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USING MODEL PREDICTIVE CONTROL FOR COOPERATIVE TRAFFIC SIGNAL CONTROL

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Abstract. *In this document, an approach for a cooperative traffic signal control will be introduced that is based on the technique of model predictive control. The described approach is of theoretic nature and comprises a simple microscopic traffic flow model in order to integrate the estimation of the traffic state and the derivation of optimal signalization. Data from conventional detection as well as from cooperative vehicles is used to obtain a control that despite its flexibility offers predictability in a way that reliable speed advisory information for drivers can be obtained. Model predictive control is used in order to determine an optimized signal timing under consideration of constraints.*

1 INTRODUCTION

In light of emerging communication technologies, the development of strategies to realize the potential benefits of vehicle-2-x (V2X) communication has become of major interest in the field of traffic engineering in recent years. The main goals are to increase the efficiency and improve the safety of transportation systems. As intersections can be seen as the bottleneck of urban traffic flow, the improvement of traffic signal control by making use of the data generated by V2X technologies and by informing drivers about signal phase and timing is investigated in several research projects. These applications mainly address a raise of efficiency in urban areas due to an optimized adaptive traffic signal control as well as an increase in driver comfort by reducing the number of stops. It is difficult to generate reliable information for drivers because modern traffic signal control systems are continually adapting. This paper proposes a theoretic approach towards a highly flexible but predictable control of traffic signals that incorporates information provided by equipped vehicles and conventional detection. This paper is based on a German publication by the author [1].

2 CONTROL APPROACH

The aim of the proposed control approach is to obtain an optimized signal timing by taking into account non-aggregated microscopic data from conventional detection and floating vehicle data (FVD), which are provided by equipped vehicles via vehicle-2-infrastructure (V2I) communication. Conventional detection, provided by inductive loops for example, is considered because a high equipment rate of cooperative vehicles cannot be expected in the near future. A state estimation is used to fuse data from different sources and to estimate the traffic state in cases where incomplete measurement data are available. The same traffic flow model that the state estimation relies on is used to obtain an optimized signal timing while taking into account several constraints according to the principles of model predictive control (MPC). By implementing MPC, future information about the signal timing and the traffic state is calculated and can be used to provide green light optimal speed advisory (GLOSA) information to equipped vehicles via infrastructure-2-vehicle (I2V) communication, allowing drivers to avoid stopping.

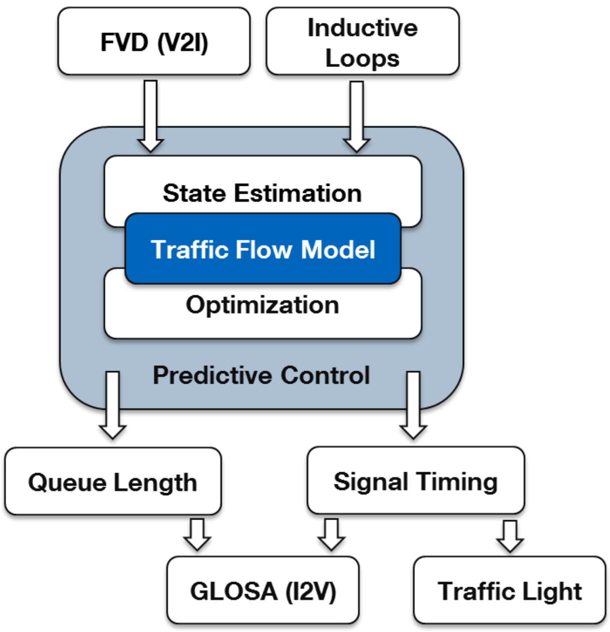

Figure 1: Control Approach

Figure 1 gives an overview of the proposed control approach. The different elements of the control approach are described in Section 3 to 5. The results of a functional test are shown in Section 6 and Sections 7 and 8 provide an outlook and summary.

3 TRAFFIC FLOW MODEL

The traffic flow model builds the core of the traffic state estimation and the control. The model is formulated in state-space to facilitate the usage of standardized methods of control theory such as the Kalman-filtering for state estimation (Section 4) or MPC for controlling (Section 5). Furthermore, reusability and interchangeability of different parts of the proposed concept are increased by using standardized methods. According to the time-discrete state-space formulation, the state of a system in the following time step k+1 is defined by the system matrix A, the input matrix B, the current system state x_k and the current input u_k. The output of the system is obtained by a multiplication of the output matrix C with the current state x_k. The respective formulation is as follows:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k \\ y &= Cx_k \end{aligned} \tag{1}$$

Despite the previously stated advantages, traffic flow models are generally not formulated in this manner. However, the well-established traffic flow model by Daganzo [2] can be formulated in state-space as shown by Tampère & Immers [3]. Similar to this approach, a formulation of the microscopic cellular automaton originally proposed by Nagel & Schreckenberg [4] is feasible. Both models are not time-invariant, which makes the implementation of MPC very difficult. For this reason, Sun & Bayen [5] propose a simplified model where the matrices A and B in eq. (1) are constant over time, which makes the use of MPC with standardized procedures possible, as shown for example by Camacho [6]. Thus, the use of the simplified model is justified despite its low level of detail.

