Simulation Study of a Traffic Light Assistant Based on Vehicle-Infrastructure Communication

Martin Treiber\(^1\) and Arne Kesting\(^2\)
\(^1\)University of Dresden
\(^2\)TomTom, Berlin

Abstract
Vehicle-infrastructure communication opens up new ways to improve traffic flow efficiency at signalized intersections. In this study, we assume that equipped vehicles can obtain information about switching times of relevant traffic lights in advance, and additionally counting data from upstream detectors. By means of simulation, we investigate, how equipped vehicles can make use of this information to improve traffic flow. Criteria include cycle-averaged capacity, driving comfort, fuel consumption, travel time, and the number of stops. Depending on the overall traffic demand and the penetration rate of equipped vehicles, we generally find several percent of improvement.

Keywords: Traffic light assistant, intelligent-driver model, adaptive cruise control, ACC, V2X, infrastructure-to-vehicle communication

1 Introduction
Individual vehicle-to-vehicle and vehicle-to-infrastructure communication, commonly referred to as V2X, are novel components of intelligent-traffic systems (ITS). Besides more traditional ITS applications such as variable speed limits on freeways or traffic-dependent signalization [HRBW81, Low82], V2X promises new applications to make traffic flow more efficient or driving more comfortable and economic. While there are many investigations focusing on technical issues such as connectivity given a certain hop strategy, communication range, and percentage of equipped vehicles (penetration rate), e.g., [TTK08], few papers have investigated actual strategies to improve traffic flow characteristics. On freeways, a jam-warning system based on communications to and from road-side units (RSUs) has been proposed [KP08]. Furthermore, a traffic-efficient adaptive-cruise control (ACC) has been proposed which relies on V2X communication to determine the local traffic context influencing, in turn, the ACC parameterization [KTH10]. Regarding city traffic, early forms of
V2X have been investigated in the European projects Prometheous/Drive [CM91]. However, these initiatives were more focussed on safety and routing information without explicitly treating any interactions with traffic lights. The investigation which is arguably most related to our work is the thesis [Ott11] on cooperative traffic control in cities discussing in depth the possibly destructive interplay between V2X (traffic-dependent signalization) and X2V (driver information relying on predetermined signalization).

In this contribution, we focus on city traffic at signalized intersections and investigate a set of strategies that is complementary to the self-controlled signal control strategy of Lämmer and Helbing [LH08]: While, in the latter, the traffic lights “know” the future traffic, we assume that equipped vehicles know the future states of the next traffic light. In principle, the resulting traffic-light assistant (TLA) can operate in the information-based manual mode, or in the ACC-based automatic mode on which we will focus in this work.

In the next section, we lay out the methodology of this simulation-based study and define the objectives. Section 3 presents and analyzes the actual strategies “economic approach”, “anticipative start”, and “flying start”. In the concluding Section 4, we discuss the results and point at conditions for implementing the strategies in an actual TLA.

2 Methodology

2.1 Car-Following Model

In order to get valid results, the underlying car-following model must be (i) sufficiently realistic to represent ACC driving in the automatic mode of the TLA, (ii) simple enough for calibration, and (iii) intuitive enough to readily implement the new strategies by re-parameterizing or augmenting the model. We apply the “Improved Intelligent-Driver Model” (IIDM) as described in Chapter 11 of the book [TK13]. As the original Intelligent-Driver Model (IDM) [THH00], it is a time-continuous car-following model with a smooth acceleration characteristics. Assuming speeds \(v\) not exceeding the desired speed \(v_0\), its acceleration equation as a function of the (bumper-to-bumper) gap \(s\), the own speed \(v\) and the speed \(v_l\) of the leader reads

\[
\frac{dv}{dt} = a_{\text{IIDM}}(s, v, v_l) = \begin{cases} 
(1 - z^2) \alpha & \text{if } s \geq 1, \\
(1 - z^2 \frac{2a}{a_{\text{free}}}) a_{\text{free}} & \text{otherwise},
\end{cases}
\]

where the expressions for the desired dynamic gap \(s^*(v, v_l)\) and the free-flow acceleration \(a_{\text{free}}(v)\) are the same as that of the IDM,

\[
s^*(v, v_l) = s_0 + \max \left[ vT + \frac{v(v - v_l)}{2\sqrt{ab}}, 0 \right],
\]

\[
a_{\text{free}}(v) = a \left[ 1 - \left( \frac{v}{v_0} \right) ^\delta \right].
\]
2 Methodology

