# INTEGRATING RELIABLE SPEED ADVISORY INFORMATION AND ADAPTIVE URBAN TRAFFIC CONTROL FOR CONNECTED VEHICLES

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## ABSTRACT

In this paper, a control algorithm is presented that integrates connected vehicles in the feedback loop of traffic signal control, which results in highly flexible, signal-group based signalization and speed adaptation of vehicles. The method is based on Model Predictive Control and incorporates a mutual optimization of both traffic signal timings and vehicle trajectories. In light of emerging communication technology, connected vehicles are expected to deliver more detailed data about the current traffic flow compared to stationary detection. This data can be used to influence the signal timing. By capitalizing on the possibility of providing information to connected vehicles, a second means of influence is enabled: Information about future signal timings can be provided to the drivers and hence, further reductions in the number of stops and an increase of traffic flow at the beginning of the green time can be achieved. The complexity increases when both ways of influence are combined, which is often omitted in previous research. This combination is addressed in this paper by introducing an optimized signal control with an integrated speed advisory system. The presented algorithm features an innovative functionality to adjust the predictability of signal timings to account for the reliability of speed advisory messages. A simulation study is carried out as a proof of concept and to evaluate the trade-off between optimality and predictability of the traffic signal control algorithm.


*Keywords*: Traffic Signal Control, Connected Vehicles, Predictability, Model Predictive Control

# INTRODUCTION

In the US 63% of on-road $CO_2$ emissions are caused by urban traffic *(1)*, which makes it worthwhile to investigate and exploit potentials to raise the efficiency of urban traffic. Among the possibilities are Intelligent Transportation Systems, which often focus on the operation of intersections as they have a prevailing effect on the urban traffic flow. Control of traffic flow by electric traffic signals was introduced in 1914 *(2)* to raise efficiency and safety at urban intersections. Further improvements have been reached by adapting to varying traffic demands. Detection of vehicular traffic has been used extensively for decades to enable this adaptation. Relying on data from stationary detection as a feedback from the road system, algorithms ranging from rule-based traffic actuation to model-based traffic adaptive control have been developed.

In light of emerging communication technologies, cooperative systems are expected to mitigate the negative effects of vehicular traffic. The potentials to increase traffic efficiency at urban intersections can be exploited mainly in two ways. First, the signal timing can be optimized based on data from connected vehicles, which is more detailed than data obtained from stationary detection. Second, vehicle speeds can be actively adapted by providing information about future signal timings – the Green Light Optimized Speed Advisory (GLOSA). The goal of GLOSA systems is a reduction in the number of stops by recommending a speed, whenever it is reasonable, that avoids the arrival at the stop line or the tail of a possible queue during red. Additionally, an increase in traffic flow due to minimizing the need for accelerations from a stop at the beginning of the green phase can be achieved. Due to the reduction in the number of stops, a reduction in emissions and fuel consumption is expected. Although the usage of infrastructural countdown displays is often limited to pedestrian signals (as described in the MUTCD *(3)* for the US), an in-vehicle indication of the remaining red time can help to reduce red light violations and decrease losses of efficiency in the beginning of green due to driver distraction. It can also be used to improve the functionality of start-stop systems.

A large number of research activities have been undertaken, focusing either on influencing connected vehicles with a given signal control or on making use of data from connected vehicles to improve the signal control. A selection of these activities is reviewed in the next chapter. However, to exploit the entire potential of optimizing the operation of signalized intersections with connected vehicles, both ways of communication and influence have to be used simultaneously. Only limited research in this area exists and a new method to integrate both ways of influence is presented in this paper. The interdependency between the signal timing and the influence on vehicle speeds becomes apparent by extending a standard control loop of traffic signal control by functionalities of connected vehicles as shown in Figure 1. Advanced driver assistance systems (ADAS) are used as an actuator to influence vehicle trajectories based on information about the traffic signal control, leading to an influence on the traffic flow at the intersection. The traffic flow is estimated by taking into account data from stationary detectors and floating vehicles and this estimation is used to calculate signal timings. If the traffic signal control does not take the influence on vehicles' behavior into account, the performance of the overall system deteriorates, especially if both traffic signal control and influence on vehicles' trajectories are highly dynamic. A tangible, simplified example can be given as follows: At an intersection with local actuated control by means of a passage timer, a connected vehicle approaches a red signal that will turn green within a few seconds. Assuming a correct prediction of the beginning of green and the queue length, the connected vehicle receives a recommendation to reduce the speed in order to avoid hitting the end of the queue and thus avoiding a stop. The speed recommendation leads to an extension of the time gap between the connected vehicle and the leading vehicle. If this time gap exceeds the set passage time, the green time will not be extended and the connected vehicle will have to stop and wait for the next cycle. In this case, a green time extension, either by raising the passage time or by accepting the stop of the connected vehicle, might have been beneficial. This example shows that not only correct prediction of signal timings and queue lengths is necessary for the performance of the overall system, but that influencing the measurement parameter of the signal control, here the time gap, by influencing vehicles can lead to deterioration of the system performance as well.

