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Using connected vehicles in a variable speed limit system

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Abstract

Variable speed limit systems are used to improve the traffic conditions on specific road stretches. This is done by adjusting the speed limits according to current traffic situations. A variable speed limit system usually consist of stationary detectors to estimate the traffic state and variable message signs at predefined locations for the application of new speed limits. Advances in vehicle technology have made it possible to use connected vehicles to improve existing variable speed limit systems. Connected vehicles can continuously transmit information about speed and location. This can be used to get more detailed information about the traffic state. By including information from connected vehicles in a variable speed limit system there is a potential to identify bottlenecks also in between stationary detectors. Further, it is possible to use direct control of the connected vehicles to adjust vehicle speeds towards the new traffic situation. In this study, we propose such a variable speed limit system based on connected vehicles. The aim is to allow for application of variable speed limits in connection with non-recurrent bottlenecks. The proposed system is evaluated with respect to traffic efficiency using microscopic traffic simulation. An incident is simulated as an example of a non-recurrent bottleneck. The traffic performance when the proposed VSL system is applied is compared to the performance without the system. The results indicate that the VSL system manage to improve traffic efficiency in a majority of the simulated cases.

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Keywords: connected vehicles; variable speed limit; traffic management; microscopic traffic simulation; traffic efficiency

1. Introduction

Variable Speed Limit (VSL) systems make use of an estimate of the current traffic state, described by traffic density, speed and flow, to adjust the speed limit towards the traffic situation on a specific road stretch. The goal is to improve the traffic situation with respect to safety and/or efficiency. However, the estimate of the traffic state is usually based on data from stationary detectors and the VSL is displayed on variable message signs at predefined locations. The development in vehicle technology has opened up for a new type of VSL systems based on connected vehicles. Connected vehicles are able to continuously transmit and receive information about their current speed, position on the road, speed limit, etc. Therefore, an enhanced VSL system can take advantage of connected vehicles both for traffic state estimation and for the application of VSLs.

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In this paper, we propose a VSL system including connected vehicles with the potential to increase traffic efficiency at non-recurrent bottlenecks. The aim is to allow application of VSLs at non-recurrent bottlenecks with limited use of stationary detectors and variable message signs (VMSs). In the proposed VSL system, connected vehicles are used as sensors and to communicate variable speed limits to individual vehicles. This allow for traffic state estimation at arbitrary locations, unlike today's VSL systems which uses traffic state estimates based on data from stationary detectors at fixed locations. Thereby, the need for expensive infrastructure can be reduced. The current speed limit is communicated directly to the connected vehicles instead of using VMSs. This allows direct control of the speed of connected vehicles towards the new speed limit, similar to an adaptive cruise control. Hence, the proposed VSL system consists of three parts: (1) estimation of the traffic state using information from connected vehicles, (2) calculation of an appropriate variable speed limit by identification of non-recurrent bottlenecks based on changes in the traffic state, (3) application of the variable speed limit through direct control of the speed of the connected vehicles. In this study, we use microscopic traffic simulation for evaluation of the effects on traffic efficiency of the proposed VSL system. An incident scenario is simulated as an example of a non-recurrent bottleneck. Traffic performance with the proposed VSL system is compared to the performance without the system.

The reminder of the paper is organized as follows. In Section 2, a background to the methods used in the different parts of the VSL system is given. The proposed VSL system is presented in Section 3. In Section 4, the evaluation method and the simulated incident scenario are described. Simulation results are presented in Section 5. Finally, conclusions are given in Section 6.

2. Background

The proposed VSL system consists of an estimate of the traffic state based on data from connected vehicles; identification of non-recurrent bottlenecks as changes in the traffic state; and application of a VSL control strategy based on the estimated capacity levels by direct control of connected vehicles.

The most common way to estimate the traffic state is to make use of data from stationary detectors, such as for example loop and radar detectors (Kurkjian et al., 1980; Coifman, 2003; Singh and Li, 2012). This is limiting the traffic state estimation to specific points in space, and the conditions in between detectors remains unknown. Data assimilation and fusion techniques based on filters and traffic modelling are common methods to get the complete picture of the traffic state in between the detectors, see for example Munoz et al. (2003), Mihaylova et al. (2007), Wang and Papageorgiou (2005) and Duret et al. (2016). As more sources of traffic data are becoming available, e.g. data from connected vehicles and mobile phones, these have been used as input to update the modelled traffic state. Examples are presented by Herrera and Bayen (2007), Work et al. (2010) and Seo et al. (2015b). Other methods that are making use of data from connected vehicles for traffic stated estimation without an underlying traffic model are presented by Herrera et al. (2010), van Lint and Hoogendoorn (2010), Ma et al. (2011), Seo et al. (2015a), Montero et al. (2016) and Grumert and Tapani (2017b).

