Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 37 (2019) 481–488

Transportation Research Procedia

www.elsevier.com/locate/procedia

21st EURO Working Group on Transportation Meeting, EWGT 2018, 17th – 19th September 2018, Braunschweig, Germany

Adaptive traffic signal control for real-world scenarios in agent-based transport simulations

Theresa Thunig[a,*], Nico Kühnel[b], Kai Nagel[a]

[a]*Technische Universität Berlin, Transport Systems Planning and Transport Telematics, Salzufer 17-19, 10587 Berlin, Germany*
[b]*Technische Universität München, Modeling Spatial Mobility, Arcisstr. 21, 80333 Munich, Germany*

Abstract

This study provides an open-source implementation of a decentralized, adaptive signal control algorithm in the agent-based transport simulation MATSim, which is applicable for large-scale real-world scenarios. The implementation is based on the algorithm proposed by Lämmer and Helbing (2008), which had promising results, but was not applicable to real-world scenarios in its published form. The algorithm is extended in this paper to cope with realistic situations like different lanes per signal, small periods of overload, phase combination of non-conflicting traffic, and minimum green times. Impacts and limitations of the adaptive signal control are analyzed for a real-world scenario and compared to a fixed-time and traffic-actuated signal control. It can be shown that delays significantly reduce and queue lengths are lower and more stable than with fixed-time signals. Another finding is that the adaptive signal control behaves like a fixed-time control in overload situations and, therefore, ensures system-wide stability.

Keywords: decentralized, adaptive traffic signal control; agent-based transport simulation; large-scale real-world scenario

1. Introduction

The implementation of SCOOT (Split, Cycle and Offset Optimisation Technique) saved about 12% delay in the first applications by a small cycle-by-cycle adaption of split, cycle time, and offset (Hunt et al., 1981). Until today it is the most established traffic-responsive control method, used in more than 250 towns and cities. In contrast to fixed-time signals, traffic-responsive signals react to current traffic by adjusting signal states based on sensor-data (e.g. from upstream inducting loops). One distinguishes different levels of adjustment: *actuated* signals use a fixed-time base

* Corresponding author. Tel.: +49-30-314-78783; fax: +49-30-314-26269.
E-mail address: thunig@vsp.tu-berlin.de

10.1016/j.trpro.2018.12.215

plan and adjust parameters like green split, cycle time or offset (see e.g. SCOOT). In contrast, *(fully) adaptive* signals decide about the signal states on the fly. They can modify stage orders or even combine signals into different stages over time. With this, the flexibility of the signal optimization is augmented, which increases the possible improvement, but makes the optimization problem more complex. In order to reduce complexity and communication effort between sensors and a central computation unit (which controls signal states system-wide, e.g. in SCOOT), *decentralized* (also called *self-controlled*) signal methods decide locally about signal states without complete knowledge of the system. Usually, every signalized intersection has its own processing unit that takes upstream (and sometimes downstream) sensor data of all approaches into account. A challenge of decentralized systems is to still ensure system-wide stability, especially when dealing with oversaturated conditions. A number of methods were developed that tackle these challenges. Some can be considered as rule-based (e.g. Gershenson, 2005; Lämmer and Helbing, 2008), others use techniques from reinforcement learning and model signals as learning agents (e.g. Bazzan, 2005; El-Tantawy et al., 2013), and some base their signal control on V2I communication instead of sensor data (e.g. Priemer and Friedrich, 2009). As installation and running costs of traffic-responsive signals in general are high, new methods should be systematically tested in simulations before applying them in the field.

To make a contribution in this regard, the present study provides an open-source implementation of an adaptive signal control algorithm in the agent-based transport simulation MATSim (Horni et al., 2016b). The code is open source[1] and scenarios for the multi-agent simulation can be build based on open data (e.g. Ziemke and Nagel, 2017). Since MATSim is a suitable tool for large-scale simulations, the impact of the adaptive signal control algorithm can be easily analyzed for arbitrary scenarios.