The IIDM has the same parameter set as the IDM: desired speed $v_0$, desired time gap $T$, minimum space gap $s_0$, desired acceleration $a$, and desired deceleration $b$. However, it resolves two issues of the basic IDM when using it as an ACC acceleration controller: (i) the IIDM time-gap parameter $T$ describes exactly the time gap in steady-state car-following situations while the actual IDM steady-state time gaps are somewhat larger \cite{THH00}, (ii) a platoon of vehicle-drivers with same desired speed $v_0$ will not disperse over time as would be the case for the IDM. Notice that a slightly different formulation, the “IDM plus” with the acceleration function $a_{\text{IDM+}}(s, v, v_l) = \min[a_{\text{free}}, (1 - z^2)a]$, would serve this purpose as well.

By describing the vehicle motion with a time-continuous car-following model, we have neglected the in-vehicle control path since such models implicitly reflect an acceleration response time of zero. It might be necessary to explicitly model vehicle responses by a sub-microscopic model (e.g., PELOPS) when actually deploying such a system.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Calibration of the microscopic model with respect to the starting times and positions of a queue of waiting vehicles relative to the begin of the green phase (solid circles). Data are of the measurements in \cite{Küc08}.}
\end{figure}

2.2 Calibration

Since we will investigate platoons travelling from traffic light to traffic light, the acceleration model parameters $v_0$, $T$, $s_0$, $a$, and $b$ and the vehicle length $l_{\text{veh}}$ (including their variances) should be calibrated to data of starting and stopping situations.

For calibrating $a$, $T$, and the combination $l_{\text{eff}} = l_{\text{veh}} + s_0$ (effective vehicle length), we use the empirical results of Kücking \cite{Küc08} taken at three intersections in the city of Hannover, Germany. There, the “blocking time” of the $n^{\text{th}}$ vehicle of a waiting queue (the time interval this vehicle remains stopped after the light has turned green) has been measured vs. the distance of this vehicle to the stopping line of the traffic light. Figure \ref{fig:figure1} reproduces these data together with the simulation results (orange bullets) for the calibrated parameters.
$l_{eff} = 6.5\, \text{m}, a = 1.5\, \text{m/s}^2$, and $T = 1.2\, \text{s}$ assuming identical driver-vehicles. Further simulations with heterogeneous drivers and vehicles reveal that independently and uniformly distributed values for $l_{eff}$, $T$ and $a$ with standard deviations of the order of 30\% of the respective expectation value can reproduce the observed data scatter and its increase with the vehicle position (for positions $n = 5$ and higher, the scattering does no longer allow to identify $n$). Moreover, since trucks are excluded from the measurements, it is reasonable to assume that the observed cars have an average length of 4.5\, m resulting in an expectation value $s_0 = 2\, m$ for $s_0$.

For estimating the comfortable deceleration, the approach to a red traffic light is relevant. Investigations on the Lankershim data set of the NGSIM data \cite{Tra} including such situations show that a typical deceleration is $b = 2\, \text{m/s}^2$ \cite{VHZ10}. Finally, for the desired speed, we assumed a fixed value of $v_0 = 50\, \text{km/h}$ representing the usual inner-city speed limit in Germany.

### 2.3 Simulation

While the parameters clearly are distributed due to inter-vehicle and inter-driver variations, it is nevertheless necessary to use the same vehicle population for all the following simulation experiments. Specifically, we use following sequence of four vehicle-driver combinations: 1. average driver (expectation values for the parameters), 2. agile driver ($a$ increased to $2\, \text{m/s}^2$, $T = 1.8\, \text{s}$), 3. less agile but anticipative driver ($a$ and $b$ decreased to $1.2\, \text{m/s}^2$ and $1\, \text{m/s}^2$, respectively), and 4. a truck ($l_{veh} = 12\, \text{m}$, $T = 1.7\, \text{s}$, and $a = b = 1\, \text{m/s}^2$). If necessary, this sequence is repeated. Figure 2 shows the simulation result for the start-and-stop reference scenario against which the strategies of the traffic light assistant will be tested in the next section.