The process of identifying changes in the traffic state is often referred to as incident detection. In order for the incident detection to be useful in a VSL system it has to be automatically triggered by an underlying algorithm. In automatic incident detection algorithms the approach is either statistical using artificial intelligence and machine learning (Payne et al., 1976; Samant and Adeli, 2001; Wang et al., 2013; Kinoshita et al., 2015) or based on traffic modelling (Wang et al., 2009; Dabiri and Kulcsár, 2015; Grumert and Tapani, 2017a). Traffic modelling based algorithms use a traffic model to estimate the traffic state and changes in the model parameters are monitored to identify an incident. The model parameters can be estimated based on on-line calibration, such as described by Wang and Papageorgiou (2005), Antoniou et al. (2007) and Tampère et al. (2007).

Finally, a VSL is applied at the identified non-recurrent bottlenecks based on the observed changes in the traffic state. VSL systems can be categorized into two main types, *incident detection* systems and *homogenization* systems. Incident detection systems, sometimes also referred to as warning systems, have as main objective to resolve congestion caused by an incident and limit the risk of further breakdown. Homogenization systems have as aim to reduce differences in speed to reduce potential instabilities and to keep the capacity as high as possible. The main difference between the systems is that homogenization systems are often applied before reaching congested traffic states, while incident detection systems are triggered when a breakdown, i.e. very low speed situations, in the traffic states is detected. As a result, the speed limit is often reduced gradually, while more abrupt speed limit changes often are applied in incident detection systems. Up until now, most real implementations of variable speed limit systems are of incident detection systems, although combinations of incident detection and homogenization systems does also exist. Empirical studies of the effects of incident detection systems (van den Hoogen and Smulders, 1994; Smulders and Helleman, 1998; Highway Agency, 2007; Nissan and Koutsopoulos, 2011) have shown a reduction in the number of incidents and a decreased variance in mean speed between lanes. No increase, or even a decrease, is seen in the throughput, i.e. traffic efficiency is not increased by the systems. Since the aim of the proposed VSL system is to increase traffic efficiency at non-recurrent bottlenecks it is suitable to use a homogenization algorithm, such as the one described in Carlson et al. (2011).

The growing amount of technology related to connected vehicles have resulted in recent studies where connected vehicles are used as a part of VSL systems. Kattan et al. (2015) extend a VSL algorithm by Hegyi et al. (2005) which is based on model predictive control. The aim is to minimize travel time by including measurements of speed from connected vehicles. Khondaker and Kattan (2015) take into account estimates of each connected vehicle's total travel time, time to collision and emission levels and optimize the corresponding aggregated values in the model predictive control strategy. The goal of the optimization is to find the VSL to be displayed on VMSs. Wang et al. (2016) introduce a car-following control algorithm taking into account the surrounding environment of the connected vehicles. Here, the desired speed of the individual vehicle control is based on the VSL algorithm SPECIALIST by Hegyi et al. (2008). Han et al. (2017) use connected vehicles to control the inflow at a recurrent one-lane bottleneck in a way that maximum throughput is guaranteed and the capacity drop is avoided. Hence, connected vehicles have shown to be useful for both data collection and to estimate the traffic state, which is used as input to the VSL system (Kattan et al., 2015; Khondaker and Kattan, 2015), and for control of the speed of individual vehicles as part of the control strategy of the VSL system (Wang et al., 2016; Han et al., 2017). As a conclusion, using connected vehicles in a VSL system for estimation of traffic states, and to control the speed of connected vehicles, is a promising strategy to fulfil the goal of increasing traffic efficiency at arbitrary locations along a road.

In this study, we estimate the traffic state based on connected vehicles and sparsely placed detectors following the approach developed in earlier research (Grumert and Tapani, 2017b). The identification of non-recurrent bottlenecks is traffic model based with estimation of model parameters to identify changes in the traffic state, similar to what has been proposed by Wang and Papageorgiou (2005), Wang et al. (2009) and Tampère et al. (2007). Finally, the VSLs are set according to the method by Carlson et al. (2011).

3. A variable speed limit system using connected vehicles

The previously introduced steps; (1) traffic state estimation, (2) identification of non-recurrent bottlenecks by estimation of model parameters (capacity levels), and (3) calculation of a suitable control strategy for direct control of the speed of the connected vehicles; are described in more detail in this section. First, consider a road stretch divided into K segments, with an arbitrary length X_k. These segments are further divided into equally long sub-segments $i = 1,2,\cdots,I_k$. I_k is the number of sub-segments in segment k. The length of sub-segment i is calculated as $x_{k,i} = X_k/I_k$. Since connected vehicles are able to receive and transmit information continuously they can be used to estimate the traffic state for each sub-segment. See Figure 1 for an illustration of the division of a segment into sub-segments.