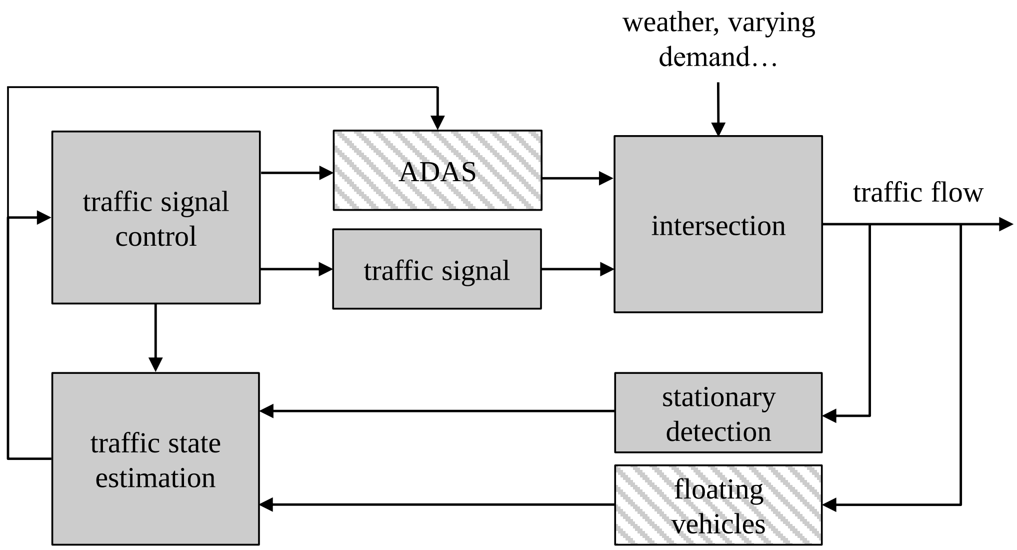


**FIGURE 1 Control loop of traffic signal control extended by connected vehicle functionalities (striped pattern), adapted from Kaths et al.** *(4)***.**

Based on these considerations, an algorithm is presented in this paper that leads to a full integration of the vehicles in the feedback loop and as such, delivers optimized signal timings and speed advisory information at the same time. The algorithm relies on the theory of Model Predictive Control (MPC) and therefore includes an intrinsic prediction of the future signal timing. The obtained signal control is highly flexible since it is based on signal groups and a minimal set of constraints. A trade-off between flexibility and predictability of signal timings can be identified: For example, fixed-time control is a highly predictable, but inflexible signal control, whereas a fully actuated control can be highly flexible, but is inherently harder to predict. The algorithm presented in this paper aims at the combination of high flexibility and predictability. It allows for the adjustment of the predictability of signal timings to account for the reliability of speed recommendations. A simulation study is used to prove the concept and to evaluate the trade-off between flexibility and predictability for the presented control algorithm.

## REVIEW OF PREVIOUS RESEARCH

Connected vehicles can deliver detailed information about the current traffic state, which can enable improvements in signal timing optimization. Furthermore, the drivers, or in case of an automated vehicle the vehicle itself, can be influenced by providing information about future signal timings. The following overview of previous research is categorized by the type of influence used. As a large number of research acitivities focus on using one type of influence, only a selection of the activities in the first two categories is reviewed here.

**Using data from cooperative vehicles to improve signal timing**

Goodall et al. *(5)* present a control algorithm that makes use of data from connected vehicles in order to optimize signal timings in a rolling horizon fashion according to a cost functional that can include a combination of delay, stops and decelerations. After a rule-based priority assignment of signal phases, the phases with highest priorities are selected for simulation with VISSIM and the phase with the lowest cost is selected for the operation. The control algorithm does not make use of stationary detection or further state estimation and improvements compared to a reference control on a coordinated road stretch are achieved with equipment rates from 25% on. Priemer and Friedrich *(6)* introduce another decentralized control method that is based on the rolling horizon principle. The optimization aims at minimizing the total queue length at intersections. Both of the aforementioned methods do not directly consider the possibility of influencing the speed of connected vehicles. One way to integrate data from connected vehicles is the usage for the estimation of queue lengths. Queue lengths can be an important input factor in traffic responsive control, but cannot be explicitly measured. Priemer and Friedrich *(7)* propose a queue length estimator for the associated control algorithm *(6)* that is related to the one from *(8)*, but allows for the consideration of connected vehicles as “virtual detectors”.

**Influencing cooperative vehicles by providing information about signal timing**

Kamalanathsharma and Rakha *(9)* propose an optimization of vehicle trajectories based on dynamic programming. The method aims at a minimizing fuel consumption and considers information from surrounding equipped vehicles and connected traffic signals. The future signal timings are regarded as a given input and are not subject to optimization in the presented procedure. Stevanovic et al. *(10)* investigate the effect of influencing vehicles’ speeds based on the future signal timing with fixed-time control and actuated control. The authors show in simulation studies that the waiting time can be greatly reduced by introducing GLOSA functionalities. Furthermore, they observe erratic behavior and a reduction in system performance when combining actuated control and speed advisory information. This is due to a lack of knowledge concerning the future signal timing.

Since most of the existing urban traffic control systems were developed before cooperative systems arose, predictability of signal timings was not a system requirement. At the same time, this prediction is the main requirement to enable reliable speed advisory systems. Under these considerations, several algorithms have been developed to predict signal timings for traffic dependent signal control. They can be divided into those using system knowledge of the control algorithm and those that omit such knowledge. For example, system knowledge of hierarchical traffic control systems such as MOTION *(11)* and BALANCE *(12)* offers possibilities for the prediction of traffic signal timings. In urban traffic control systems of this type, network-wide frame signal plans are generated and adapted by local control on the intersection level. A field study on a coordinated road stretch with local adaptation where the information from a frame signal plan is used to enable a GLOSA system can be found in *(13)*. Other urban traffic control systems, such as the one introduced in this paper, rely on the rolling horizon principle. Due to this principle, such systems (for example UTOPIA *(14)*, RHODES *(15)*, OPAC *(16)*) possess an intrinsic prediction of the signal timing. Accordingly the authors in *(17)* present a field study and mention that information about future signal timings is obtained from the intrinsic prediction of UTOPIA. Bauer et al. *(18)* present an online prediction system for local actuated control, which relies on supply data from the considered intersection.