To apply the model, the considered road segment must be discretized into cells as shown in the example in Figure 2.

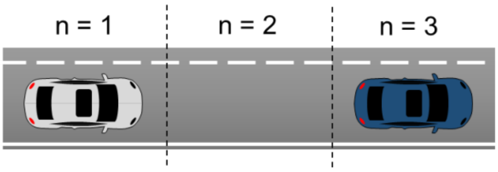

Figure 2: Discretized Road Segment

The state vector contains zeroes for empty cells and ones for occupied cells. For the example shown in Figure 2 it therefore would be:

$$x^T = [1 \quad 0 \quad 1] \tag{2}$$

For this example, the simple traffic flow model is given by the following system and input matrices:

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{3}$$

$$B = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix}$$

The system matrix A moves the entries of the state vector x one position forward as long as the corresponding entry in vector u is zero. If the entry in vector u is one, the state vector's entry will not change due to the input matrix B and thus, the vehicle will remain in its cell. An occupied downstream cell or a red traffic signal can cause this behavior. The input vector is a result of the optimization that is depicted in Figure 1 and it represents the signalization as well as a part of the model behavior. The signalization is modelled in such a way that the cell positioned downstream of the stop line contains a zero in the input vector u for a green signal and a one for a red signal. The microscopic behavior of the model is achieved by setting up constraints for the occupation of the cells as described in Section 5. In the simple form that is described here, the model behaves like a deterministic cellular automaton with only two discrete speed states, zero and one.

The output matrix C from eq. (1) is composed of two components. The first part is the identity matrix, which is necessary to impose the already mentioned constraints on the state variables. The second part performs a weighted summation of the vehicles that are currently occupying the approach. The weight increases with the distance of the vehicles from the intersection. As explained in Section 5, the objective of the optimization is an output y of zero, which leads to a downstream propagation of vehicles through the weighting and a maximum outflow through the summation of vehicles. For the example given in Figure 2, the output matrix would be:

$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 3 & 2 & 1 \end{bmatrix} \tag{4}$$

4 TRAFFIC STATE ESTIMATION

In order to use a standardized method for fusing data from conventional detection and cooperative vehicles, a Kalman-filter is implemented, which relies on the traffic model described in the previous section. Based on the current state, a prediction is made using the model, which is then corrected using position data as depicted in Figure 3.

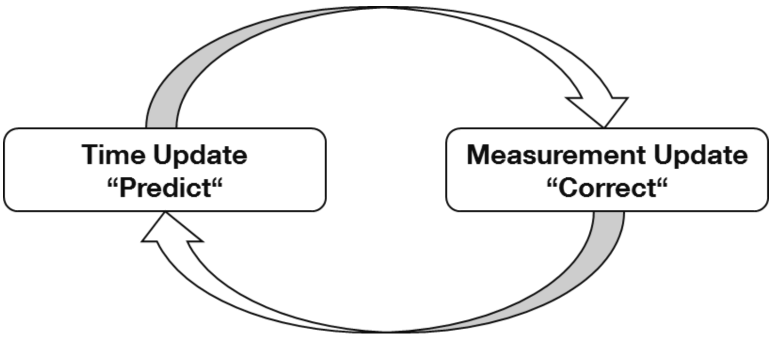

Figure 3: Principle of Kalman-filter (according to [7])

The mathematical description of the Kalman-filter is not given here as it is described extensively in the literature, for example by Welch & Bishop [7]. It should be highlighted here that the filter can be implemented in a straightforward manner thanks to the standardized mathematical formulation of the model in state-space. Because the measurements used in the example that is described in this paper are not noisy and the model depicts microscopic behavior, the use of the Kalman-filter is not mandatory. To achieve the desired behavior, the measurement noise covariance is set very small compared to the process noise covariance. Nevertheless, Kalman-filtering is used in order to raise transferability and interoperability of the proposed approach and to facilitate the integration of further data sources or different traffic flow models. For example, cooperative vehicles with Lidar-sensors as stated by Dittrich & Busch [8] could be used as a further data source to provide the distance to downstream vehicles.