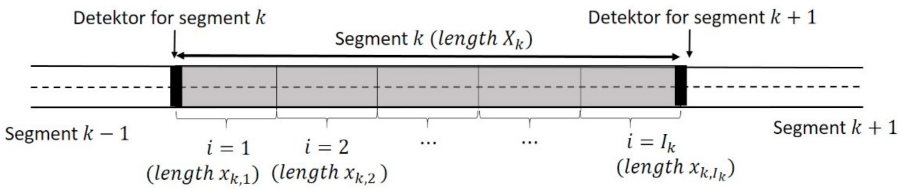

Figure 1: Illustration of one segment k and how it is further divided into sub-segments i.

In this study connected vehicles are used together with sparsely placed detectors, as suggested in earlier research (Grumert and Tapani, 2017b), to estimate traffic density and speed for each sub-segment. The Count Connected Vehicle (CCV) method presented by Grumert and Tapani estimate the traffic density based on the connected vehicle penetration rate for segment k, together with the average number of connected vehicles, $\overline{P_{k,i}(T, x_{k,i})}$, located within each sub-segment i. Thereby, the density on each sub-segment can be estimated even though the penetration rate is only based on the detector data in the beginning of the segment. The penetration rate is calculated as the number of connected vehicles, M_k, divided by the total number of vehicles, N_k, gathered from the detector station located in the beginning of segment k. The detector data and the connected vehicle data is collected and processed over an aggregation time period T. The density estimate for sub-segment i on segment k becomes,

$$\rho_{k,i}(T, x_{k,i}) = \frac{\overline{P_{k,i}(T, x_{k,i})}}{x_{k,i}} \frac{1}{M_k/N_k}. \tag{1}$$

By assuming that the distribution of speed is the same for connected and non-connected vehicles the speed estimates, $v_{k,i}(T, x_{k,i})$, for a sub-segment is given as an average over the speed of all connected vehicles located on the sub-segment.

The density and speed estimates are used as input to a filtering approach. The filter is applied to estimate the current capacity level by on-line calibration of the model parameters of a traffic model. This is similar to the methods described by Wang and Papageorgiou (2005), Antoniou et al. (2007) and Tampère et al. (2007). The filtering and the macroscopic traffic model is only used for estimation of the model parameters in the fundamental diagram. Hence, a first-order model of the traffic evolution is deemed to be enough to identify non-recurrent bottlenecks and to find the current capacity levels. This is supported by Tampère et al. (2007), who conclude that a first-order model is enough to capture the capacity levels by on-line estimation of the model parameters. An ensemble Kalman filter (Evensen, 2003; van Lint and Hoogendoorn, 2010) is used to adjust the model output according to the estimated speed and density given from the CCV method. In an ensemble Kalman filter an ensemble, represented by a set of samples of the traffic state, are propagated in time based on the traffic model. The distribution of the ensemble, represented as a mean and a covariance matrix, is calculated in each time step. The mean is used to estimate the current traffic state, while the complete distribution is used for propagation of the ensemble to a future traffic state. In our case, the traffic model is a first order model (Lighthill and Whitham, 1955) based on the vehicle conservation and assuming local equilibrium, i.e. the continuity equation,

$$\frac{\partial \hat{\rho}_{k,i}}{\partial t} + \frac{\partial Q_e}{\partial x} = 0. \tag{2}$$

$\hat{\rho}_{k,i}$ is the traffic density in the traffic model on segment k and sub-segment i. The flow in local equilibrium, $Q_e(\hat{\rho}_{k,i})$, is assumed to be represented by a triangular fundamental diagram,

$$Q_e(\hat{\rho}_{k,i}) = \begin{cases} V_{k,i}^{f}\hat{\rho}_{k,i}, & \hat{\rho}_{k,i} \le \hat{\rho}_{k,i}^{cap} \\ \dfrac{1}{g_{k,i}}\left(1 - \dfrac{\hat{\rho}_{k,i}}{\hat{\rho}_{k,i}^{max}}\right), & \hat{\rho}_{k,i}^{cap} < \hat{\rho}_{k,i} \le \hat{\rho}_{k,i}^{max} \end{cases} \tag{3}$$

where $\hat{\rho}_{k,i}^{cap}$ is the traffic density at capacity, $V_{k,i}^{f}$is the free flow speed, $g_{k,i}$ is the time gap to the vehicle in front and $\hat{\rho}_{k,i}^{max}$ is the maximum traffic density, or the jam density. The modeling parameters are specific for each sub-segment i on segment k. The above traffic dynamics are modeled with the Cell Transmission Model (CTM) (Daganzo, 1994). The CTM uses a Godunov scheme to discretize the model equations in time and space. A noise term of the CTM model is included in order to take into account that the model is not perfect in describing the true state. This is similar to what is done in Seo et al. (2015b). The model parameters and the boundary conditions are modeled as random walks. Thereby, the ensembles with highest probability of representing the true state at each time steps are the once that are most probable to correspond to the best values of the model parameters as well.