The algorithm developed in this study is based on Lämmer and Helbing (2008), who present a first version of Lämmer's adaptive signal control, which is, however, in this form not applicable to real-world situations. Extended versions of the algorithm were tested with the traffic simulation VISSIM for a real-world scenario (Lämmer and Helbing, 2010) and successfully implemented in the field at two intersections in the city of Dresden, Germany (Lämmer, 2016). The results look very promising, encouraging further research on this topic. The extended algorithms have, however, not been published. This paper, therefore, gives an alternative, open-source extension of the adaptive signal control algorithm developed by Lämmer and Helbing (2008) that is applicable to real-world scenarios. It extends the implementation of the first version of Lämmer's self-controlled signals in MATSim of an earlier study (see Kühnel et al., 2018) to be able to deal with realistic traffic situations like lanes, phase combination with opposing traffic, minimum green times, and overload. After a brief explanation of self-controlled signals in the sense of Lämmer and Helbing (2008), and an overview about the agent-based transport simulation MATSim in Sec. 2, Sec. 3 describes and discusses the extensions implemented in this study. In Sec. 4 the extended self-controlled signals are applied to a scenario of the city of Cottbus, Germany, and compared to other signal approaches.

2. Methodology

2.1. Lämmer's adaptive traffic signal control algorithm

The idea of the self-controlled signals proposed by Lämmer and Helbing (2008) is to minimize waiting times and queue lengths at decentralized intersections while also granting stability through minimal service intervals. The algorithm makes use of two combined strategies. The *optimizing strategy* selects the link i to be served next as the one with the highest priority index π_i (see Eq. 1), which considers outflow rates and queue lengths of waiting and approaching vehicles that are registered by sensors. Given a prediction of the expected queue length $\hat{n}_i(t,\tau)$ at time $\tau > t$ and the maximum outflow rate $q_i^{\max}$ for link i, one can derive the expected required green time $\hat{g}_i(t,\tau)$ for clearing the queue at time t using $\hat{g}_i(t,\tau) = \frac{\hat{n}_i(t,\tau)}{q_i^{\max}}$. With this, the priority index is calculated as

[1] An example how to start a MATSim simulation using the adaptive signal control presented in this paper can be found at http://matsim.org/javadoc → signals → RunAdaptiveSignalsExample.

$$\pi_i(t) = \begin{cases} \max\limits_{\tau_i(t) \le \tau \le \tau_i^0} \frac{\hat{n}_i(t,\tau)}{\tau + \hat{g}_i(t,\tau)}, & \text{if } i = \sigma(t) \\ \frac{\hat{n}_i(t,\tau_i^0)}{\tau_{\sigma(t)}^{\text{pen}}(t) + \tau_i^0 + \hat{g}_i(t,\tau_i^0)}, & \text{if } i \neq \sigma(t). \end{cases} \tag{1}$$

Two cases are distinguished depending on whether the signal i is already selected or not. In either case, the equation basically divides the number of vehicles by the time needed to clear the queue including the (remaining) intergreen time. The priority index can, therefore, be interpreted as a clearance efficiency rate. Time horizon τ in the first case includes the effect of remaining intergreen time $\tau_i(t)$ for the selected signal (when it has not yet switched to green), and, simultaneously, a lookahead beyond the end of the current queue. It is bounded from above by the full intergreen time τ_i^0, since beyond that it is possible to just switch back from some other state. For the non-selected signal (i.e. $i \neq \sigma(t)$), the priority index is reduced by a canceling penalty $\tau_{\sigma(t)}^{\text{pen}}(t)$. This prevents the optimizing regime from frequently switching signals. The penalty can be interpreted as the average additional waiting time for vehicles at the previously served link that would occur upon cancellation. More details are provided by Lämmer and Helbing (2008).

An enclosing *stabilizing strategy* ensures that each link is at least served once during a specified minimal service interval to prevent spillbacks. Approaches that have to be stabilized are added to a stabilization queue. If the queue is non-empty, its first element is switched to green for a guaranteed green time g_i^s depending on the average capacity utilization of the link i. If the stabilization queue is empty, the optimizing strategy takes over. The combined control claims to provide intrinsic green waves and locally optimal service, which also results in system-wide optimal service.

2.2. The agent-based transport simulation MATSim

In MATSim (Horni et al., 2016b) traffic is modeled by agents that follow a daily plan of activities and trips. Traffic flow is modelled mesoscopically by spatial first-in-first-out (FIFO) queues. Vehicles at the end of a queue can leave a link when the following criteria are fulfilled: (1) The link's free-flow travel time has passed, (2) the flow capacity of the link is not exceeded in the given time step, and (3) there is space on the next link. Despite this simplistic modeling approach, congestion as well as spillback can be modeled.