5 USING MODEL PREDICTIVE CONTROL FOR AN ADAPTIVE TRAFFIC SIGNAL CONTROL

The MPC control concept was used for the first time in the mid 1970's in the chemical industry. An advantage of this type of controller is the fact that it includes the principle of optimality while offering the possibility to directly consider constraints. For example, constraints on inputs can be imposed and the search for the optimal solution will take place within these boundaries. The main disadvantages of MPC are the necessity for knowledge of models and the high computational effort for the optimization. Due to the latter disadvantage, the application of MPC was first restricted to systems with low dynamics such as chemical processes. However, with increased computing capacity, the application is now possible for systems with higher dynamics as well [9]. Several examples can be found where MPC or its generic methodology is applied to control traffic in urban areas [10], [11], [12] or on highways [13].

MPC is chosen as a control algorithm for the work presented in this document because of the possibility to explicitly set a goal with an objective function and to impose constraints. The latter is essential for traffic signal control as, for example, legal restrictions have to be taken into account. Another reason to use MPC is the implied predictability of signalization and traffic state while still offering a very flexible control. The predicted states can be used to generate reliable speed advisory information for the drivers of equipped vehicles and thus, reducing the number of stops.

The main principle of MPC is, as the name of the concept implies, the prediction of a system's future behavior using a model. In the discrete case, this is done in a defined step size over the prediction horizon N_p based on the prior estimated state x_k. The calculation of optimal control inputs is subsequently carried out over the control horizon N_c, which must be equal to or shorter than the prediction horizon. Only the first of the calculated control inputs u_k is applied to the system and the calculation is carried out again at the subsequent time step. An analogy that is often used is a car driver who subconsciously plans steering maneuvers for a certain amount of time in the future. The maneuvers are carried out on a very short term basis and the prediction is renewed constantly. The principle is shown in Figure 4, where the subsequent time step is illustrated with dashed lines.

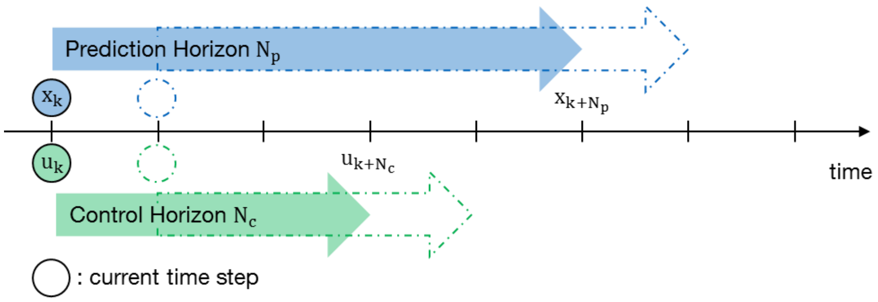

Figure 4: Basic principle of model predictive control

Again the modelling in state-space allows for the straightforward implementation of the control approach using formulations that are given in literature. The formulation given by Camacho & Bordons [6] is briefly described below.

In a first step, the state-space formulation from eq. (1) is extended such that the input vector becomes the change of the actual input to the system:

$$\begin{bmatrix} x_{k+1} \\ u_k \end{bmatrix} = \begin{bmatrix} A & B \\ 0 & I \end{bmatrix} \begin{bmatrix} x_k \\ u_{k-1} \end{bmatrix} + \begin{bmatrix} B \\ I \end{bmatrix} \Delta u_k$$
$$y = \begin{bmatrix} C & 0 \end{bmatrix} \begin{bmatrix} x_k \\ u_{k-1} \end{bmatrix} \tag{5}$$

The resulting extended matrices and the state vector from eq. (5) can be shortened to A_e, B_e, C_e and $x_{e,k}$ respectively. The predicted system outputs over the prediction horizon based on the current state $x_{e,k}$ can be given in a clear form by using the auxiliary matrices F and Φ:

$$Y = Fx_{e,k} + \Phi\Delta U \tag{6}$$

In order to do so, the state vector is effectively inserted into eq. (5) repeatedly to predict the next state and the respective output. Thus, the matrices F and Φ are given as follows:

$$F = \begin{bmatrix} C_e \cdot A_e \\ C_e \cdot A_e^2 \\ \vdots \\ C_e \cdot A_e^{N_p} \end{bmatrix}$$

$$\Phi = \begin{bmatrix} C_e \cdot B_e & 0 & 0 & \cdots & 0 \\ C_e \cdot A_e \cdot B_e & C_e \cdot B_e & 0 & \cdots & 0 \\ C_e \cdot A_e^2 \cdot B_e & C_e \cdot A_e \cdot B_e & C_e \cdot B_e & \cdots & 0 \\ \vdots & & & & \\ C_e \cdot A_e^{N_p-1} \cdot B_e & C_e \cdot A_e^{N_p-2} \cdot B_e & C_e \cdot A_e^{N_p-3} \cdot B_e & \cdots & C_e \cdot A_e^{N_p-N_c} \cdot B_e \end{bmatrix} \tag{7}$$