The non-recurrent bottlenecks are identified through changes in the triangular fundamental diagram. The VSL system will be continuously controlled towards the current estimated capacity based on the VSL algorithm, presented by Carlson et al. (2011). The VSL algorithm is developed for recurrent bottlenecks where the capacity is estimated in advance. However, by estimating the capacity level for each sub-segment based on on-line calibration, non-recurrent bottlenecks can be identified. A suitable VSL can be applied based on the estimated capacity level. The difference between the estimated capacity and the current estimated traffic state on the road is used to adjust the speed limit. Let $e_{k,i}^{\rho}(t)$ be the density error at time t and for sub-segment i on segment k, calculated as the difference between the estimated critical density (at capacity), $\hat{\rho}_{k,i}^{cap}(t)$, and the estimated density, $\rho_{k,i}(t)$. The final output of the VSL algorithm is the fraction of the maximum speed limit on the road to be applied at time t and for sub-segment i on segment k,

$$b_{k,i}(t) = b_{k,i}(t-1) + K_I' e_{k,i}^{\rho}(t), \tag{4}$$

where K_I' is an integral gain. The critical density is in our case given from the on-line calibration of the model parameters in the triangular fundamental diagram. The final variable speed limit becomes $VSL_{k,i-2}(t) = b_{k,i}(t) \cdot VSL_{max}$ and is applied to connected vehicles at the segment 500 meters upstream of the considered segments, i.e. at segment i, based on the approach in Carlson et al. (2011). Here, VSL_{max} is the basic speed limit on the road. At the edge of the segments the VSL is applied to sub-segments on the upstream segment, $k-1$.

4. Evaluation method

The proposed VSL system require communication of information from, and control of, individual connected vehicles. Therefore, since it describes individual vehicles in the simulated traffic stream, a microscopic traffic simulator is used to evaluate the VSL system. We use the open-source microscopic traffic simulation tool SUMO (Krajzewicz et al., 2012; DLR and contributors, 2016). The connected vehicle and detector data is accessed during the simulation through SUMO's Traffic Control Interface (TraCI). Python scripts are used to implement the VSL algorithm and for assigning VSLs to the connected vehicles during the simulation.

The simulation scenario consists of a one directional two-lane motorway, divided into twenty 250 meter sub-segments. Further, a segment for loading of vehicles on to the simulated road and an end segment are included to avoid boundary effects, resulting in a 6 km long simulated road. The basic speed limit on the road is assumed to be 100 km/h. The road stretch is divided into 2 segments with a detector in the beginning of each segment. This is resulting in a distance of 2500 meters between the two detectors. The simulation is performed for a 30 minutes period, excluding a warm-up period of 5 minutes to prevent from loading effects. The simulations are performed at a flow level of 3500 veh/h. The communication of connected vehicle data and the updated control of the connected vehicles is made every second. The aggregation time period, T, i.e. the time interval over which the density is estimated and given to the Kalman filter, is assumed to be 60 seconds based on earlier research (Grumert and Tapani, 2017b). The first-order traffic model used for calculating the traffic state in the ensemble Kalman filter is based on the time and space discretization of 8 seconds and 250 meters, respectively. To capture changes in the parameters of the triangular fundamental diagram due to changes in the traffic conditions, and to trigger the VSL algorithm, an incident is modeled by letting one vehicle slow down to 20 km/h on segment 6. The vehicle will increase the speed again when entering segment 9. This will create a backward propagating shockwave, which in turn will result in a substantial change in the traffic conditions on the affected segments.

The vehicle parameters are in most cases set to the default values in SUMO version 0.27.1 (DLR and contributors, 2016). Exceptions are the maximum acceleration ability and the reaction time. These are set to 0.8 m/s^2 and 1.3 seconds, respectively, based on an investigation of merging behavior in SUMO presented by (Grumert, 2014). The desired speed factors are drawn from a normal distribution with mean 1.0 and speed deviation 0.1, based on a study by Varedian (2013) in which speed distributions were estimated for all vehicle types on Swedish roads with a speed limit of 100 km/h. Thereby, we implicitly assume a typical composition of vehicle types in the simulated traffic. Differences in vehicle length are, however, not considered. Vehicles are generated with exponentially distributed headways. The connected vehicles are assumed to be evenly distributed in the total flow.

It is assumed that all vehicles are able to send and retrieve information, as well as adapt to new speed limits, to be able to evaluate how the VSL system perform under ideal conditions with a 100% connected vehicle penetration rate. The integral gain in the VSL algorithm is set to 0.003 based on the range suggested in Carlson et al. (2011). Further, the variable speed limit is assumed to be at minimum the current estimated free flow speed, $V_{k,i}^{f}$, and at maximum the allowed speed limit on the road, which is 100 km/h. The speed limit is increased and decreased in increments of 10 km/h. It is assumed that the connected vehicles are continuously controlled towards the current capacity level. This means that the control is applied also for the maximum speed limit.