The signal module was developed by Grether (2014) as an extension to MATSim. If a signal exists on a link, leaving the link is not possible while it shows red. First studies focused on fixed-time signals, but also a traffic-actuated signal control has been implemented. Grether et al. (2011) analyzed its positive effect for large unexpected events and compared it to fixed-time signals. Separated waiting queues at intersections can be modeled in MATSim by lanes (see Fig. 1), which is especially useful to model protected left turns. Signals and lanes in MATSim are more extensively described by Grether and Thunig (2016).

Events of vehicles entering or leaving links and lanes are thrown on a second-by-second time resolution in the simulation. Sensors on links or lanes that detect single vehicles can be easily modeled by listening to these events. As in reality, the maximum forecast period of such sensors is limited – vehicles can only be detected when they have entered the link. If a link is short, forecasts might not be accurate. In the simulation, adaptive signals use these sensor data to react dynamically to approaching vehicles. For every signalized intersection, the control unit is called every second to decide about current signal states.

As MATSim is able to run large-scale simulations in reasonable time, it is a suitable tool to evaluate the effects of signal control algorithms before implementing them in the field. Because of its agent-based structure, agent-specific waiting times and varying queue lengths over time at traffic lights can be directly analyzed and compared with other signal approaches.

Fig. 1. Links with multiple lanes in MATSim. Each lane is represented by its own FIFO queue. Traffic signal control for different turning moves is captured. Vehicles on different lanes can pass each other, unless the queue spills over. Source: Grether and Thunig (2016).

3. Extending the signal control algorithm for more realistic applications

As a first extension, the self-controlled signals should be able to handle approaches that are separated into **lanes**, i.e. parallel waiting queues. The extension allows different lanes of one link to be controlled by different signals. On the other hand, signals that control multiple lanes are extended to process sensor information from different lanes. With this, it can be captured that lanes leading into different directions may have different outflow rates and queuing lengths, which allows to model more complex signal stages, e.g. protected left turns. To incorporate lanes into the signal control, Lämmer's algorithm had to be adapted: The signal controller no longer chooses between approaches, but between signals to be selected (i.e. to show green). While the number of predicted waiting vehicles $\hat{n}_{i,j}$ among lanes j of a signal i are simply added up, the required green time $\hat{g}$ that is proposed by the extended algorithm has to be the maximum of required green times of all controlled lanes, as their queues are cleared simultaneously. If, say, there are three lanes instead of one, but $\hat{g}$ remains approximately the same, then this means the priority index increases by approximately a factor of three, consistent with three times as many waiting vehicles. This leads to the following adjusted equation for the priority index in the optimizing regime:

$$\pi_i(t) = \begin{cases} \max\limits_{\tau_i(t) \leq \tau \leq \tau_i^0} \frac{\sum_j \hat{n}_{i,j}(t,\tau)}{\tau + \max_j \hat{g}_{i,j}(t,\tau)}, & \text{if } i = \sigma(t) \\ \frac{\sum_j \hat{n}_{i,j}(t,\tau_i^0)}{\tau_{\sigma(t)}^{\text{pen}}(t) + \tau_i^0 + \max_j \hat{g}_{i,j}(t,\tau_i^0)}, & \text{if } i \neq \sigma(t). \end{cases} \tag{2}$$

Analogously, the canceling penalty τ_i^{pen} was adjusted to consider waiting times of vehicles on all lanes of a signal. The stabilizing regime is extended to activate whenever the most occupied lane of a signal needs stabilization. This is justified by the fact that, if the most occupied lane is served often enough, all other less occupied lanes are on average also stable. Or, as Webster (1961) puts it: "Each phase can be represented by one approach only – the one with the highest ratio of flow to saturation flow." In the following, for each signal the lane that has the highest average capacity utilization will be called the *determining lane* for that signal.

