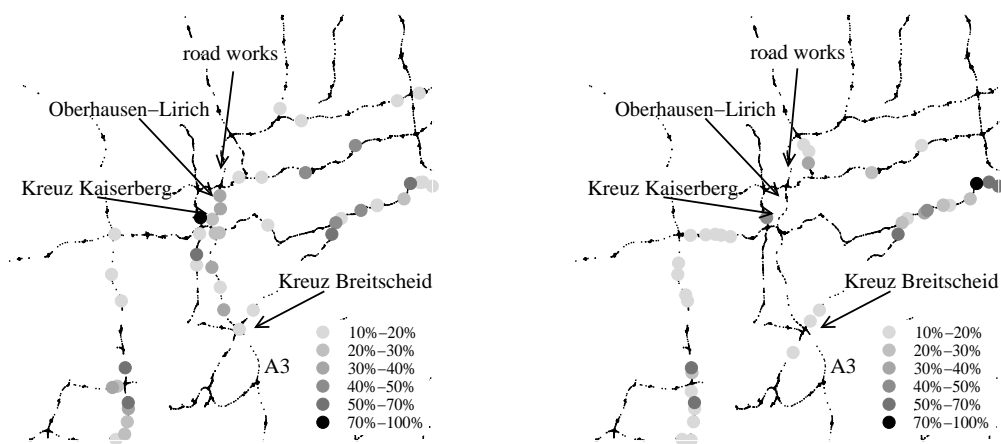


Figure 7.10: Jam probability in the driving direction north/east in October 2000 during the road constructions north of the junction Oberhausen-Lirich (left) and in October 2001 after finishing the road construction (right).

the whole day. In addition, on Fridays, the main traffic load is shifted from the morning to the afternoon rush-hour.

The correlation analysis of the activity takes the temporal occurrence of a jam at consecutive measurement locations into account. Large correlations between succeeding detectors in the four regions can be measured. Nevertheless, the jams are mainly restricted to single highways and do not branch on other highways via intersections. The only topological bottleneck that can be identified is the highway intersection Westhofener Kreuz. A

more detailed calculation of the correlation by means of a classified activity confirms these results.

The bottlenecks of the network are therefore predominantly on- and offramps rather than topological peculiarities of the highway system. It is the large in- or outflow at ramps that perturbs the stream of vehicles on the main highway. As proposed in [56, 124], it has to be expected that ramp metering systems are able to counteract these destabilization of the flow and reduce the formation of jams. Moreover, the restriction of a jam to a certain highway section supports the application of localized optimization strategies. Indeed, the optimum of the network's traffic throughput can only be reached by a global traffic management system. Nevertheless, in contrast to urban traffic [14], the local character of the bottlenecks will allow a further improvement of the road capacities by means of locally applied strategies and without modifications of the underlying infrastructure.

## 8 Summary and outlook

The objective of this thesis has been to give insight into the vehicle interactions in the various traffic states and to develop a microscopic model for traffic flow that provides a satisfactory description of the empirical findings. Moreover, the question has been raised which effects of the human driving behavior are responsible for the formation of the elusive synchronized traffic.

As the main conclusion of this thesis it turns out that the incorporation of the human desire for smooth and comfortable driving into the driving strategy of vehicles leads to a model that is able to reproduce synchronized traffic.

Most of the present modeling approaches concentrate on the fact that drivers want to avoid accidents. In these models the velocity adjustment of a vehicle is calculated within an interaction horizon limited by the speed of a vehicle that often leads to abrupt velocity changes. In contrast, the analysis of empirical single-vehicle data reveals that especially in the synchronized state the velocity of a vehicle is considerably smaller than the distance to its predecessor would allow and that, therefore, a vehicle is able to avoid strong accelerations and abrupt brakings. In the present study this driving behavior is incorporated in a cellular automaton model that is based on the model of Nagel and Schreckenberg [106] and that is able to reproduce *all* empirically observed traffic states even on a microscopic level. The accordance with the empirics is already obtained by the simulation of a single-lane road with periodic boundaries without tuning the boundary conditions. The extension to two-lane traffic, however, allows the synchronization of the lanes and even the coexistence of synchronized traffic and wide moving jams that both have been observed empirically. The detailed results of the thesis are the following:

Based on an analysis of one of the largest set of single-vehicle data used so far, the microscopic properties of the various traffic states have been refined in chapter 3. Furthermore, a description of the driving behavior of the vehicles in the three traffic states has been provided: In free flow, platoons of vehicles driving bumper-to-bumper with a large velocity and a small time-headway can be found. Within these platoons, the vehicles are driving with nearly the same velocity, leading to a large stability of the clusters. In synchronized traffic, the clusters are dissolved but, nevertheless, large correlations of the velocity of single-vehicles can be observed, while the distance-headways are not correlated – the vehicles are moving in unison, e.g., synchronized. As a result, the velocity-headway curve saturates for even small headways and shows a small asymptotic velocity that depends not only on the density but also on the traffic state. In a wide jam, the retarded acceleration behavior of the vehicles at rest (a vehicle needs about 2 s to escape from a jam) results in a considerably reduced outflow from a jam compared with the maximum possible flow. Besides, the analysis presented in chapter 3 confirms the basic results of other empirical studies [110, 133]. However, the time-headway distribution found in [110] cannot be reproduced but can be traced back to errors of the measurement software that has been used.

Since existing cellular automaton models cannot reproduce all of the traffic states observed empirically, the driving behavior of the vehicles is mimicked in the model developed in

chapter 4 by the incorporation of anticipation and brake lights and can be summarized as follows: In free flow, the anticipation of the predecessor's movement allows the reduction of the headway at a given velocity and decreases velocity fluctuations which enables the vehicles to drive bumper-to-bumper. In synchronized traffic, large headways can be observed because of the retarded acceleration of the vehicles. Moreover, brake lights signalize acceleration changes of the downstream vehicles and help the vehicle to adjust its velocity timely. Finally, in a wide jam the limited acceleration capability of a vehicle at rest allows to reduce the outflow from a jam considerably compared to free flow.

It turns out that the model is able to reproduce the three empirically observed traffic states on a macroscopic level. But more important is the fact that the calibration and validation of the model by means of empirical single-vehicle data reveals a good agreement with the empirics even on the microscopic level of description.

In chapter 5 it was shown that the desire for smooth and comfortable driving stabilizes the flow in dense traffic and gives rise to the synchronized state. Therefore, a two-lane segment of a highway with open boundary conditions was considered. Vehicles can enter the highway at the left boundary as well as from an onramp that is explicitly simulated as a merging road and not as a defect [25]. A large input from the onramp generates, in combination with a large flow on the highway segment, a synchronized region that is pinned at the onramp. A wide jam induced by an obstacle propagates undisturbed through this synchronized region in accordance with empirical findings [73]. This coexistence of traffic states and the propagation of a wide jam through free flow as well as synchronized traffic, which so far could not be observed in traffic flow models [44, 45], clearly demonstrates that the model is capable to reproduce *all* empirically observed traffic states. Moreover, in contrast to other model approaches [137] where parameters have to be adjusted in order to implement inhomogeneities, the onramp is only used to trigger the traffic states that can already be observed in a periodic system.

Although these results are quite robust and do not depend on the special choice of the lane changing rules, the application of the model to more sophisticated topologies should be accompanied by a more detailed description of the empirical lane changing characteristics. To this end, in chapter 6 an asymmetric two-lane rule set was developed. The separation of the velocity and the lane changing update allows the validation and calibration of the two-lane rules without modifying the vehicle dynamics. It turns out that only the simultaneous application of a right lane preference and a right lane overtaking ban is capable to reproduce the lane-usage inversion empirically observed on German highways [94, 130]. Moreover, the model shows a realistic density-dependence of the number of lane changes. But more important is that local measurements of the minute averaged velocity and flow confirm the strong correlation of neighboring lanes in the synchronized regime. As a consequence, it is possible that a jam on the right lane induced by an onramp spreads to both lanes.