Other methods purposely do not include system knowledge for the prediction of signal timings, which is done in favor of general applicability. These methods either rely solely on historical switching data or integrate online detector values. Weisheit and Hoyer *(19)* use support vector machines as a statistical instrument, allowing for learning based on historical data and the usage of online data from detectors. In contrast, Protschky et al. *(20)* present a method that relies solely on historical data and is therefore widely applicable with minimal effort. Frequency distributions of green times with regard to the cycle times are obtained from historical data and a Kalman Filter is implemented to predict future signal timing.

To enable reliable speed advisory information, queue lengths should be considered in addition to the information about future signal timings. Queue lengths can be estimated using the procedures mentioned earlier.

### Integrated use of data from connected vehicles and speed advisory systems

The aforementioned procedures focus on the usage of connected vehicles to influence either the traffic signal control or the vehicles' speeds. Using data from connected vehicles and influencing their speeds at the same time was already conducted in some of the research projects reviewed by Kaths et al. *(4)*. This however, does not lead to a full integration of the speed advisory system as it is working independently from the traffic responsive control. Different to these methods, Menig *(21)* and Erdmann *(22)* propose algorithms that mutually optimize vehicle trajectories and signal timings. In both approaches, simulation studies are presented where only two conflicting streams are present and the control is realized in a phase-based manner where the respective signal groups are combined. The method proposed by Menig *(21)* allows to set up intergreen times and is investigated including scenarios with equipment rates lower than 100%, whereas Erdmann's approach *(22)* additionally allows to constrain minimum phase durations, but does not seem to easily allow for an integration of non-equipped vehicles.

## MUTUAL OPTIMIZATION OF SIGNAL TIMINGS AND VEHICLE TRAJECTORIES

In this paper, a new control method based on MPC is introduced that mutually optimizes signal timings and vehicle trajectories, leading to an integrated use of data from connected vehicles and speed advisory systems. In contrast to the reviewed approaches from *(21)* and *(22)*, more than two conflicting streams are considered and the resulting optimized signalization is based on signal groups and is therefore highly flexible. The formulation of constraints allows for the adjustment of minimum green times, intergreen times and maximum red times. Furthermore, the presented algorithm incorporates a choice of predictability of signal timings in order to facilitate smooth and reliable speed advisory messages.

The chosen control method is MPC of which principles are used likewise in some of the procedures mentioned earlier. The method arose in the 1970s and is treated comprehensively in literature for example by Camacho and Bordons *(23)*. Therefore, only the main ideas and advantages for the application in traffic signal control are adapted here from *(23)*:

- MPC makes explicit use of a model to predict the system behavior over a number of time instants (prediction horizon $N_p$)
- a control sequence is calculated for a number of time instants (control horizon $N_c \leq N_p$) by minimizing an objective function
- only the first control signal of the calculated sequence is applied at each time step

using a receding strategy

- constraints such as intergreen times and minimum green times are explicitly taken into account within the minimization
- multi-variable control can be easily implemented

However, drawbacks of MPC include a large computational effort to solve the minimization problem and the necessity for an appropriate model for the controlled system.

The model that is implemented here to reflect the movement of connected vehicles is a microscopic model that is continuous in space and discrete in time. It describes a vehicle's distance from the stop line $x_{k+n_c|k}$ at the instant $k+n_c$ calculated at time step $k$ for the computed steps $n_c \in [1,Nc]$ of the control sequence with the following equation:

$$x_{k+n_c|k} = x_{k+n_c-1|k} - \left(v^{max} - u^{GLOSA}_{k+n_c|k} - u^{STOP}_{k+n_c|k}\right)\Delta t \qquad (1)$$

where $v^{max}$ equals the speed limit and $u^{GLOSA}_{k+n_c|k}$ and $u^{STOP}_{k+n_c|k}$ are speed reductions originating from speed recommendations and further speed reductions due to impeding vehicles downstream respectively. The separation of the two speed reductions allows for the explicit consideration of speed advisory information by setting different constraints and optimization weights.

Equation 1 is only meaningful if a number of boundary conditions is included such as restrictions on the speed reductions at each step $n_c$. Equation 2 assures that vehicles only have positive speeds and do not drive backwards. Equation 3 is used to limit the speed reduction due to recommendations with the preset parameter $r^{GLOSA}$ as a percentage of the speed limit. To avoid speeds greater than the speed limit, equations 4 and 5 are introduced.

$$u^{GLOSA}_{k+n_c|k} + u^{STOP}_{k+n_c|k} \leq v^{max} \qquad (2)$$

$$u^{GLOSA}_{k+n_c|k} \leq \left(1 - r^{GLOSA}\right) \bullet v^{max}, \quad 0 \leq r^{GLOSA} \leq 1 \qquad (3)$$

$$u^{GLOSA}_{k+n_c|k} \geq 0 \qquad (4)$$

$$u^{STOP}_{k+n_c|k} \geq 0 \qquad (5)$$

In microscopic simulation or real environments, speeds above the speed limit can be observed. However, the model does not consider such speeds since otherwise speeding would be rewarded with earlier green times and recommendations above the speed limit are not acceptable for reasons of safety. Further restrictions on the speed reductions are introduced to include minimum and maximum accelerations by comparing speeds between consecutive steps $n_c$. Equation 6 leads to a constrained positive acceleration with the boundary $a^{accel,max}$ while equation 7 is used to limit the maximum deceleration that can be used for speed recommendations. This is done, since high decelerations are not accepted by drivers when considering speed recommendations *(21)*.