### 2.4 Traffic Flow Metrics

In the ideal case, the TLA reduces the travel time of the equipped and the other vehicles, increases driving comfort and traffic flow efficiency, and reduces fuel consumption. To assess travel time, we use the average speed of a vehicle, or average over all vehicles during the complete simulation run. As proxy for the driving comfort, we take the number of stops during one simulation, or, equivalently, the fraction of stopped vehicles. Traffic flow efficiency is equivalent to the cycle-averaged dynamic capacity, i.e., the average number of vehicles passing a traffic light per cycle in congested congestions in the absence of gridlocks. Finally, we determine the fuel consumption by a physics-based modal consumption model as described in Chapter 20.4 of the book \cite{TK13}. Such models take the simulated trajectories and some vehicle attributes as input and return the instantaneous consumption rate and the total consumption of a given vehicle. To be specific, we assume a mid-size car with following attributes: Characteristic map of a 118 kW gasoline engine as in Fig. 20.4 of \cite{TK13}, idling power $P_0 = 3\, \text{kW}$, total mass $m = 1500\, \text{kg}$, friction coefficient $\mu = 0.015$, air-drag coefficient $c_d = 0.32$, frontal cross-section $A = 2\, \text{m}^2$, a dynamic tyre radius $r_{\text{dyn}} = 0.286\, \text{m}$. Further-
Figure 2: Start and stop of the simulated platoon of heterogeneous vehicle-drivers in the reference case.

more, we assume a five-gear transmission with transmission ratios of 13.90, 7.80, 5.25, 3.79, and 3.09, respectively, and chose the most economic gear for a given driving mode characterized by $v$ and $\frac{dv}{dt}$. The engine power management includes overrun-fuel cutoff, idling when the vehicle is stopped, and no energy recuperation during braking.

3 Strategies of the Traffic Light Assistant and their Simulation

The appropriate TLA strategy depends essentially on the arrival time at the next traffic light relative to its phases. We distinguish following approaching situations (cf. Fig. 3):

- A stop is unavoidable (the first seven of the red trajectories of Fig. 3),
- anticipative start compensating for the reaction time of the first vehicle (last red trajectory),
- flying start realized by anticipative braking (blue trajectories),
- free passage (green trajectories),
- temporary “boost” to catch the last part of the green phase (violet trajectories).

Nothing can be done in the situation of a free passage while the “boost” strategy implies temporarily exceeding the speed limit. Therefore, we will only develop and simulate strategies for the first three situations. Generalizing the above sketch, we will also investigate how
Figure 3: Approach situations relative to the phases of the traffic light. Each trajectory corresponds to an individual simulation of the considered vehicle with no interactions to other vehicles. For the color coding, see the main text.

other (equipped or non-equipped) vehicles will affect the strategies. Furthermore, by a complex simulation over several cycles, we investigate any (positive or negative) interactions between the strategies and between equipped and non-equipped vehicles.

3.1 Approach to a Stop

In certain situations, a stop behind a red light or a waiting queue is unavoidable. This situation is true if (i) extrapolated constant-speed arrival occurs during a red phase, and (ii) the “flying-start” strategy of Sect. 3.3 would produce minimum speeds below a certain threshold which we assumed to be $v_{\text{flying\_min}} = 10 \text{ km/h}$. Notice that this scenario may also apply for approaching green traffic lights if the car cannot make it to the traffic light before switching time: In such a situation, drivers of non-equipped cars would just go ahead braking later and necessarily harder. While this situation is not relevant for improving flow efficiency, it is nevertheless possible to reduce fuel consumption by early use of the engine brake, i.e., early activation of the overrun cut-off.

In the car-following model, we implement this strategy by reducing the comfortable deceleration from $b = 2 \text{ m/s}^2$ to $1 \text{ m/s}^2$ (homogeneous driver-vehicle population), or by 50% for each vehicle (heterogeneous population). Reducing the desired deceleration means earlier braking, in line with this strategy.