In chapter 7 an analysis of empirical traffic data of the highway network of North-Rhine-Westfalia was presented that clarifies the nature of its bottlenecks and supports the applicability of ramp metering systems [111]. Such systems restrict the onramp flow in order to inject the amount of vehicles that can be absorbed by the gaps between the vehicles on the highway. One can observe jams having a large spatial extension and which predominantly do not spread to other highways across highway intersections. The analysis of the correlation of the activity between measurement locations confirms this fact. Consecutive detectors are strongly correlated, since a jam covers a large highway section leading to a similar time-series of the activity at different measurement locations. However, the strong correlations are restricted to detectors between two highway intersections. Thus,

---

the bottlenecks of the network are in the majority of cases on- and offramps that are characterized by a large inflow rather than topological peculiarities of the underlying infrastructure. In contrast to urban traffic where road intersections determine the system's throughput [14], highway traffic is dominated by the dynamics between but not at highway crossings.

To conclude, the model proposed in this thesis and that has been developed by means of a systematical and empirically validated advancement of the Nagel and Schreckenberg model provides a basis for the detailed microsimulation of highway traffic. The degree of realism of the model opens the perspective for future applications of traffic simulations for traffic forecasting and dynamic route guidance systems.

The results presented in this study motivate new research in various fields of traffic flow modeling:

First of all, simulations of realistic traffic scenarios will reveal the optimization potential of the approach. One of the most realistic scenarios the model can be tested with is given by the highway network of North-Rhine-Westfalia. The embedding of the model into the existing online simulation of this network [62] allows the comparison of the simulation with real traffic dynamics and further improvements of the model.

However, these applications require the extension of the lane changing rules in order to provide a detailed description of more sophisticated lane changing situations like three-lane traffic, onramps and merging traffic in the vicinity of bottlenecks. Here, the introduction of indicators may help to reproduce lane changing situations that require an interaction of the changing vehicle with its neighbors on the destination lane.

In this context, the behavior of a single-lane system with open boundaries and defect sites (the analogue to onramps) should systematically be analyzed. Due to the anticipation of breakdowns, disturbances of the flow will probably not be pinned at the defect but move in upstream direction, and therefore the impact of defect sites is reduced compared to other variants of the Nagel and Schreckenberg model [116].

Moreover, it seems to be useful to compare the phase diagram of an open system equipped with an onramp with empirical findings and other models [137] in order to validate the dynamics in the synchronized state. In particular, empirical observations suggest that the outflow of the synchronized region can strongly fluctuate, but these fluctuations are related to changes in the upstream flows rather than to fluctuations of the discharge flow [72].

Theoretical studies of the Asymmetric Simple Exclusion Process with open boundary conditions show the existence of boundary induced phase transitions between several traffic phases in dependency of the inflow and outflow rates [83]. However, the introduction of meta-stability changes the characteristics of the various phases and leads for finite systems to flows larger than those in the maximum-current phase [1]. In the presence of synchronized states a further change of the phase diagram has to be expected, especially regarding the maximum-current phase that is important for the optimization of the capacity of a highway. Moreover, empirical observations of boundary induced phase transitions that confirm the existence of such a phase are still missing (see [115]).

It has been shown that an increment of the possible states of a vehicle, i.e., the maximum velocity, leads to meta-stable states that cannot be observed in the original model of Nagel and Schreckenberg. The underlying mechanisms giving rise to these states are, unfortunately, far from being clarified [36] and may be traced back to the reduced acceleration capability of moving vehicles.

Finally, in order to improve the characterization of the complex spatio-temporal structures observed in real traffic, and especially the transitions between them, the analysis of empirical single-vehicle data that is provided by a set of *consecutive* detectors is necessary.

In particular, the identification of single vehicles at two measurement locations would provide information about correlations of their travel-times that can be used to draw further conclusions about the dynamics in the various traffic states. This is done for example for packet transport in the Internet [57].