Another extension is the **prediction of arrival rates** based on current and past traffic flow values, i.e. sensor data. Arrival rates are used to define the determining lane of a signal and to ensure a fair allocation of green times in the stabilizing regime. Before, it was assumed that average arrival rates per approach are constant and known from traffic counts. The use of non-constant, live arrival rates per lane effects that the self-controlled signals can react spontaneously to changes in demand, e.g. for unexpected events or accidents. In contrast to other microscopic simulations like SUMO or VISSIM, where often only the peak hour is modeled due to computation time, MATSim simulations usually capture a whole day, i.e. demand and arrival rates are far from constant. Also, fewer input data are needed in advance when arrival rates are predicted based on sensor data which makes it easier to implement the signal control in arbitrary scenarios. The sensors in MATSim are extended in a way that they additionally calculate past average arrival times per lane in every time step. Therefore, the total number of detected vehicles is divided by the simulation time that has passed. As the average arrival rate $\bar{q}^{exp}$ becomes time-dependent, capacity utilizations do as well and can be updated in each time step. This can cause the determining lane of a signal to change over time.

On the other hand, live arrival rates can also lead to situations where the capacity utilization Λ of an intersection temporarily exceeds one (i.e. 100%) when platoons of vehicles arrive at the same time. A constant utilization above 100% means that the demand cannot be processed in the given cycle time. This breaks one of the preconditions of Lämmer and Helbing (2008). However, as long as the average demand stays feasible, self-controlled signals should be able to handle small times of **overload**. Therefore, the stabilizing regime had to be adapted. So far, the guaranteed green time g_i^s for a signal is calculated as a share of the desired cycle time T plus a share of unused idle time T^{idle}, according to the utilization of the determining lane. In situations with $\Lambda > 1$, the idle time becomes negative, effectively worsening instability as it lowers the guaranteed green time g_i^s. As a consequence, T^{idle} is bounded by zero from below in this extension. When demand is high for a longer period in time, the self-controlled signals permanently trigger the stabilizing regime. As the stabilizing regime builds on the desired cycle time T and processes signals in a FIFO queue, periodic service times can be observed. Applied to a simple scenario of an intersection of a major and a minor road defined in Kühnel et al. (2018), this periodic behavior can be observed in Fig. 2. Demand in this scenario is doubled for 10 min from an utilization level of $\Lambda = 0.7$ to $\Lambda = 1.4$. The resulting cycle length is 60 s, which corresponds to the desired cycle time T used in the scenario. All in all, the extended self-controlled signals react like fixed-time signals in overload conditions.

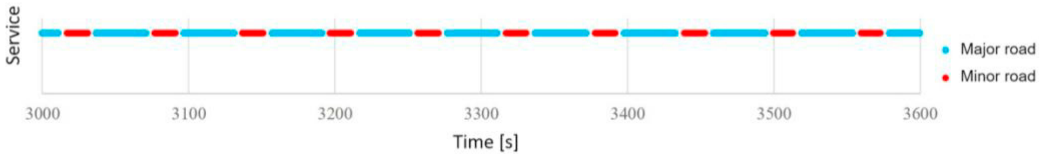

Fig. 2. Course of signal service for oversaturated conditions in a simple single-intersection scenario.

The adaptive signals by Lämmer and Helbing (2008) show green for only one approach per intersection per time, which drastically limits the throughput of an intersection. In the field, non-conflicting approaches are combined into **signal stages**, which allow different non-conflicting directions to show green at the same time. For the present implementation, signal stages are fixed a priori, i.e. all signals of a signal stage have to switch their state at the same time, and every signal can only be in one stage. Similar to the introduction of lanes, stages are included as a new layer in the algorithm that combines signals and their lanes into groups. The extended control chooses between stages p instead of signals σ. For the optimizing regime, the priority index $\pi_p(t)$ is calculated for each stage p. Thereby, the number of waiting vehicles of a stage p is the sum over all links i of the signals in p and their lanes j:

$$\pi_p(t) = \begin{cases} \max\limits_{\tau_p(t) \le \tau \le \tau_p^0} \dfrac{\sum_i \sum_j \hat{n}_{i,j}(t,\tau)}{\tau + \max_{i,j} \hat{g}_{i,j}(t,\tau)}, & \text{if } p = \sigma(t) \\ \dfrac{\sum_i \sum_j \hat{n}_{i,j}(t,\tau_p^0)}{\tau_{\sigma(t)}^{\text{pen}}(t) + \tau_p^0 + \max_{i,j} \hat{g}_{i,j}(t,\tau_p^0)}, & \text{if } p \ne \sigma(t). \end{cases} \quad (3)$$

As for Eq. 2, the required green time $\hat{g}$ is the maximum of required green times of all lanes belonging to the stage. The determining lane of every stage for stabilization is the one with highest capacity utilization.