Figure 4 shows speed and consumption profiles for an equipped vehicle (solid lines) vs. the reference (dotted). The equipped vehicle itself saves about 3.5 ml of fuel (6 % for the complete start-stop cycle). The two next (non-equipped) followers save about 3 % and 1 %, respectively.
Figure 4: Fuel-saving approach to a waiting queue. Left: speed profile and instantaneous consumption rate; right: cumulative consumption during the complete start-stop cycle.

3.2 Anticipative Start

Figure 5: Start at green from the first position of a queue of waiting vehicles. (a) reference; (b) anticipative start; (c) anticipative start plus 1 m additional gap; (d) anticipative start plus 3 m additional gap.

The rationale of the strategy of the anticipative start is to compensate for the reaction time delay \( \tau \). Since the reaction time is only relevant for the driver of the first vehicle in a queue, the anticipative-start strategy is restricted to this vehicle. In the reference case corresponding to the calibrated parameters (Fig. 5(a)), the front of the first vehicle crosses the stopping line about 1.5 s after the change to green corresponding to \( \tau \approx 0.7 \) s (the rest
of the time is needed to move the first meter to the stopping line). If this vehicle started one second earlier, i.e., before the switching to green (Fig. 5(b)), the situation is yet safe but an average of 0.5 additional vehicles can pass during one green phase assuming an outflow of 1800 veh/h after some vehicles. Considering the 12 vehicles that would pass in the reference scenario during the 30 s long green phase of the 60 s cycle, this amounts, on average, to an increase by 4%. An additional second can be saved, allowing 13 instead of 12 vehicles per green phase, if the first vehicle stops 4 m upstream of the stopping line (instead of 1 m) allowing an even earlier start without compromising the safety (Fig. 5(d)). However, there are limits in terms of acceptance and available space, so stopping 2 m before the stopping line (Fig. 5(c)) is more realistic. In effect, the latter strategy variants transform the anticipative start in a “flying start” which we will discuss now.

3.3 Flying Start

If, relative to the phases, a vehicle arrives later than in the previous two situations but too early to have a free passage, preemptive braking may avoid a stop or, at least, increase the minimum speed during the approaching phase. As depicted in Fig. 6, the strategy consists in controlling the vehicle's ACC such that a certain spatiotemporal target point (Δx, Δt) relative to the stopping line and the switching time to green is reached. This point is determined such that a minimum of speed reduction is realized without impairing traffic efficiency by detaching this vehicle from the platoon of leaders.

![Figure 6: Preemptive braking to avoid a stop: Spatiotemporal target for the 4th vehicle (pink circle). The arrows indicate how the target changes when varying the reaction time τ or the effective length l_{eff}.](image)

From basic kinematic theory [LW55] and the properties of the IDM it follows that the propagation velocity \( c \) of the positions of the vehicles at the respective starting times is constant and given by \( c \approx -l_{eff}/\dot{T} \) where \( \dot{T} \) is of the order of the IDM parameter \( T \). Assuming a gap \( s_0^* \) of the first waiting vehicle to the stopping line and a reaction delay \( \tau \) of its driver, the
The estimated spatiotemporal starting point of the $n^{\text{th}}$ vehicle reads

$$(\Delta x, \Delta t) = (s_0^* + (n - 1) l_{\text{eff}}, \tau + (n - 1) \bar{T}).$$

(6)

The points lie on a straight line which is consistent with observations (filled circles in Fig. 1). While we assume that, by additional V2X communication from a stationary detector to the vehicle, the equipped vehicle knows its order number $n$, there are uncertainties in $\tau$, $l_{\text{eff}}$, and $T$ which depend on unknown properties of the vehicles and drivers ahead. Furthermore, since the strategy tries to avoid a stop, the target point lies several meters upstream of and/or a few seconds after the anticipated starting point.

![Figure 7: Robustness of the preemptive braking strategy. Shown is its efficiency for the 3rd vehicle in terms of the minimum speed during the approach (left) and the gap once this vehicle is 50 m downstream of the traffic light (right).](image)

Is this strategy nevertheless robust? In order to assess this, we treat $\tau$ and $l_{\text{eff}}$ as free parameters of (6) to be estimated and plot the performance metrics minimum speed $v_{\text{min}}$ characterizing driving comfort and spatial gap $s$ to the platoon (cf. Fig. 6) characterizing the dynamic capacity as a function of $\tau$ and $l_{\text{eff}}$.