$$\left(u^{GLOSA}_{k+n_c-1|k} + u^{STOP}_{k+n_c-1|k}\right) - \left(u^{GLOSA}_{k+n_c|k} + u^{STOP}_{k+n_c|k}\right) \leq a^{accel,max} \bullet \Delta t, \quad a^{accel,max} \geq 0 \qquad (6)$$

$$u^{GLOSA}_{k+n_c|k} - u^{GLOSA}_{k+n_c-1|k} \leq a^{decel,max} \bullet \Delta t, \quad a^{decel,max} \leq 0 \qquad (7)$$

Note that equations 1, 6 and 7 include references to the previous step in the control horizon. In the first step of the optimization, the available measurements are used instead.

Equations 1 to 7 describe the behavior of a single vehicle in one lane and are used repeatedly $N$ times for a lane with a maximum number of vehicles $N$. To keep a minimum distance $d^{min}$ between subsequent vehicles, equation 8 is used. This constraint also implies that overtaking within one lane is impossible:

$$x^{n}_{k+n_c|k} \geq x^{n+1}_{k+n_c|k} + d^{min},\ \ n \,\epsilon\, [0, N] \tag{8}$$

Additionally, a constraint on the deceleration depending on the distance to the next vehicle downstream is used in order to guarantee that $u^{STOP}_{k+n_c|k}$ is only activated to slow down vehicles when necessary. The distance between subsequent vehicles has to be lower than the threshold $d^{STOP}$ for the activation of $u^{STOP}_{k+n_c|k}$:

$$u^{STOP,n}_{k+n_c|k} - u^{STOP,n}_{k+n_c-1|k} \leq \begin{cases} a^{decel,max} \bullet \Delta t & if\ x^{n}_{k+n_c|k} - x^{n+1}_{k+n_c|k} \leq d^{STOP} \\ 0 & otherwise \end{cases},\ \ n \,\epsilon\, [0, N] \tag{9}$$

Traffic signals are modelled as a vehicle at the position *N+1* standing at the stop line if the signal is red ($u^{TL}=1$) or far downstream of the stop line if the signal is green ($u^{TL}=0$). The condition in equation 10 is necessary, because otherwise switching from green to red within the control horizon would not be possible if a vehicle passed the stop line within the control horizon:

$$x^{N+1}_{k+n_c|k} = \begin{cases} 0 & if\ u^{TL}_{k+n_c|k} = 1 \\ -\infty & if\ u^{TL}_{k+n_c|k} = 0 \end{cases} \tag{10}$$

In the same way that equation 8 limits the distance between subsequent vehicles, the distance $d^{TL}$ between each vehicle and the traffic signal has to be maintained:

$$x^{n}_{k+n_c|k} \geq x^{N+1}_{k+n_c|k} + d^{TL},\ \ n \,\epsilon\, [0, N] \tag{11}$$

Equations 1 to 11 describe the behavior of vehicles and traffic signals under the influence of the control inputs $u^{GLOSA}_{k+n_c|k}$, $u^{STOP}_{k+n_c|k}$ and $u^{TL}_{k+n_c|k}$.

These constraints influence solely the model behavior, but do not take restrictions of the signalization into account. Applying the MPC control would lead to constant green for all streams at the same time, as this would be optimal. Under this consideration, further constraints are incorporated on the signalization. For the sake of compactness, detailed mathematical expressions of these constraints are omitted in this paper. The implemented constraints include:

- minimum green times per signal group
- maximum green times per signal group
- intergreen times between signal groups and
- exclusion of simultaneous signalization of conflicting streams.

These constraints are adjustable and can be seen as a minimal set of constraints for the signalization where no definition of phases or sequences is necessary. The decision variables do not directly include green splits, offset or cycle time. Instead, a second-by-second decision is made to determine which signal-groups receive green. Therefore, the resulting online optimization leads to a highly flexible, signal-group based signalization including the speed adaptation of connected vehicles.

The MPC strategy is used to find an optimal set of these control inputs over the control horizon $N_c$ under consideration of the given constraints. Most implementations of optimal control strategies use a quadratic cost function to represent quadratic energy consumption of control inputs. However, in traffic applications, linear costs are generally more reasonable, since criteria like stops or the total time spent can be penalized linearly and control actions of traffic signals do not result in quadratic costs. Therefore, and to achieve faster solving times, a linear cost function is used. The cost function is given in equation 12, where $J$ is the cost, $\eta$ the decision variable and $f$ the linear weighting vector. Inequality and equality constraints in form of the equations 13 and 14 are incorporated by creating matrices $M$, $E$ and the corresponding vectors $g$, $d$. Additionally, selected variables can be restricted to integer variables leading to a leading to a Mixed-Integer Linear Program (MILP).