The input vector ΔU in eq. (5) contains all inputs over the control horizon and is therefore composed as follows:

$$\Delta U = \begin{bmatrix} \Delta u_k & \Delta u_{k+1} & \Delta u_{k+2} & \Delta u_{k+3} \ldots \Delta u_{k+Nc-1} \end{bmatrix}^T \tag{8}$$

The goal is to determine this extended input vector by solving the following quadratic optimization problem:

$$\text{minimize } J = \Delta U^T \left(\Phi^T \Phi + S\right) \Delta U - 2\Delta U^T \Phi^T \left(R_s - Fx_{e,k}\right) \tag{9}$$

Where S enables the consideration of the magnitude of ΔU and is used, to achieve sufficiently long green times in case of high traffic volumes. If S is chosen very small, short gaps lead to frequent transitions of the traffic signal and therefore to a lower capacity of the intersection. R_S is the command variable and is set to zero in this example as previously mentioned. Because of the chosen output matrix C a propagation of vehicles is achieved and the set target is an empty approach with the goal to reach highest outflow of vehicles.

If there were no constraints and the variables were continuous, a usual search for extreme values through a derivation of eq. (9) could be carried out. As constraints should be imposed and all entries of the input vector are integers, the optimization problem is of the type Mixed-Integer Quadratic Programming (MIQP). To solve such problems, several commercial algorithms are available, such as the "IBM ILOG CPLEX Optimizer", which has been used for the simulation study in Section 7.

5.1 Formulation of Constraints

Two types of constraints are input into the optimization algorithm:

$$\begin{gathered} \mathrm{M}\Delta\mathrm{U} \leq \gamma \\ \mathrm{E}\Delta\mathrm{U} = \mathrm{d} \end{gathered} \tag{10}$$

The matrices M and E as well as the vectors γ and d have to be formulated such that the desired restriction of the behavior of the control is achieved. As described by Wang [14], constraints can be formulated in order to restrict the:

- change of the input
- amplitude of the input
- amplitude of the output.

As mentioned before, the output matrix is built such that the state variables are accessible as outputs in order to constrain them. The concrete numeral formulation of the quantities in eq. (10) are omitted here for the sake of clarity. In order to achieve the desired microscopic behavior of the modelled traffic flow and the control, the following constraints are imposed:

- restriction of the input signal to values between zero and one
- restriction of the cell occupation to values between zero and one

Furthermore, constraints are introduced in order to include specifications given, for example, in the German Guidelines for Traffic Signals [15]. In the scenario described in the following section, these constraints include:

- a minimum of one signal group has to show "red"
- minimum green times
- intergreen times
- maximum green times (in order to constrain the cycle time)

6 PROOF OF CONCEPT

In this section, a simulation study is presented with the intension of proving the concept in principle. For this reason, the proposed algorithm is embedded in the microscopic traffic flow simulation "SUMO" [16]. Figure 5 depicts the embedment of the algorithm as shown in Figure 1 into the simulation via the Python interface "TraCI" that is part of SUMO. Calculated signal timing for traffic signals is input into the simulation as well as speed advice for equipped vehicles. Data from detectors and vehicles is fed back to the algorithm as an input. Because the presented investigation is of purely theoretic nature, no real data is used to calibrate the parameters of the car-following model. Instead, the typical parameter set proposed by Krauss [17] is used (response time T = 1s; maximum acceleration a = 0.8m/s^2; maximum deceleration b = 4.5 m/s^2).