Another extension motivated by Lämmer (2016) is the consideration of **minimum green times**. Minimum green times are used in the field to ensure acceptance and safety. For self-controlled signals, they require a longer period of forecasts to exactly predict vehicle queues for the time after the minimum green time is reached. This causes problems when sensors can not be installed far enough from the intersection, e.g. because links are too short. Additionally, forecasts of a sensor further upstream of an intersection are less accurate in reality. On the other hand, the signal control becomes more realistic, although less flexible for lower traffic volumes. In this extension, forecasts are calculated for the remaining intergreen time plus remaining minimum green time $g_p^{\min}(t)$ of the active signal stage. The minimum green time is defined by $g^{\min,0}$. The calculation of the priority index changes to

$$\pi_p(t) = \begin{cases} \max\limits_{\tau_p(t) \le \tau \le \tau_p^0} \dfrac{\sum_i \sum_j \hat{n}_{i,j}(t,\tau + g_p^{\min}(t))}{\tau + \max(g_p^{\min}(t),\ \max_{i,j} \hat{g}_{i,j}(t,\tau + g_p^{\min}(t))}, & \text{if } p = \sigma(t) \\ \dfrac{\sum_i \sum_j \hat{n}_{i,j}\left(t,\tau_p^0 + g^{\min,0}\right)}{\tau_{\sigma(t)}^{\text{pen}}(t) + \tau_p^0 + \max(g^{\min,0},\ \max_{i,j} \hat{g}_{i,j}\left(t,\tau_p^0 + g^{\min,0}\right)}, & \text{if } p \ne \sigma(t). \end{cases} \quad (4)$$

The maximum-term in the denominators effects that the selected signal has to stay green for at least $g^{\min,0}$ seconds, even when the required green time for clearing a queue is smaller. Analogously, the stabilizing regime ensures a minimum green time of $g^{\min,0}$seconds by extending the guaranteed green time in case it is smaller.

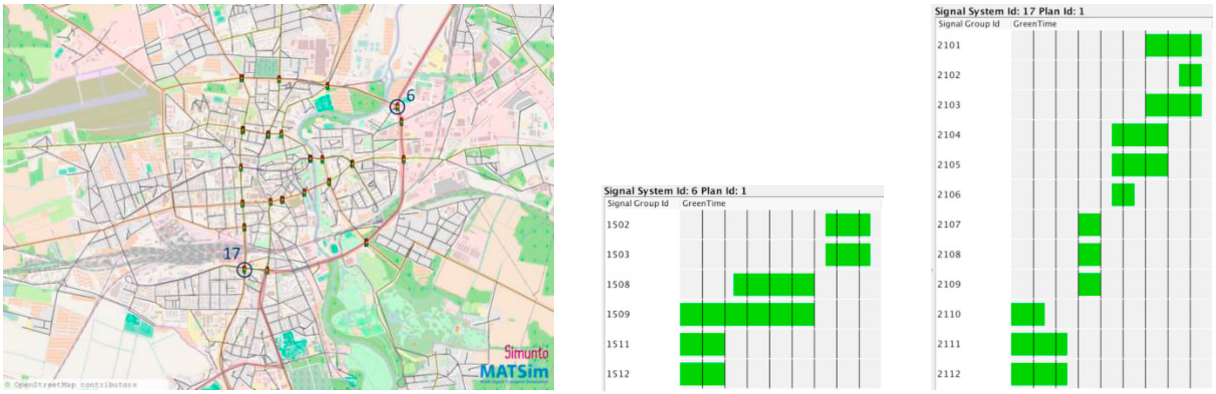

Fig. 3. Traffic lights in the scenario of the city of Cottbus, Germany, which is used in Sec. 4. Two exemplary intersections with IDs 6 and 17 are marked on the left. Their fixed-time plans are shown on the right.