Figure 7 shows these metrics for the $n = 3^{\text{rd}}$ vehicle arriving at a timing such that the minimum speed would be $v_{\text{min}} = 10 \text{ km/h}$ if this vehicle were not equipped. For the best estimates (e.g., $l_{\text{eff}} = 6.5 \text{ m}$ and $\tau = 2 \text{ s}$), this minimum speed is nearly doubled without compromising the capacity which would be indicated by an increased following gap $s$. The simulations also show that estimation errors have one of three consequences: (i) if the queue length and dissolution time are estimated too optimistically ($l_{\text{eff}}$ and $\tau$ too small), there is still a positive effect since the minimum speed is increased without jeopardizing the efficiency; (ii) if the queue is massively overestimated ($l_{\text{eff}}$ and $\tau$ significantly too large), the whole strategy is deemed unfeasible and the approach reverts to that of non-equipped vehicles; (iii) if, however, the queue is only slightly overestimated, the strategy kicks in ($v_{\text{min}}$ increases) but the capacity is reduced since $s$ increases as well: the car does no longer catch the platoon. A look at the parameter ranges (the plots range over factors of five in both $\tau$ and $l_{\text{eff}}$) indicates that this strategy is robust when erring on the optimistic side, if there is any doubt.
Finally, we mention that counting errors (e.g. due to a vehicle changing lanes when approaching a red traffic light meaning that this vehicle has not passed the correct stationary detector) will lead to similar errors for the estimated target point as above. Consequently, this strategy should be robust with respect to counting errors as well.

### 3.4 Complex Simulation

In the previous sections, we have investigated the different strategies of the TLA in isolation. However, there are interactions. For example, the optimal target point of the flying-start strategy is shifted backwards in time when equipped leading vehicles apply the anticipative-start strategy. Furthermore, the question remains if the TLA remains effective if there is significant surrounding traffic (up to the level of saturation) and whether the results are sensitive to the order in which slow and fast, equipped and non-equipped vehicles arrive.

We investigate this by complex simulations of all strategies over several cycles where we vary, in each simulation, the overall traffic demand (inflow) $Q_{in}$, and the penetration rate $p$ of equipped vehicles. Unlike the simulations of single strategies, we allow for full stochasticity in the vehicle composition. At inflow, we draw, for each new vehicle, the model parameters from the independent uniform distributions specified in Sect. 2.3 and assign, with a probability $p$, the property “is equipped”.

![Graphs showing complex simulation results](image)

**Figure 8:** Complex simulation of the overall effectiveness for all vehicles over several cycles (see the main text for details).

Figure 8 shows the results for the performance metrics “average speed” (which is related to the average travel time), and “average consumption” as a function of the penetration rate for a small traffic demand (top row), and a demand near saturation (bottom). Each symbol corresponds to a simulation for given values of $Q_{in}$ and $p$. Due to the many stochastic
factors and interactions, we observe a wide scattering. Determining the local average (solid lines) and ±1σ bands (colored areas) by kernel-based regression (kernel width 15%), we nevertheless detect significant systematic effects. For low traffic demand, we observe that both travel times and fuel consumption are reduced by about 4% when going from the reference to $p = 100\%$ penetration. Furthermore, the effects essentially increase linearly with $p$, so the relative performance indexes $I_T$ and $I_C$ with respect to travel time $T_t$ and fuel consumption $C$,

$$I_T = -\frac{1}{T_t} \frac{\partial T_t}{\partial p}, \quad I_C = -\frac{1}{C} \frac{\partial C}{\partial p}$$ (8) 

are both constant and of the order of 4%. Similar performance indexes are obtained for the performance metrics “number of stops”. For higher traffic demand (lower row of Fig. 8), the relative performance of the TLA decreases except for the metrics “dynamic capacity”.