Traffic operations with the VSL system activated is compared to a situation without the system, referred to as the base case. By using the same random seed in the simulation, a comparison can be done to investigate if there are any improvements with respect to traffic efficiency when applying the proposed VSL compared to the base case. The average empirical cumulative distribution function of individual vehicle travel time is utilized to investigate how the individual travel times of the vehicles are distributed in the base case and when using the proposed VSL. The presented confidence intervals are for a 95% confidence level, assuming independent and identically normal distributed results from individual simulation runs. The average and the confidence intervals are based on 50 simulation runs. Further, the average travel time of all vehicles in a specific simulation run is considered to give an indication on how many of the simulation runs that result in an overall improvement.

5. Results

The aim of the proposed system is to increase traffic efficiency. Overall, including all simulation runs, the average travel time per vehicle is significantly decreased by 3.15 ± 1.05 seconds when applying the VSL system. This is corresponding to a decrease of 1.4± 0.5 hours in average total travel time for all vehicles during the simulated period. Further, the average travel time per vehicle is reduced in 84% of the simulation runs, and in 28% of the simulation runs the decrease is larger than 5 seconds.

By looking at the empirical cumulative distribution function of individual vehicle travel times in Figure 2 it is concluded that there is a significant difference between the two functions from the 30-percentile and above. The VSL case is shifted to the left showing that the individual travel times are on average shorter when applying the VSL system compared to the base case. The gap between the base case and the VSL case is largest at travel times around 4.5 minutes, which is 25% above the free flow travel time. Thus, the VSL system manage to decrease the percentage of long travel times (above 4.5 minutes). This indicate that the VSL system manage to decrease the difference in speeds between individual vehicles, with more homogeneous speed levels and a more equal distribution of individual travel times as a result of that. This result confirms that the assigned VSL algorithm works as intended since the main goal is to have a more homogeneous distribution of speed.

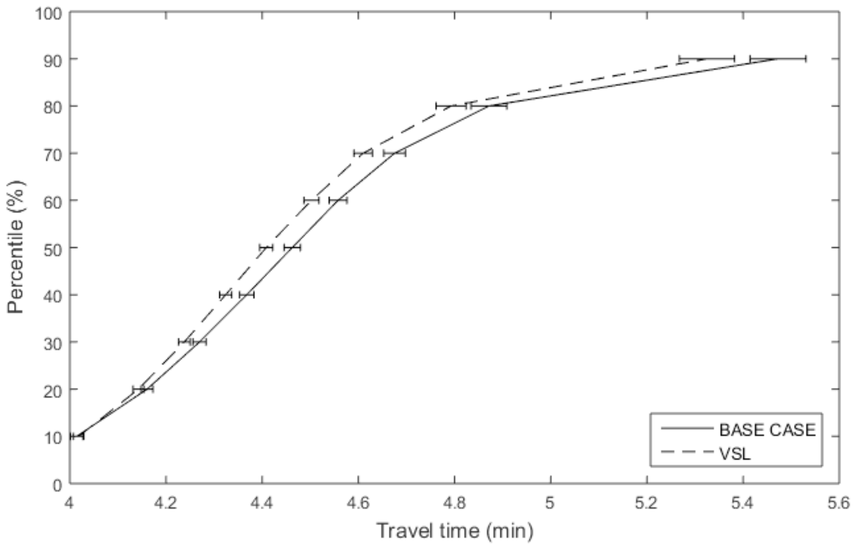

Figure 2: Empirical cumulative distribution functions of individual vehicle travel time for the base case and with the proposed VSL system.

Figure 3 show the simulation run where the average travel time per vehicle decreased the most (column 1 of the figure), and the simulation run with largest increase in travel time per vehicle, i.e. a simulation run where the VLS system did not manage to improve the traffic efficiency (column 2 of the figure). Figure 3(a) and 1(b) show the observed mean speed for the simulation run with improvements and negative impacts of the VSL system, respectively. The mean speed is calculated for each aggregation time period and for all sub-segments. This is done to get an overview of how the congestion is propagating in the network for the two different simulation runs. Figure 3(c) and 3(d) show the difference between the base case and the VSL case for the simulation run with improvements and negative impacts of the VSL system, respectively, and for all aggregation time periods and sub-segments. No change is indicated by white, while an increase in mean speed for the VSL case, i.e. a positive value, is indicated by a blue color and a decrease in mean speed for the VSL case, i.e. a negative value, is indicated by a red color. Both the increase and the decrease in mean speed is ranging from 0 to 40 km/h.