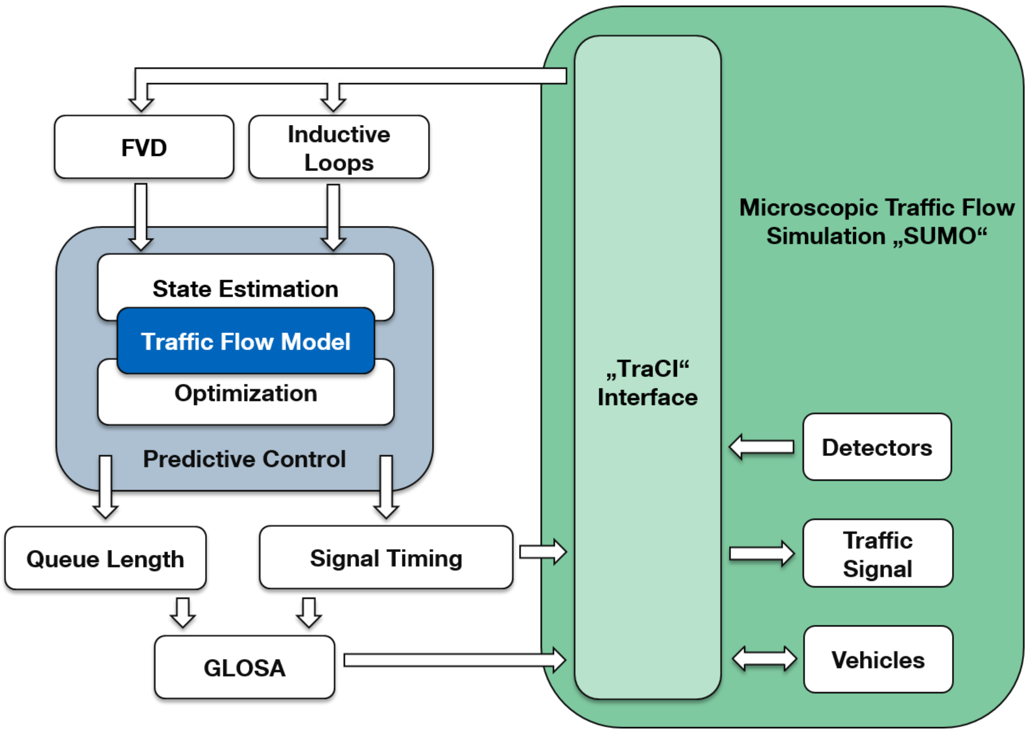

Figure 5: Embedment of the algorithm in a microscopic traffic flow simulation

In the following sections, the considered scenario and the reference control are described. The results of the simulation study are presented subsequently. In contrast to Figure 5, the results shown in the following section do not include any information of the drivers, i.e. no speed advisory messages are provided. Nevertheless, an equipment rate of 100% is assumed in order to have a comprehensive detection of vehicles.

6.1 Scenario

The chosen scenario consists of a simple intersection with four arms that is controlled with a two stage signal. One lane is available in each direction and turning vehicles and pedestrians are not considered, as only a principle proof of the proposed concept is intended.

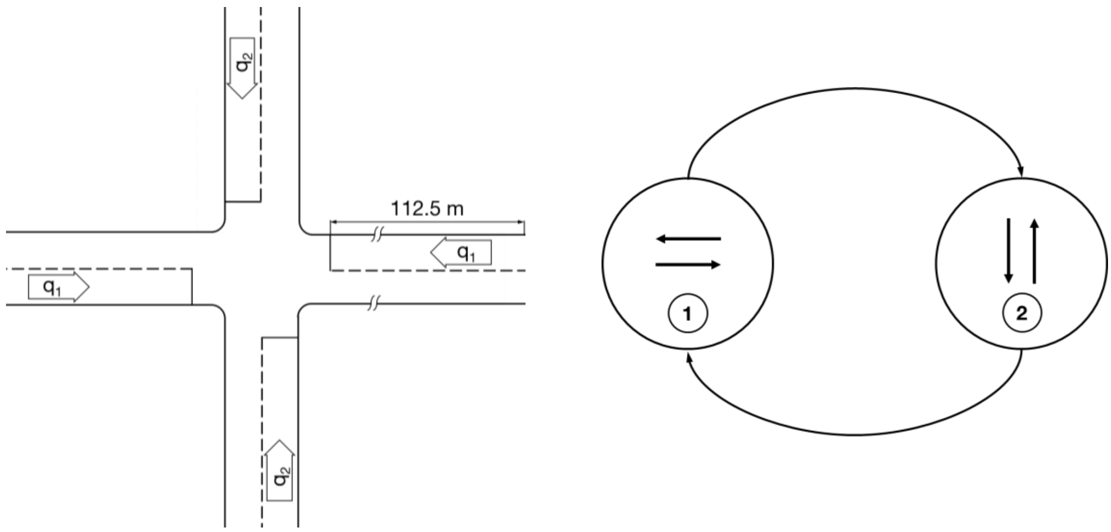

Figure 6: Intersection with respective transition diagram

Figure 6 shows the intersection and the respective stage diagram in a schematic way. The considered length of the approaches is set to 112.5m, which leads to 15 cells as their length is set to 7.5m.