4 Discussion

We have investigated, by means of simulation, a concept of a traffic-light assistant (TLA) containing three strategies to optimize the approach to and starting from traffic lights: “economic approach”, “anticipative start”, and “flying start”. The strategies are based on V2X communication: In order to implement the TLA, equipped vehicles must obtain switching information of the relevant traffic lights and – as in the self-controlled signal strategy [LH08] – counting data from a detector at least 100 m upstream of the traffic light. Complex simulations including all interactions show that, for comparatively low traffic demand, the TLA is effective. To quantify this, we introduced relative performance indexes which we consider to be the most universal approach to assess penetration effects of individual-vehicle based ITS. For our specific setting (maximum speed 50 km/h, cycle time 60 s, green time 30 s), we obtained performance indexes of about 4% for most metrics if traffic demand is low. We obtain higher values for higher maximum speeds and lower cycle times, and lower values for a higher demand. While the relative performance is generally lower than that of the traffic-adaptive ACC on freeways (about 25%) [KTH10], the individual advantage kicks in with the first equipped vehicle, in contrast to traffic-adaptive ACC.

Acknowledgements

We would like to thank the Volkswagen AG who has sponsored part of this work in a project.
Bibliography

[CM91] Catling, Ian; McQueen, Bob: Road transport informatics in Europe-major programs and demonstrations. In: Vehicular Technology, IEEE Transactions on 40 (1991), Nr. 1, S. 132–140

[HRBW81] Hunt, PB; Robertson, DI; Bretherton, RD; Winton, RI: SCOOT: A traffic responsive method of coordinating signals. 1981. – Forschungsbericht

[KP08] Kranke, Florian; Poppe, Holger: Traffic Guard - Merging sensor data and C2I/C2C information for proactive congestion avoiding driver assistance systems. In: FISITA World Automotive Congress, 2008

[KTH10] Kesting, A.; Treiber, M.; Helbing, D.: Enhanced Intelligent Driver Model to access the impact of driving strategies on traffic capacity. In: Philosophical Transactions of the Royal Society A 368 (2010), S. 4585–4605

[KüC08] Kücking: Analyse des Verkehrsablaufs an signalisierten Kreuzungen - wie schnell lösen sich Rückstaus auf? 2008. – Volkswagen AG, unpublished

[LH08] Lämmerr, Stefan; Helbing, Dirk: Self-control of traffic lights and vehicle flows in urban road networks. In: Journal of Statistical Mechanics: Theory and Experiment 2008 (2008), Nr. 04, S. P04019

[Low82] Lowrie, PR: The Sydney coordinated adaptive traffic system—principles, methodology, algorithms. In: International Conference on Road Traffic Signalling, 1982, London, United Kingdom, 1982

[LW55] Lighthill, M.J.; Whitham, G.B.: On kinematic waves: II. A theory of traffic on long crowded roads. In: Proc. Roy. Soc. of London A 229 (1955), S. 317–345

[Ott11] Otto, Thomas: Kooperative Verkehrsbeeinflussung und Verkehrssteuerung an signalisierten Knotenpunkten. Bd. 21. kassel university press GmbH, 2011

[THH00] Treiber, M.; Hennecke, Ansgar; Helbing, D.: Congested traffic states in empirical observations and microscopic simulations. In: Physical Review E 62 (2000), S. 1805–1824

[TK13] Treiber, M.; Kesting, A.: Traffic Flow Dynamics: Data, Models and Simulation. Berlin: Springer, 2013
[Tra]  NGSIM - Next Generation Simulation. 2012. http://ngsim-community.org/. Accessed August 14, 2012.

[TTK08] THIEMANN, Christian; TREIBER, Martin; KESTING, Arne: Longitudinal hopping in inter-vehicle communication: Theory and simulations on modeled and empirical trajectory data. In: Physical Review E 78 (2008), S. 036102

[VHZ+10] VITI, Francesco; HOOGENDOORN, Serge P.; ZUYLEN, Henk J.; WILMINK, Isabel R.; VAN AREM, Bart: Microscopic data for analyzing driving behavior at traffic signals. In: Traffic Data Collection and its Standardization. Springer, 2010, S. 171–191

Corresponding author: Martin Treiber, University of Dresden, Institute of Traffic Economics, e-mail: treiber@vwi.tu-dresden.de