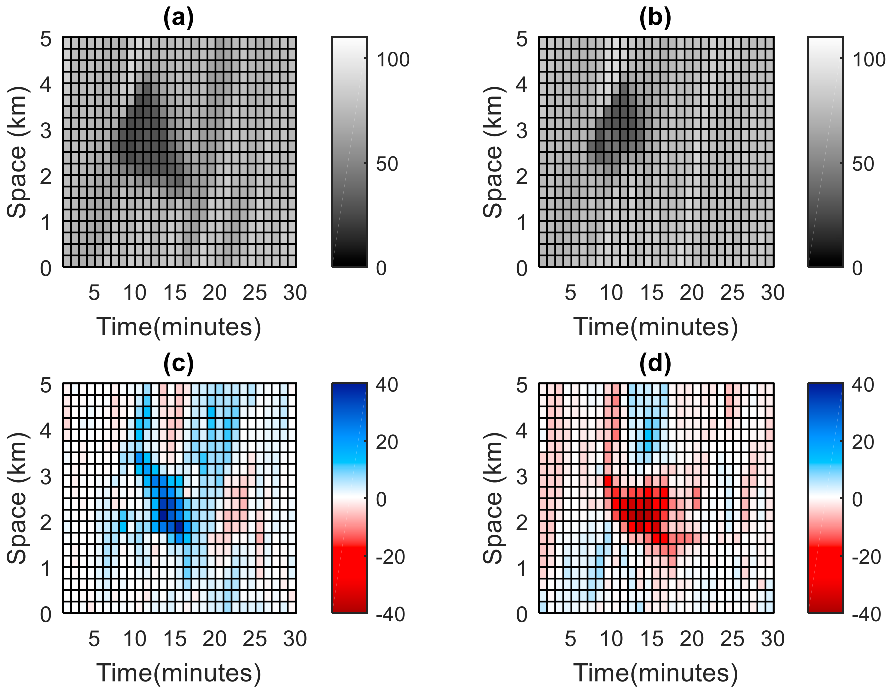

Figure 3: One simulation run which results in a success, represented by (a) and (c), and the simulation run which results in a failure, represented by (b) and (d). (a) and (b) shows the mean speed in time and space to given an overview of the development of the congestion for the base case and the second. (c) and (d) gives the difference with and without the VSL system in a range from -40 to 40 km/h, where white means no change, blue a positive change with the VSL system and red a negative change with the VSL system.

As shown in Figure 3(c) the mean speed is higher for the VSL case most of the time in the simulation run with improvments. The largest increase is seen in the tail of the congestion, meaning that the propagation area and the heavy speed decrease in the tail is reduced. This is due to that the VSL system manage to control the traffic flow at the bottleneck towards a higher capacity than in the base case, which is corresponding to the goal of the VSL algorithm by Carlson et al. (2011). Figure 3(d) show a simulation scenario where the VSL system does not manage to improve the conditions on the road. Instead a decrease in mean speed is seen in the tail of the congestion. In situations where the VSL system is not effective in improving the traffic efficiency, the tail of the congestion is usually the part where the algorithm fail to improve the traffic conditions. The reasons for this might be twofold, either the traffic state estimation is too simple and fail to accurately estimate the capacity levels; or since the algorithm does not include prediction of the future traffic flows approaching the bottleneck there might be an overreaction to the observed changes in capacity at the bottleneck when applying the VSL. Further, a low VSL, that does not well-enough correspond to the traffic conditions on the road, will also affect the recovery phase negatively. It is concluded that the propagation of the congestion is very different for the two simulation runs as a result of the randomness in the simulation. In the simulation run with negative impact of the VSL system the tail does not have the same propagation rate as in the simulation run resulting in an improvement, which is a result of the traffic composition in the simulation at this point in time. This indicate that in cases when the congestion can be resolved efficiently without applying VSL, the application of a VSL algorithm will result in an overreaction with too low speed levels as a result. On the other hand, the VSL system seems to be effective in cases when the backwards propagtion rate of the tail is high. This corresponds well with the other simulation runs, where similar behavior of the propagation of the tail can be observed.

6. Conclusions

We propose a variable speed limit system including connected vehicles. The connected vehicles are used to communicate information about their speed and position. The information is used for estimation of the traffic state based on the Count Connected Vehicle method proposed by (Grumert and Tapani, 2017b) in earlier research. The current capacity is estimated based on on-line calibration of the model parameters in the triangular fundamental diagram of a first-order traffic model, following the approach by Wang and Papageorgiou (2005). The changes in the model parameters are then used to identify non-recurrent bottlenecks. A VSL control strategy is applied that continuously adapt the speed limit towards the current estimated capacity of each segment of the road.

The results indicate that connected vehicles are useful for identification of non-recurrent bottlenecks. Further, by controlling the speed limit of the connected vehicles to maintain the estimated capacity level, based on the VSL algorithm proposed by Carlson et al. (2011), the traffic performance at the identified bottleneck can be increased. The resulting average empirical cumulative distribution functions of the individual travel times are significantly different from the 20-percentile and above. Hence, by applying the proposed VSL system the percentage of long travel times are reduced. Further, the average travel time per vehicle, and consequently the total travel time spent by all vehicles during the simulated period, is significantly reduced. As a conclusion, it is shown that even for a simple road design, the traffic efficiency can be increased by using connected vehicles in a VSL system.