4. Applying the signal control algorithm to a real-world

With the extensions described in the previous section, the adaptive signal algorithm can be applied to real-world scenarios and compared to other signal approaches to evaluate its performance. This section presents the simulation results of an application to the city of Cottbus, Germany. Input data for network, demand, and offset-optimized fixed-time signal plans are taken from a previous study Grether (2014). The network consists of approx. 10,000 links and 4,000 nodes and captures a region of about 1800 km^2 around the city. Daily home-work-home activity chains of around 33,000 commuters living and working in the region are simulated. As depicted in Fig. 3, 22 signalized intersections are modeled in the inner city of Cottbus. The fixed-time signal plans were provided by Strehler (2012) who measured signal stages and green splits in the field. Offsets were optimized by an MIP formulation (Köhler and Strehler, 2015). To be able to run the extended adaptive signals from Sec. 3, fixed signal stages were built based on the existing fixed-time plans. This process is described here for intersection 17, which is marked in Fig. 3. This intersection has four approaches that are separated into three lanes each (a left-turning, a through, and a right-turning lane each). Signal stages for the north and south direction (see last six lines of the signal plan in Fig. 3) could directly be used for the self-controlled signals, as they do not overlap. The overlapping signal stages for east-west traffic (see first six lines of the signal plan in Fig. 3) had to be separated into two distinct signal stages for the adaptive signal control. This was done by combining the two left turns with the short green time into one group and the four remaining signals (through and right-traffic) into another group. Furthermore, the desired and maximum cycle time T and $T^{\max}$ for this application had to be chosen. For the desired cycle time, the fixed-time cycle time of 90 s is used such that self-controlled signals fall back to a fixed-time signal plan with the same cycle time when demand is high (see Sec. 3). As proposed by Lämmer and Helbing (2008), the maximum cycle time is set to $T^{\max} = 1.5\,T = 135$ s.

Table 1. Aggregated travel times and delays in the real-world application described in Sec. 4.

Signal control type	Avg. travel time per trip [mm:ss]	Total delay [s]
Fixed-time signals	13:24	3,751,316
Actuated signals	13:06	2,544,233
Adaptive signals	13:04	2,412,533
No signals	12:33	346,955

Despite its inflexible signal stages, the adaptive signal control is able to significantly improve overall travel time and delays compared to the fixed-time approach (see Tab. 1). While the self-controlled signals reduce travel time only by 2%, delay is significantly reduced by 35%. This can be explained by the fact, that (1.) travel time includes all trips, i.e. also those that do not go through the inner-city area and are not affected by signals, and, (2.) delay is mainly caused by signals, as the comparison with the no-signals benchmark shows. Without signals, vehicles drive through each other at intersections in the simulation and are only delayed by congestion on links (due to capacity). As a comparison, the scenario was also run with the actuated SYLVIA signals (see Schlothauer and Wauer, 2011) implemented in MATSim by Grether et al. (2011). SYLVIA takes the fixed-time control as input, reduces signal phases to 5 s, and extends them if vehicles are approaching. With this, the combination of signals to stages and the order of stages stays the same, but green times can be adjusted (in this setup up to 1.5 times the green time of the fixed-time plan). Based on the aggregated values from Tab. 1, SYLVIA produces similar results as the adaptive signals presented in this paper, and reduces delay by 32% compared to the fixed-time signals. Fig. 4 shows some more detailed analysis: Queue lengths at traffic lights over time are the most stable with the adaptive control, since it can directly react to growing queues. The actuated control produces slightly higher oscillations, as it is less flexible with the order of stages, whereas queue length for the fixed-time signal are significantly higher and oscillating a lot. As one can see in the second graph of Fig. 4, the adaptive and actuated signals produce lower waiting times than the fixed-time signals at all intersections. The highest decrease can be observed at intersection 17, where green times of the fixed-time plan are not sufficient for some directions (left-turning and through traffic from north-south direction, i.e. signals 2018, 2019, 2010 and 2012 shown in the third graph of Fig. 4). This presents a typical use case where actuated and adaptive signals benefit. Another finding of Fig. 4 is that waiting times for the actuated control are usually similar or higher than for the adaptive signals presented in this paper, except for intersection 6. As shown in Fig. 3, the fixed-time plan combines the approaches at this tree-arm intersection more flexibly than the current version of the adaptive signals are able to: Signal 1509 shows green in two stages. As the actuated control extends this fixed-time plan, it benefits from the same flexible stage combination. The adaptive control from this paper has to build distinct stages and, therefore, restricts green time of signal 1509. Still, its waiting time at this intersection is not worse than the fixed-time plan.