$$J = \eta^T f \tag{12}$$

$$M\eta \leq g \tag{13}$$

$$E\eta = d \tag{14}$$

The decision variable $\eta$ contains the state-variable $x^n$ and the control inputs $u^{GLOSA}$ and $u^{STOP}$ for each step $n_c$ of the control horizon $N_c$ and for each considered vehicle. Additionally, the state variable $x^{N+1}$ and the control input $u^{TL}$ are included for each signal group, where $u^{TL}$ is an integer variable restricted to the values 0 and 1. Furthermore, two auxiliary variables are introduced. One indicates for each vehicle if it has a positive (*aux,sl*=1) or negative (*aux,sl*=0) distance to the stop line, meaning if it is upstream or downstream of the stop line. The second auxiliary variable indicates if the distance to the next downstream vehicle is smaller (*aux,ds*=1) or greater (*aux,ds*=0) than the threshold value $d^{STOP}$. The auxiliary variables are necessary to make use of the conditional constraints given in equations 9 and 10. For the methods to create the auxiliary variables and conditional constraints the reader is referred to *(24)*. The vector with the decision variables for one signalized lane are expressed as follows:

$$\eta = \begin{bmatrix} \eta_k^1 & \cdots & \eta_k^N & \eta_k^{TL,N+1} \end{bmatrix}^T \tag{15}$$

with:

$$\begin{aligned} \eta_k^n = \Big[ & x_{k+1|k}^n \quad \cdots \quad x_{k+N_c|k}^n \quad u_{k+1|k}^{n,GLOSA} \quad \cdots \quad u_{k+N_c|k}^{n,GLOSA} \quad u_{k+1|k}^{n,STOP} \quad \cdots \quad u_{k+N_c|k}^{n,STOP} \\ & \cdots \quad aux,sl_{k+1|k}^n \quad \cdots \quad aux,sl_{k+1|k}^n \quad aux,ds_{k+1|k}^n \quad \cdots \quad aux,ds_{k+N_c|k}^n \Big]^T \end{aligned} \tag{16}$$

$$\eta_k^{TL,N+1} = \begin{bmatrix} x_{k+1|k}^{N+1} & \cdots & x_{k+N_c|k}^{N+1} & u_{k+1|k}^{TL} & \cdots & u_{k+N_c|k}^{TL} \end{bmatrix}^T \tag{17}$$

In order to obtain a mutual optimization of signal timings and vehicle speeds, equations 1 to 11 and the constraints regarding the signalization are transformed into the form of equations 13 and 14. Using an MILP solver, the cost function from equation 12 can be minimized under consideration of the given constraints. The decision variables in vector $\eta$ from equation 15 and the cost value $J$ are retrieved as a result.

The choice of weights for vector $f$ from equation 12 can be adjusted for each component of the decision vector separately. This is the main reason for separating the speed reductions in equation 1 into speed recommendations on one hand and other factors such as impeding downstream vehicles or red signals on the other hand. Due to different penalties and the different constraints on these control inputs, the optimization will yield different results for $u_{k+n_c|k}^{GLOSA}$ and $u_{k+n_c|k}^{STOP}$. A first natural choice for the weights of vector $f$ is a high penalty on all $u_{k+n_c|k}^{STOP}$ and a low penalty on all $u_{k+n_c|k}^{GLOSA}$. Vehicles will then be slowed down with speed recommendations, but stops and speeds below the recommendation limit (see equation 3 with the factor $r^{GLOSA}$) will be avoided due to higher penalization. Furthermore, the weights can be differentiated to account for different priority levels for different modes such as private vehicles, public transport vehicles or emergency vehicles.

By choosing appropriate weighting factors, another functionality that addresses the predictability of the signal timing can be enabled. Because speed recommendations are obtained directly from the decision variables, an explicit prediction of queue lengths and signal timing is unnecessary for the chosen approach. However, currently messages are stipulated that include signal phases and timing (SPaT) instead of direct speed recommendations. For this reason and for a general stabilization of the signal timing, a penalty is introduced that punishes deviations of the current prediction compared to the previous prediction shifted by one time step. The penalty decreases quadratically over the prediction horizon to punish deviations in the near future harder than those that might occur later. Deviations in the last steps of the control horizon are not penalized to avoid strong limitations on the flexibility of the optimization. The deviations in the prediction occur due to the limited lengths of the control horizon and due to differences between the model described in this paper and the one that is provided by the microsimulation. By introducing these weights, the algorithm incorporates the innovative possibility of a choice of predictability compromising optimality of the overall system.

## SIMULATION STUDY

To prove the concept of a mutual optimization of signal timings and vehicle speeds a simulation study is carried out. The optimization algorithm is coupled with the microscopic traffic simulator SUMO *(25)*. SUMO's TraCI interface is used to retrieve data from floating vehicles (FVD) and detectors and to influence vehicle speeds and traffic signals. At each time step, the updated objective function and constraints are given to the CPLEX solver using a dedicated Python API. Figure 2 shows how the algorithm is embedded into the microsimulation.