## A Cross-correlation of unevenly sampled data

The main problem in the analysis of empirical time-series are irregular observation times or gaps in the observations, i.e., data that are not evenly spaced. In contrast, the classical definition of the correlation function of two observables  $X$  and  $Y$  measured at  $N$  points

$$c_{XY}(\tau) = \frac{1}{N} \sum_{n=1}^{N-\tau} X_n Y_{n+\tau}$$

requires evenly spaced data. There are some approaches for filling the gaps in the time-series, but nevertheless the original time-series is changed by these methods. In order to circumvent these problems, the correlation is calculated in the frequency domain and then transformed back to the time domain. The correlation theorem [60] states, that the cross spectrum of two functions is the Fourier transform  $F$  of its cross-correlation function:

$$c_{XY} = F^{-1}[F_X(\omega)F_Y^*(\omega)].$$

The Fourier transform of unevenly spaced data  $\{X_n = X(t_n), n = 1, 2, \dots, N\}$  is computed after [126] and is defined to be:

$$F_X(\omega) = F_0 \sum_{n=1}^N \left( AX_n \cos(\omega t'_n) + iBX_n \sin(\omega t'_n) \right)$$

where

$$F_0(\omega) = \sqrt{\frac{N}{2}} e^{-i\omega t_1}, \quad t'_n = t_n - \tau(\omega)$$

and

$$A(\omega) = \frac{1}{\sqrt{\sum_n \cos^2(\omega t'_n)}}, \quad B(\omega) = \frac{1}{\sqrt{\sum_n \sin^2(\omega t'_n)}}$$

and

$$\tau(\omega) = \frac{1}{2\omega} \tan^{-1} \left( \frac{\sum_n \sin(2\omega t_n)}{\sum_n \cos(2\omega t_n)} \right).$$

$t_1$  is determined by the origin of time. See [126] for details of the computing the Fourier transform and for a Fortran code. Inversion back to the time domain can be accomplished using the Fourier transform for evenly spaced frequencies.



## B Continuous limit of the NaSch model

The adjustment of the acceleration of the vehicles in the original NaSch model to empirical values (that are about  $1 \text{ m/sec}^2$  [135]) requires the decrement of the length of a cell. This, however, entails an increment of the maximum possible velocity for a given fixed absolute value of  $v_{\max}$ . It turns out, that already the increment of the number of states a vehicle is allowed to adopt leads to hysteresis effects of the flow. In particular, the flow can be enhanced in a certain density regime by initializing homogeneously the vehicles on the lattice compared to a pure random initial setup. As a result, in the limit  $v_{\max} \rightarrow \infty$  [55, 125] the system exhibits meta-stable states (Fig. B.1) with a flow increasing proportional with  $v_{\max}$ , but with a rapidly decreasing lifetime.

Unfortunately, increasing only  $v_{\max}$  leads to a significant decrement of the density of maximum flow. Thus, in order to keep the maximum velocity fixed the limit  $v_{\max} \rightarrow \infty$  with  $v_{\max}/l = \text{const.}$ , where  $v_{\max}$  and the vehicle length  $l$  are given in cells, has to be considered. As one can see in Fig. B.1 hysteresis occurs with finer discretizations. Since the acceleration step of a vehicle is decreased considerably, velocity fluctuations and vehicle interactions in free flow are reduced. A random initialization of the system does not allow the high flow states so that hysteresis can be observed due to different initial conditions (Fig. B.2). On one hand, with increasing deceleration probability  $p_{\text{dec}}$  the stability of the homogeneous flow branch of the fundamental diagram decreases, but on the other hand the capacity drop increases (Fig. B.2).

Unlike in the VDR model [8], the origin of the high flow states cannot be traced back to a reduction of the outflow from a jam but to the stability of the free flow state (Fig. B.3). A system with cars of length  $l$  and deceleration probability  $p_{\text{dec}}$  behaves like a NaSch model with cars of length 1 and a considerably smaller deceleration probability of about  $p_{\text{dec}}/l$  (unlike in the cruise control limit of the NaSch model [105] where cars that are driving with  $v_{\max}$  have a deceleration probability  $p_{\text{dec}}(v_{\max}) = 0$ ). In contrast, in the congested regime the influence of the cell length can be neglected and a system with decreased cell length behaves analogously to the NaSch model with the same deceleration probability, e.g., the dynamics of the vehicles in the congested regime of the NaSch model is maintained.