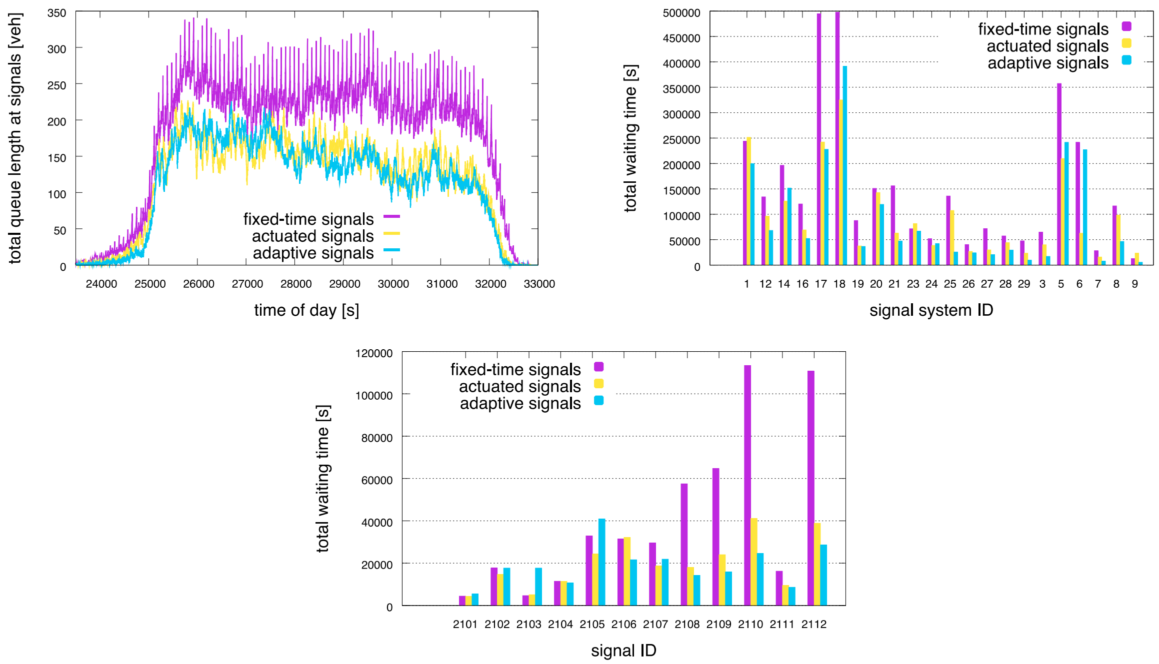

Fig. 4. Simulation results of the real-world application for different signal settings described in Sec. 4. Upper left: total queue length at signalized links over time; upper right: total waiting time per signalized intersection; center low: total waiting time per signal at intersection 17.

5. Discussion

This study provides an open-source implementation of an adaptive signal control algorithm in an agent-based transport simulation that is applicable for real-world scenarios. The algorithm is an extension of the self-controlled signals developed by Lämmer and Helbing (2008). In contrast to its previous version, the extended signal control allows different approaches to be combined into a signal stage. Also, approaches with multiple lanes can be modeled, minimal green times are satisfied, and small periods of overload can be captured. Without these extensions, the algorithm could not handle real-world situations. Impacts and limitations compared to fixed-time and actuated signals are analyzed in a real-world scenario of the city of Cottbus, Germany. Besides resulting lower travel times, significantly reduced delays and stabilized waiting queues for the adaptive signals, it is found that the adaptive signal control behaves like fixed-time signals in overload situations.