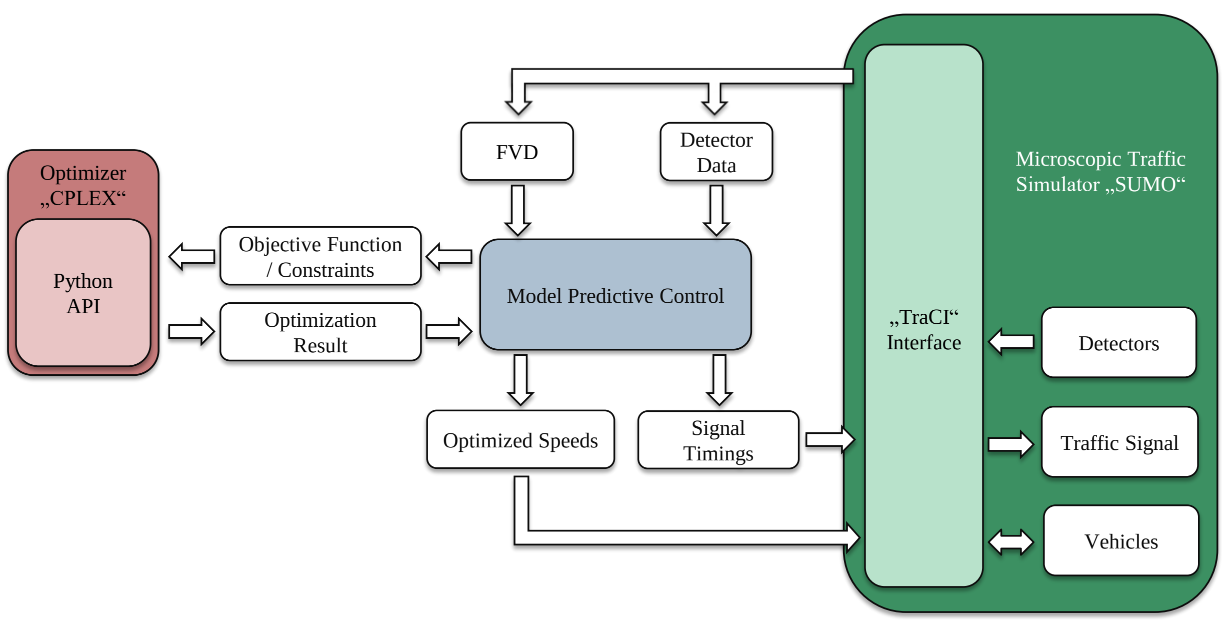


**FIGURE 2 Embedment of the optimization algorithm into the microsimulation.**

The simulation study is carried out on a hypothetical intersection shown in Figure 3 with four symmetric approaches and long separate left turning lanes. The left turning movements are signalized separately without permissive movements. Intergreen times of 4s are found to be sufficient and are chosen between signal groups of all conflicting movements starting with a yellow signal. A low traffic flow of 180veh/h per lane is set as an input to allow for high flexibility in the optimization. SUMO standard parameters are used and a standard deviation of 10% of the speed limit is applied to introduce a uniform distribution of vehicle speeds around the speed limit.

Four different scenarios are carried out in order to investigate the performance of the presented control algorithm. Per scenario 20000s of simulation are considered for the evaluation. The scenarios 2 to 4 make use of the presented control algorithm and comprise weights on stopped or stopping vehicles ($u^{STOP}_{k+n_c|k}$) with a chosen control horizon $N_c$ of 15s with steps of 1s. In scenario 4 penalties on the deviation of predictions are included.

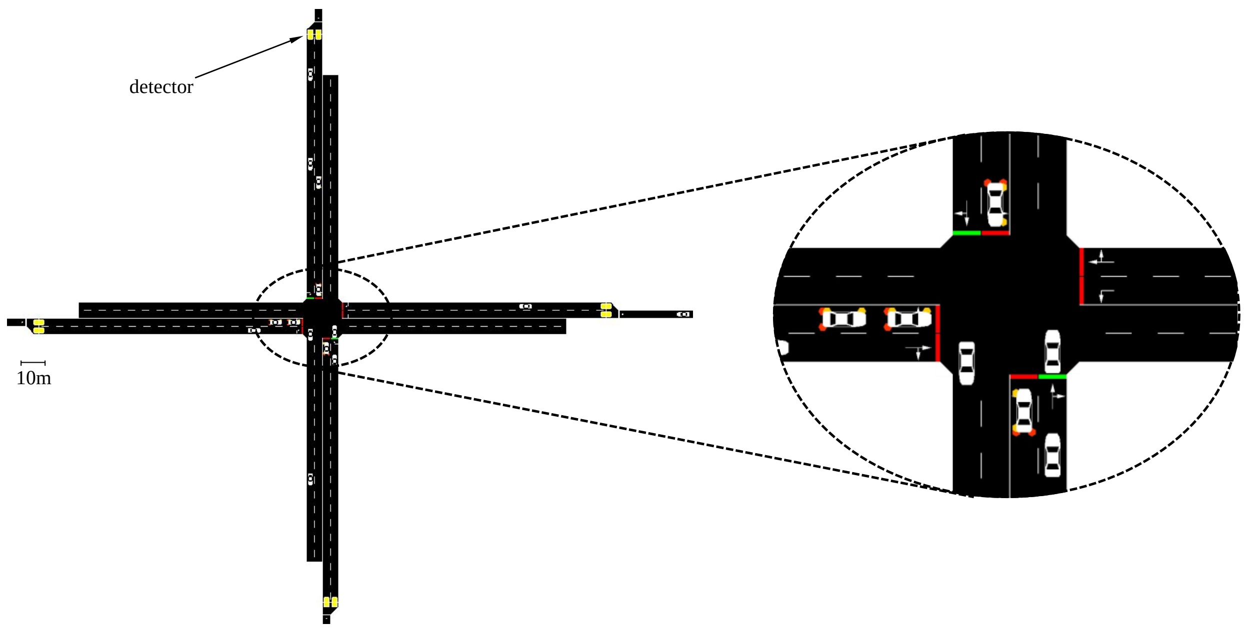


**FIGURE 3 Details of the simulation network showing the whole intersection and the different signal groups.**

**Scenario 1 – actuated control**

A simple traffic actuated control that is commonly used in Germany is considered as a baseline scenario to allow for a general evaluation of the presented algorithm. The passage timer is set to 2.5s and the detectors are, in contrast to what is shown in Figure 3, positioned 34.7m upstream of the stop line considering the speed limit of 13.89m/s according to German guidelines *(26)*. The phase sequence is set such that first straight movements and then the respective left turning movements are given right of way. For the actuated control, 5s of minimum green time were found to be too short to resolve queues that build up downstream of the detector during the red phase. Therefore, a minimum green time of 7s is chosen, which leads to best results for the baseline scenario.