In this study, we use a simple road design to investigate the characteristics of the proposed system. The next step is to test the method for a more complex road design. This will show if the proposed VSL system has a potential to improve the traffic efficiency also for more complex scenarios. The applied VSL algorithm can also be subject to further studies, both with respect to the sensitivity of the results to the chosen parameter values for the applied VSL algorithm, and by considering other VSL algorithms. It should be noted that the effectiveness of VSL algorithm is highly dependent on the estimate of the traffic state and the model parameters. Hence, a more complex model of the traffic state might result in larger benefits. In the study, a connected vehicle penetration rate of 100% is assumed in order to be able to investigate how good the VSL system can perform given ideal conditions. The traffic performance for other connected vehicle penetration rates has to be investigated to evaluate how large the benefits of the VSL system can be for a mixed traffic flow, including both connected and non-connected vehicles.

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References

Antoniou, C., Ben-Akiva, M., & Koutsopoulos, H. N. (2007). Nonlinear Kalman Filtering Algorithms for On-Line Calibration of Dynamic Traffic Assignment Models. *IEEE Transactions on Intelligent Transportation Systems, 8*(4), 661-670.

Carlson, R. C., Papamichail, I., & Papageorgiou, M. (2011). Local feedback-based mainstream traffic flow control on motorways using variable speed limits. *IEEE Transactions on Intelligent Transportation Systems, 12*(4), 1261-1276.

Coifman, B. (2003). Estimating density and lane inflow on a freeway segment. *Transportation Research Part A, 37*, 689-701.

Dabiri, A., & Kulcsár, B. (2015). Freeway traffic incident reconstruction - A bi-parameter approach. *Transportation Research Part C: Emerging Technologies, 58*, 585-597.

Daganzo, C. F. (1994). The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory. *Transportation Research Part B: Methodological*(4), 269.

DLR and contributors. (2016). SUMO homepage. from http://sumo.dlr.de/wiki/Main_Page

Duret, A., Leclercq, L., & El Faouzi, N.-E. (2016). Data Assimilation Using a Mesoscopic Lighthill–Whitham–Richards Model and Loop Detector Data. *Transportation Research Record, 2560*(1), 26.

Evensen, G. (2003). The Ensemble Kalman Filter: theoretical formulation and practical implementation. *Ocean Dynamics, 53*(4), 343-367.

Grumert, E. (2014). *Cooperative variable speed limit systems: modeling and evaluation using microscopic traffic simulation* (Licentiate Thesis), Linköping University, Norrköping. (1670)

Grumert, E., & Tapani, A. (2017a). *Estimating the traffic state for incident detection unsing connected vehicles*. Paper presented at the Young Researchers Seminar in May 2017, Berlin, Germany.

Grumert, E. F., & Tapani, A. (2017b). Estimating traffic density by combining connected vehicles and detectors. *submitted to Transportmetrica B*.

Han, Y., Chen, D., & Ahn, S. (2017). Variable speed limit control at fixed freeway bottlenecks using connected vehicles. *Transportation Research Part B, 98*, 113-134. doi: 10.1016/j.trb.2016.12.013

Hegyi, A., De Schutter, B., & Hellendoorn, J. (2005). Optimal coordination of variable speed limits to suppress shock waves. *IEEE Transactions on Intelligent Transportation Systems, 6*(1), 102-112.

Hegyi, A., Hoogendoorn, S. P., Schreuder, M., Stoelhorst, H., & Viti, F. (2008). *SPECIALIST: A dynamic speed limit control algorithm based on shock wave theory.* Paper presented at the 11th International IEEE Conference on Intelligent Transportation Systems, Beijing, China.

Herrera, J. C., & Bayen, A. M. (2007). Traffic flow reconstruction using mobile sensors and loop detector data: University of California Transportation Center.

Herrera, J. C., Work, D. B., Herring, R., Ban, X., Jacobson, Q., & Bayen, A. M. (2010). Evaluation of traffic data obtained via GPS-enabled mobile phones: The Mobile Century field experiment. *Transportation Research Part C: Emerging Technologies, 18*(4), 568-583.

Highway Agency. (2007). M25, Controlled Motorway, Summary report.

Kattan, L., Khondaker, B., Derushkina, O., & Poosarla, E. (2015). A Probe-Based Variable Speed Limit System. *Journal of Intelligent Transportation Systems, 19*(4), 339-354.

Khondaker, B., & Kattan, L. (2015). Variable speed limit: A microscopic analysis in a connected vehicle environment. *Transportation Research Part C, 58*(Part A), 146-159.

Kinoshita, A., Takasu, A., & Adachi, J. (2015). Real-time traffic incident detection using a probabilistic topic model. *Information Systems, 54*, 169-188.