Despite its positive results, the inflexible signal stages clearly remain a limitation of the current implementation. Signals have to be grouped into fixed signal stages, which show green together, before applying the algorithm. To do this efficiently, data about average traffic flow values is necessary. In this study, the existing fixed-time plans were used to define suitable groups. The fact that every signal can only be in one stage per cycle, encourages inefficient usage of green times, especially at three-way intersections. An extension to the implementation presented in this paper that decides how to combine directions into signal stages on-the-fly based on current traffic flow, is already in development. Further steps to improve the signal control could be (1.) to prioritize public transit vehicles (as it is also done by Lämmer and Helbing (2010), (2.) to make intergreen times dependent on both approaches between which to switch, as in reality, and not only on the one which is switched to green, and (3.) to consider downstream sensors and only switch a signal to green if its downstream links are not blocked, which should help to avoid grid lock situations.

Acknowledgements

The authors wish to thank Stefan Lämmer for encouraging research on this topic and for all discussions about his self-controlled signals. The authors also thank the Deutsche Forschungsgemeinschaft (DFG) for funding the project *Optimization and network wide analysis of traffic signal control*.

References

Bazzan, A., 2005. A distributed approach for coordination of traffic signal agents. Autonomous Agents and Multiagent Systems 10, 131164.

El-Tantaway, S., Abdulhai, B., Abdelgawad, H., 2013. Multiagent Reinforcement Learning for Integrated Network of Adaptive Traffic Signal Controllers (MARLIN-ATSC), in: IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC.

Gershenson, C., 2005. Self-organizing traffic lights. Complex Systems 16, 2953.

Grether, D., Bischoff , J., Nagel, K., 2011. Traffic-actuated signal control: Simulation of the user benefits in a big event real-world scenario, in: 2nd International Conference on Models and Technologies for ITS, Leuven, Belgium.

Grether, D., Thunig, T., 2016. Traffic signals and lanes, in: Horni et al. (2016b). Chapter 12.

Grether, D.S., 2014. Extension of a Multi-Agent Transport Simulation for Traffic Signal Control and Air Transport Systems. Ph.D. thesis. TU Berlin. Berlin.

Horni, A., Nagel, K., Axhausen, K.W. (Eds.), 2016b. The Multi-Agent Transport Simulation MATSim. Ubiquity, London. doi:10.5334/baw.

Hunt, P.B., Robertson, D.I., Bretherton, R.D., Winton, R.I., 1981. SCOOT A Traffic Responsive Method of Coordinating Signals. TRRL Laboratory Report 1014. TRRL. Crowthorne, Berkshire, UK.

Köhler, E., Strehler, M., 2015. Traffic signal optimization using cyclically expanded networks. Networks 65, 244261. doi:10.1002/net.21601.

Kühnel, N., Thunig, T., Nagel, K., 2018. Implementing an adaptive traffic signal control algorithm in an agent-based transport simulation. Procedia Computer Science 130, 894899. doi:10.1016/j.procs.2018.04.086.

Lämmer, S., 2016. Die Selbst-Steuerung im Praxistest. Straßenverkehrstechnik 3, 143151.

Lämmer, S., Helbing, D., 2008. Self-control of traffic lights and vehicle flows in urban road networks. Journal of Statistical Mechanics: Theory and Experiment 2008, 04019. doi:10.1088/1742-5468/2008/04/P04019.

Lämmer, S., Helbing, D., 2010. Self-Stabilizing Decentralized Signal Control of Realistic, Saturated Network Traffic. Working Paper 10-09-019. Santa Fe Institute. Santa Fe.

Priemer, C., Friedrich, B., 2009. A decentralized adaptive traffic signal control using V2I communication data, in: IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC.

Schlothauer & Wauer Ingenieurgesellschaft für Straßenverkehr mbH & Co. KG, 2011. SYLVIA+ Short Description. URL: http://www. schlothauer.de/docs/SYLVIA_Short- Description.pdf

Strehler, M., 2012. Signalized flows optimizing traffic signals and guideposts and related network flow problems. Ph.D. thesis. BTU Cottbus.

Webster, F., 1961. Traffic Signal Settings, in: Road Research Technical Paper No. 39. Her Majestys Stationery Office, pp. 145.

Ziemke, D., Nagel, K., 2017. Development of a fully synthetic and open scenario for agent-based transport simulations. VSP Working Paper 17-12. TU Berlin, Transport Systems Planning and Transport Telematics. URL http://www.vsp.tu- berlin.de/publications.