**Scenario 2 – MPC without connected vehicles**

The MPC algorithm is evaluated with different settings. First, a scenario is considered where no connected vehicles are present. Detectors at the start of each lane, as shown in Figure 3, are used to insert detected vehicles into the distance vector of equation 1. Afterwards the distance to the stop line is estimated based on the formulations given in the previous chapter. To account for slower vehicles, the maximum speed of the control model is reduced to 10.0m/s and the maximum acceleration is set to 1.2m/s². No speed advisory information is given to vehicles. Furthermore, a delay at the start of green is introduced to avoid unreasonably short green times. This scenario aims at an evaluation of the performance of the presented proactive control with flexible signal group based signalization compared to the simple reactive traffic actuated control with a fixed phase sequence. For reasons of comparability with the first scenario, a minimum green time of 7s is chosen.

**Scenario 3 – MPC with connected vehicles and no penalties on prediction deviations**

The third scenario intends to show the full potential of a cooperative system where 100% of the vehicles are equipped. The maximum speed of the model is set to 13.89m/s and the maximum acceleration is considered as 2.5m/s². Constraints are implied to limit GLOSA speed reductions to 50% of the maximum speed with a maximum deceleration of -2m/s². The minimum green time in case of this scenarios is set to 5s, which is the minimum given by German regulations *(26)*.

**Scenario 4 – MPC with connected vehicles and penalties on prediction deviations**

The last scenario addresses the trade-off between optimality of the control and its predictability. As described in the last chapter, a penalty on deviations between the current and the last prediction is introduced that is decreasing over the prediction horizon. The last five steps of the prediction horizon are not penalized in order to limit the restrictions on the optimization. Other parameters are kept constant compared to the last mentioned scenario. As in scenario 3, a penetration rate of 100% is assumed and the minimum green time is set to 5s.

The evaluated indicators in all scenarios include:

- the average number of stops per vehicle (stops (n/veh)), vstop<1m/s
- the average waiting time per vehicle (wt (s/veh))
- the average total time spent in the network per vehicle (tts (s/veh))

Because a weighting factor is only chosen for $u^{STOP}_{k+n_c|k}$, the main focus lies on the reduction of the number of stops. However, not only the process of stopping, but also the state of being stopped leads to an increase of the cost function. Thus, an effect on the waiting times and total time spent can be expected at the same time. To increase the priority of the total time spent, the presence of vehicles upstream of the stop line could be penalized by introducing weighting factors in the cost functional of equation 12 on the distance to the stop line $x^{n}_{k+n_c|k}$.

In addition to the above-mentioned indicators in the three scenarios with MPC usage, a measurement for the reliability of the prediction is introduced. The root mean square error (RMSE) of the predicted green time 10s before the actual green time is calculated according to the following equation using *n=10*:

$$RMSE_{pred} = \sqrt{\frac{\sum_{t=1}^{n}(ttg_t - t)^2}{n}} \tag{18}$$

with $ttg_t$ being the predicted time to green *t* seconds prior to the actual beginning of green. Only the first 10s of the control horizon are considered since the penalty on deviations of the prediction is only imposed on these time instants.

The results of the simulation study are shown in Figure 4. The mean values of the indicators are shown as columns including the number of the mean value, while the standard deviation is displayed with an error bar. An arrow is displayed between the columns whenever the difference between an indicator of two scenarios is significant ($p<0.05$).

The results show that all three variants of the MPC algorithm perform better than the actuated control. If solely stationary detection is used, the waiting time (-12.2%, p=0.002), number of stops (-4.10%, p=0.004) and total time spent (-10.6%, p=0.000) can be reduced significantly compared to actuated control. The increase in performance can be expected since the MPC algorithm allows for a more flexible signalization and acts in a proactive fashion compared to the reactive actuated control. By including speed advisory information and position data from each vehicle in each time step, the performance increases significantly in scenario 3. The number of stops (-36.3%, p=0.000) and the waiting time (-56.2%, p=0.000) can be reduced