For realistic traffic simulations it is important that the high flow states are meta-stable for finite systems in the sense that the probability for a perturbation that leads to a collapse of the flow is only very small. Nevertheless, in the thermodynamic limit the high flow states become unstable so that the homogeneous branch of the fundamental diagram vanishes.

In order to study the phase transition an order parameter that exhibits a qualitatively different behavior within the two phases is introduced. Because of the mass conservation in the NaSch model with periodic boundary conditions the density  $\eta$  of jammed cars is observed:

$$\eta = \frac{1}{L} \sum_{i=1}^N \delta_{v_i,0}. \quad (\text{B.1})$$

In the NaSch model  $\eta$  decays exponentially in the vicinity of the transition [27] whereas a sharp drop occurs in the VDR model [24]. Due to the finite braking probability in

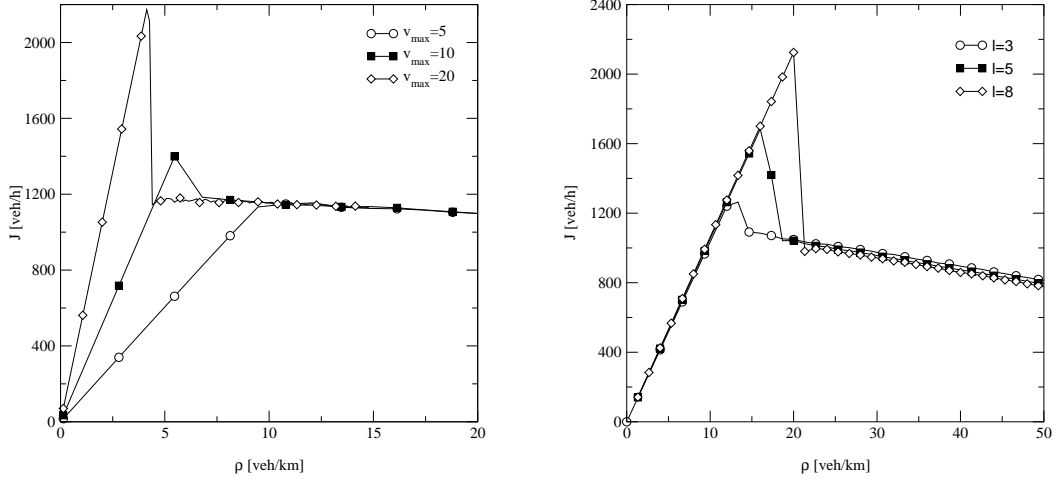


Figure B.1: Left: Fundamental diagram of the NaSch model with different  $v_{max}$  and homogeneous initialization. Right: Fundamental diagram of the NaSch model for a homogeneous initialization with  $p_{dec} = 0.5$  for different discretizations, e.g., a cell has a length of  $\frac{7.5 m}{l}$  where  $l$  is the length of a vehicle