The traffic demands q_1 and q_2 are kept at a constant level in the opposing approaches and are varied in steps of 180veh/h to a maximum of 900veh/h per approach in order to investigate the system's behavior in different situations.

6.2 Parameters of the Model Predictive Control

The constraints are chosen such that a minimum green time of five seconds is guaranteed, an intergreen time of four seconds is kept between the stages and the maximum green time is set to 40s. The prediction horizon is 15s while the control horizon is set to 10s.

6.3 Reference Control

The chosen reference control is a fixed time control based on German guidelines [15], [18]. A saturation volume of 1620veh/h results from the chosen car-following parameters and is used for the calculation of the cycle time. The used cycle time is held between 60s and 90s according to the guidelines and is denoted in Figure 7 as $t_{cyc,ref}$. The green split is chosen according to the traffic demand. To keep the proposed control approach comparable to the reference control, equivalent intergreen times and minimum green times are chosen. For the same reason, the maximum green times are chosen to be 40s for the fixed time control, although an optimal green split would in some cases lead to a higher value.

6.4 Simulation Study

The duration of each simulation run is 1000s. The number of simulation runs necessary to achieve significant results with a confidence level of 95% with an accuracy of 5% is determined according to the respective guidelines for simulations [19]. For the analysis, 20 runs were carried out for each demand scenario using the reference control and 17 runs for the model predictive control.

6.5 Results

The results presented in this section are meant to prove the functional capability of the proposed theoretical approach to control traffic signals within the mentioned assumptions.

Figure 7 shows the change in the average number of stops per vehicle when using MPC compared to the fixed time control. For lower demands the higher flexibility of MPC results in a significant decrease in the number of stops as it can be seen for example with the low demand of 180veh/h on all approaches. As Figure 7 depicts, a reduction in the number of stops of 41% is achieved. However, frequent transitions that go along with an average cycle time of only 45s lead to this improvement. Only an average value of the cycle time can be stated as the proposed approach deliberately omits a fixed cycle time. It became apparent that the results do not differ considerably when violating the guidelines by choosing a reduced cycle time of 45s for the reference control. This can be explained by the efficient distribution of green times by MPC, which leads to a clear reduction of the number of stops compared to the reference control.

Figure 7 shows that in case of higher demand, the reduction of the number of stops will be relatively low. With a demand of $q_1 = q_2 =$ 900veh/h even a slight increase arises, though the level of significance is scarcely exceeded. This behavior results from a saturated intersection as the MPC in this case makes use of the maximum green times and therefore behaves comparable to the fixed time control.

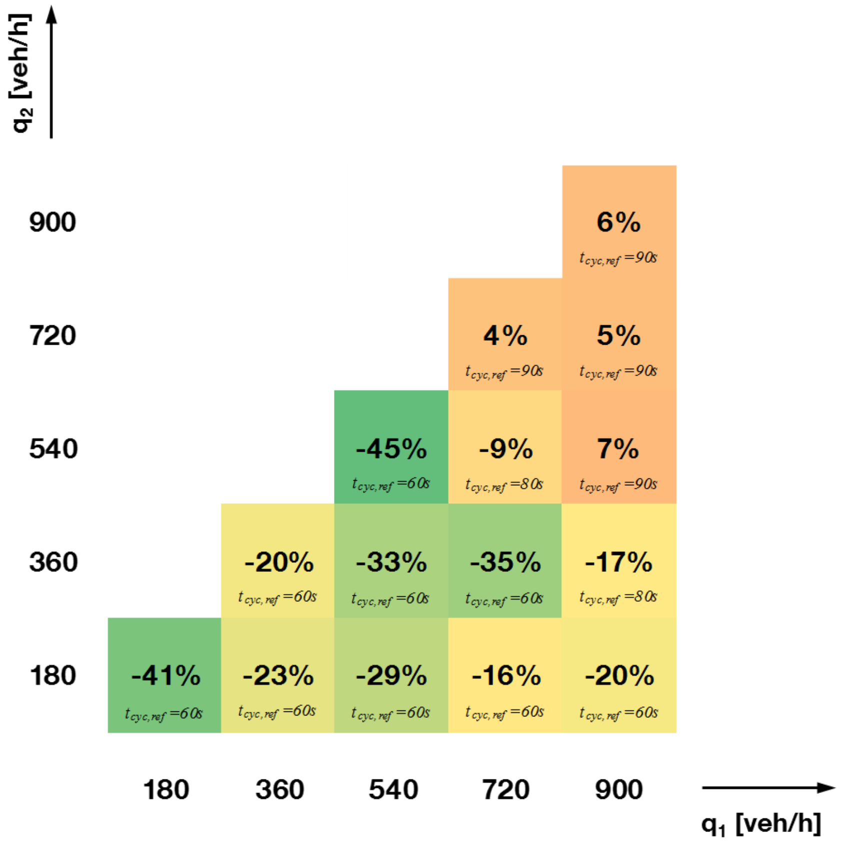

Figure 7: Change of the number of stops per vehicle compared to the reference control

To illustrate the system's behavior in case of low demand, an extract of the signal plans resulting from the demand $q_1 = q_2 = 180$veh/h by using MPC and the reference control is given in Figure 8. The fluctuation of green times can be seen, which results from the adaption to the current state of the approach.