Krajzewicz, D., Erdmann, J., Behrisch, M., & Bieker, L. (2012). Recent Development and Applications of SUMO - Simulation of Urban MObility,. *International Journal On Advances in Systems and Measurements, 5*(3&4), 128-138.

Kurkjian, A., Gershwin, S. B., Houpt, P. K., Willsky, A. S., Chow, E. Y., & Greene, G. S. (1980). Estimation of Roadway Traffic Density on Freeways Using Presence Detector Data. *Transportation Science, 14*(3), 232-261.

Lighthill, M. J., & Whitham, G. B. (1955). On kinematic waves. II. A theory of traffic flow on long crowded. *Proceedings of the Royal Society A, 229*, 317-345.

Ma, Y., Van Dalen, J., Kroon, L., & De Blois, C. (2011). Estimation of dynamic traffic densities for official statistics. *Transportation Research Record: Journal of the Transportation Research Board*(2256).

Mihaylova, L., Boel, R., & Hegyi, A. (2007). Freeway traffic estimation within particle filtering framework. *AUTOMATICA, 43*(2), 290-300.

Montero, L., Pacheco, M., Barceló, J. n. H. S., & Casanovas, J. (2016, 2016). *A case study on cooperative car data for traffic state estimation in an urban network.* Paper presented at the TRB 2016 Annual meeting compendium of papers.

Munoz, L., Xiaotian, S., Horowitz, R., & Alvarez, L. (2003, 4-6 June 2003). *Traffic density estimation with the cell transmission model.* Paper presented at the Proceedings of the 2003 American Control Conference, 2003.

Nissan, A., & Koutsopoulos, H. N. (2011). *Evaluation of the impact of advisory variable speed limits on motorway capacity and level of service.* Paper presented at the Procedia - Social and Behavioral Sciences.

Payne, H. J., Helfenbein, E. D., & Knobel, H. C. (1976). Development and Testing of Incident Detection Algorithms *Technical Report FHWA-RD-76-20 Research Methodology and Detailed Results*: Technology Service Corporation.

Samant, A., & Adeli, H. (2001). Enhancing Neural Network Traffic Incident-Detection Algorithms Using Wavelets. *Computer-Aided Civil & Infrastructure Engineering, 16*(4), 239.

Seo, T., Kusakabe, T., & Asakura, Y. (2015a). Estimation of flow and density using probe vehicles with spacing measurement equipment. *Transportation Research Part C, 53*, 134-150.

Seo, T., Kusakabe, T., & Asakura, Y. (2015b). *Traffic State Estimation with the Advanced Probe Vehicles Using Data Assimilation.* Paper presented at the IEEE 18th International Conference on Intelligent Transportation Systems (ITSC).

Singh, K., & Li, B. (2012). Estimation of Traffic Densities for Multilane Roadways Using a Markov Model Approach. *Industrial Electronics, IEEE Transactions on, 59*(11), 4369-4376.

Smulders, S. A., & Helleman, D. E. (1998). *Variable speed control: State-of-the-art and synthesis.* Paper presented at the IEE Conference Publication.

Tampère, C., U, Immers, B., & U. (2007). An extended kalman filter application for traffic state estimation using CTM with implicit mode switching and dynamic parameters. Belgium, Europe.

van den Hoogen, E., & Smulders, S. (1994). Control by variable speed signs. Results of the Dutch experiment. *IEE Conference Publication*, 145-149.

van Lint, J. W. C., & Hoogendoorn, S. P. (2010). A Robust and Efficient Method for Fusing Heterogeneous Data from Traffic Sensors on Freeways. *Computer-Aided Civil & Infrastructure Engineering, 25*(8), 596-612.

Wang, J. W., Li, X., Liao, S. S. Y., & Hua, Z. S. (2013). A Hybrid Approach for Automatic Incident Detection. *IEEE Transactions on intelligent transport systems, 14*(3), 1176-1185.

Wang, M., Daamen, W., Hoogendoorn, S. P., & van Arem, B. (2016). Connected variable speed limits control and car-following control with vehicle-infrastructure communication to resolve stop-and-go waves. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations, 20*(6), 559-572.

Wang, Y., & Papageorgiou, M. (2005). Real-time freeway traffic state estimation based on extended Kalman filter: a general approach. *Transportation Research Part B: Methodological, 39*(2), 141-167.

Wang, Y., Papageorgiou, M., Messmer, A., Coppola, P., Tzimitsi, A., & Nuzzolo, A. (2009). An adaptive freeway traffic state estimator. *Automatica, 45*(1), 10-24.

Varedian, M. (2013). Hastighetsundersökningen 2012, Resultatrapport.

Work, D. B., Blandin, S., Tossavainen, O.-P., Piccoli, B., & Bayen, A. M. (2010). A Traffic Model for Velocity Data Assimilation. United States, North America: Oxford University Press.