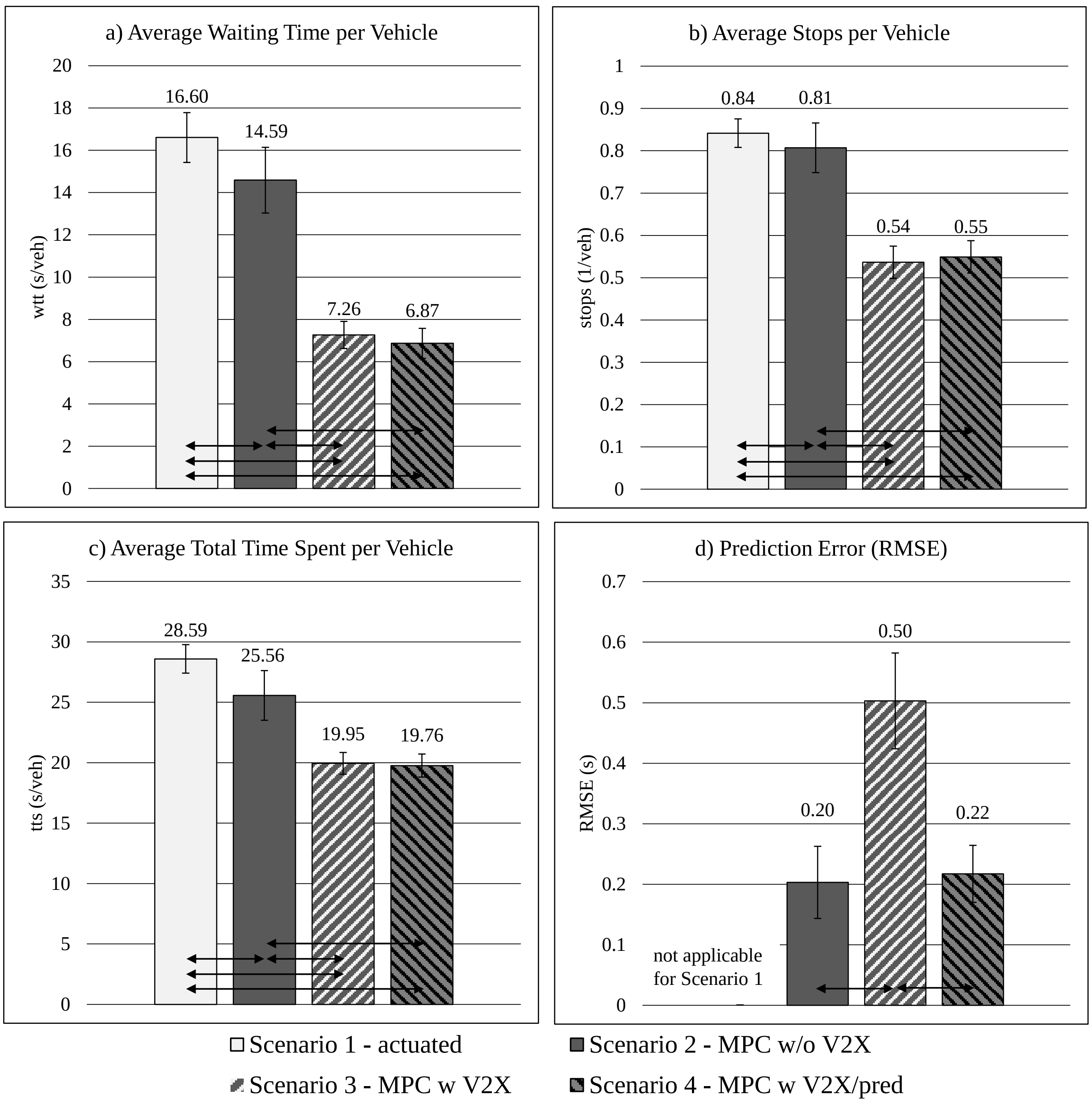


**FIGURE 4 Results of the simulation study including average waiting time per vehicle a), average stops per vehicle b), average total time spent per vehicle c) and prediction error d).**

greatly compared to MPC without connected vehicles, since this is the major effect of speed advisory systems. Furthermore, the total time spent (-30.2%, p=0.000) is reduced significantly, which is based on a more efficient signalization due to accurate position data and a reduced need for accelerations from a stop at the beginning of the green time. Figure 4 also shows that the usage of a penalty of prediction deviations reduces the prediction error introduced in equation 18 significantly when comparing scenarios 3 and 4 (-56.8%, p=0.000). However, only minimal, non-significant differences can be observed regarding the performance indicators waiting time, number of stops and total time spent, which proves the possibility to reduce the prediction errors without overly affecting the efficiency of the control. The prediction error in scenario 2 is relatively low without using a dedicated penalty. This is due to the fact that no connected vehicles are present and therefore deviations between the control model and the simulation model remain unrecognized by the control.

## CONCLUSION AND OUTLOOK

The signal control method that is introduced in this paper allows for the direct inclusion of connected vehicles considering both precise data from such vehicles as well as the possibility to influence vehicle speeds. Both, the signal timing and the vehicle speeds are optimized mutually. The control algorithm limits the flexibility of the signal control as little as possible by using a minimal set of constraints, which leads to a signal group based signalization. The achieved results show significant improvements of the performance indicators in comparison to actuated control. This increase in performance is based on the full integration of connected vehicles in the control loop and a highly flexible proactive control scheme. To raise the predictability of future signal timings, the developed algorithm includes the possibility to compromise predictability and optimality of the control by setting a weight factor. The results show an increase of predictability with a minimal deterioration of the performance indicators. Since the assignments of weights for single vehicles is possible, the proposed control algorithm also allows for a straightforward implementation of priority for public transport or emergency vehicles leading to flexible green time allocations for such modes.

Further research can be undertaken to build up on these findings. First, steps toward the application in reality can be made. Currently the computational effort is too high to consider this method for the use with state-of-the-art traffic controllers. Second, the approach has proven its functionality for undersaturated conditions on an isolated intersection. A similar control method that does not include the optimization of vehicle speeds was presented by this author *(27)* and proved performance in more saturated conditions. By connecting multiple intersections with the presented type of control, a coordination evolves automatically. However, to guarantee efficiency in a larger network with saturated or over-saturated conditions, extensions have to be made such as the integration of information from downstream links or terminal costs as it is done for example in *(28)*.

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