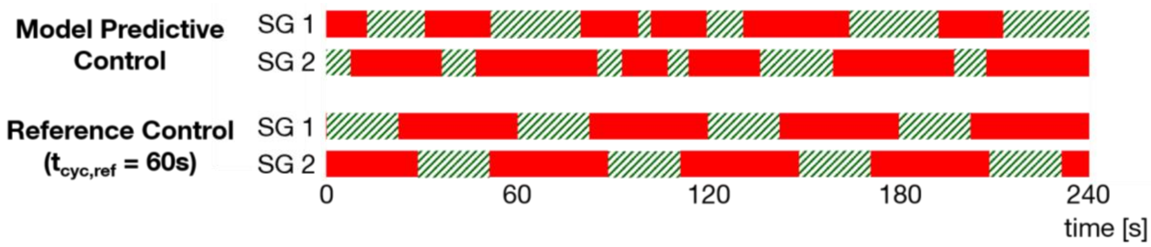

Figure 8: Extract of the signal plans of MPC (top) and reference control (bottom) for $q_1 = 180$veh/h; $q_2 = 180$veh/h

Comparable results are achieved under asymmetric demands of $q_1 = 900$veh/h; $q_2 = 180$veh/h or $q_1 = 540$veh/h; $q_2 = 180$veh/h. The use of MPC leads to average cycle times of around 60s, which corresponds to the cycle times of the reference control. Nevertheless, Figure 7 shows a decrease of the number of stops of 29% and 20% respectively. Again, green times are used more efficiently as they are chosen more accurately for the approaches with lower demand and green is given preferably when gaps are existent in the conflicting stream. Figure 9 shows an exemplary extract of the signal plans for a demand of $q_1 = 540$veh/h; $q_2 = 180$veh/h. The differences are less obvious, but a shortened green time of signal group 2 can be seen after around 140s.

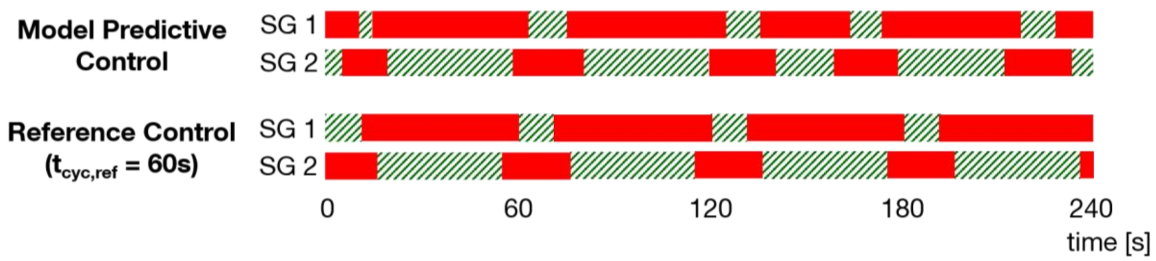

Figure 9: Extract of the signal plans of MPC (top) and reference control (bottom) for q_1 = 540veh/h; q_2 = 180veh/h

The good results shown in Figure 7 for a demand of $q_1 = q_2$ = 540veh/h result from a relatively short cycle time of 60s that was chosen for the reference control. For the MPC case, the average cycle time is clearly higher and therefore the result would be more comparable if a cycle time of 80s was used for the reference control.

For the sake of completeness, Figure 10 shows the change of the waiting time per vehicle. The results are comparable to those given in Figure 7, but as the results differ more between the simulation runs, the confidence level is not reached with the number of simulation runs that were carried out.

In summary, the proposed control algorithm leads to promising results under the given assumptions. Especially in scenarios with low and moderate demand, significant improvements compared to the chosen reference control are achieved. However, as expected, in cases with high demand, significant improvements cannot be achieved.