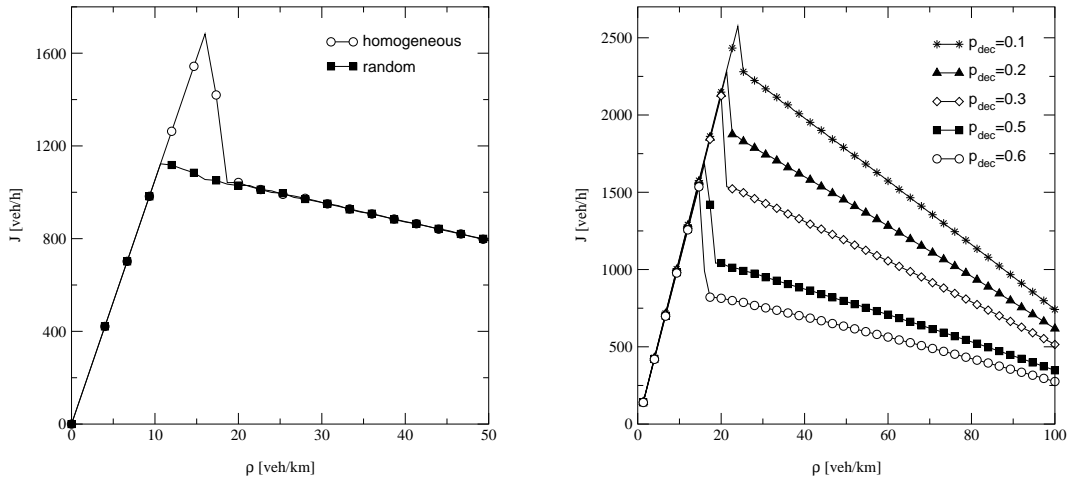


Figure B.2: Left: Fundamental diagram for a different system initialization of the NaSch model with a cell length of 1.5 m and  $p_{dec} = 0.5$ . Right: Fundamental diagram for different  $p_{dec}$  of the NaSch model with a cell length of 1.5 m for a homogeneous initialization. A car has a length of 5 cells.

the NaSch model cars with zero velocity do exist even at densities below the transition density. In contrast, due to the small deceleration probability in the VDR model one macroscopic jam forms only at densities above the transition density. With increasing  $p_{dec}$  the transition smears out.

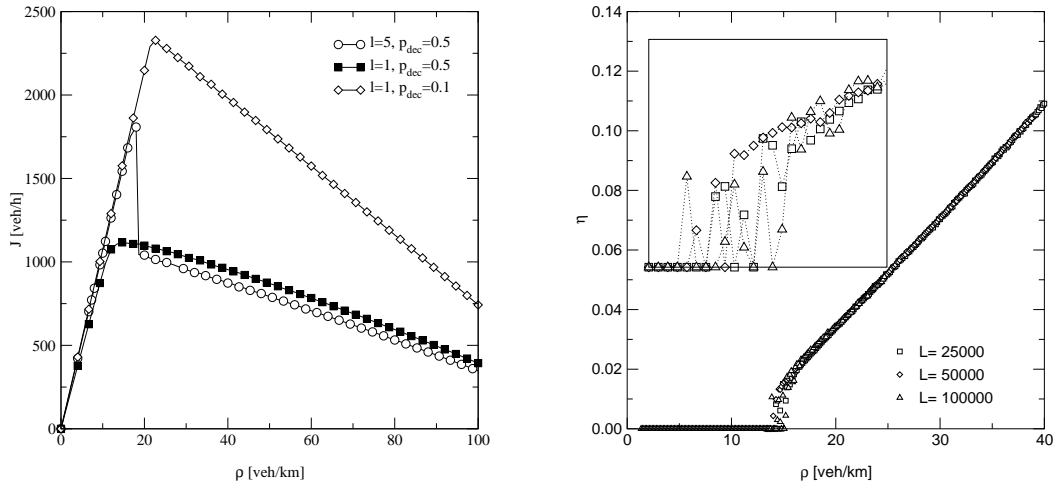


Figure B.3: Left: Fundamental diagrams of the NaSch model with a finer discretization compared with the original NaSch model with different deceleration probabilities.  $l$  denotes the length of a vehicle, a cell has a length of  $\frac{7.5}{l}$  m. Right: Order-parameter  $\eta$  for the NaSch model with a cell length of 1.5 m and different system sizes  $L$  for  $p_{\text{dec}} = 0.5$  and a homogeneous initialization. The inset zooms into the transition region.

Analogously to the VDR model, the order parameter of the NaSch model with a finer discretization (Fig. B.3) shows a transition from zero to a linear dependency of the density. With increasing system size the high flow states become unstable and the jump in the order parameter vanishes which demonstrates the meta-stability of the high flow states.