Figure 10: Change of the waiting time per vehicle compared to the reference control

7 OUTLOOK

The described control method is of theoretic nature and the further directions of research are threefold:

Firstly, the complexity has to be raised in order to cover more realistic designs of intersections and to offer the possibility for a control with multiple stages. Another increase of complexity worth to investigate is the behavior on stretches or networks where the described concept would have to be extended to a decentralized network control.

Secondly, one reason to choose MPC was the implicit prediction of control actions and traffic states. Thus, a speed advisory system for equipped vehicles is relatively easy to implement in order to further reduce the number of stops. To raise the reliability of such information, a consolidation of the predicted control inputs should be carried out. First investigations show promising results despite the relatively low level of detail of the traffic flow model. A worthwhile step beyond this simple speed advisory system would be the direct consideration and optimization of driven speeds and thus, influencing the drivers' and the traffic signals' behavior at the same time. However, a more complex traffic flow model with multiple speed states would be necessary.

Both of the aforementioned enhancements require an increase in complexity, which leads to a higher computational effort. The simulation study that is described in the previous section already led to high computation times, exceeding the requirements of a real-time control. Therefore, as a third point of action, a decrease of calculation times is desirable and could be achieved by higher computational power and the ongoing improvements in the field of optimization. Those include branch-and-cut algorithms such as ”CPLEX” but also other approaches to solve constrained MIQP such as the one described by Potočnik et.al. in [20] that is making use of neural networks.

8 CONCLUSIONS

In this document, a concept for an adaptive traffic signal control was introduced that relies on the technique of model predictive control. Input data from conventional detection as well as from equipped vehicles can be considered and fused by making use of a state estimator. A simplified traffic flow model of microscopic nature is used for the state estimation as well as the model predictive control. With a theoretical scenario, the general proof of the functional capability of the proposed approach is given. Especially for low traffic demand the increase in flexibility leads to a clear reduction in the number of stops and waiting times when compared to an optimized fixed time control. Further research is necessary to bring the theoretic approach that it is described in this document to maturity as well as to exploit further potential of cooperative systems as it is stated in the outlook.

REFERENCES

[1] J. Kaths, "Kooperative Lichtsignalsteuerung auf Basis eines mikroskopischen Verkehrsflussmodells," in *Heureka '14*, Stuttgart, 2014.

[2] C. F. Daganzo, "The Cell Transmission Model. Part I: A Simple Dynamic Representation of Highway Traffic," Berkeley, 1993.

[3] C. M. Tampère and L. H. Immers, "An Extended Kalman Filter Application for Traffic State Estimation Using CTM with Implicit Mode Switching and Dynamic Parameters," in *Intelligent Transportation Systems Conference. ITSC 2007. IEEE*, Seattle, 2007.

[4] K. Nagel and M. Schreckenberg, "A cellular automaton model for freeway traffic," *Journal de Physique I*, pp. 2221-2229, September 1992.

[5] S. Dengfeng and A. M. Bayen, "Multicommodity Eulerian–Lagrangian Large-Capacity Cell Transmission Model for En Route Traffic," *Journal of Guidance, Control, and Dynamics,* pp. 616-628, May-June 2008.

[6] E. F. Camacho and C. Bordons, Model Predictive Control, London: Springer Verlag , 2007.

[7] G. Welch and G. Bishop, "An Introduction to the Kalman Filter, TR 95-041," University of North Carolina at Chapel Hill, 2006.

[8] C. Dittrich and F. Busch, "Rückstaulängenschätzung zur verbesserten Geschwindigkeitsempfehlung im Fahrzeug," in *Heureka '11*, Stuttgart, 2011.

[9] R. Dittmar and B.-M. Pfeiffer, "Modellbasierte prädiktive Regelung in der industriellen Praxis," *at Automatisierungstechnik,* pp. 590-601, 2006.

[10] V. Mauro and C. Di Taranto, "UTOPIA," in *IFAC Control, Computers, Communications in Transportation*, Paris, 1989.

[11] N. H. Gartner, F. J. Pooran and C. M. Andrews, "Implementation of the OPAC Adaptive Control Strategy in a Traffic Signal Network," in *IEEE Intelligent Transportation Systems Conference Proceedings*, Oakland, 2001.

[12] S. Lin, B. De Schutter, Y. Xi and H. Hellendoorn, "Fast Model Predictive Control for Urban Road Networks via MILP," *IEEE Transactions on Intelligent Transportation Systems, Vol. 12, No.3,* pp. 846-856, September 2011.

[13] A. Hegyi, B. De Schutter and H. Hellendoorn, "Model predictive control for optimal coordination of ramp metering and variable speed limits," *Transportation Research Part C, vol. 13, no. 3,* pp. 185-209, June 2005.

[14] L. Wang, Model Predictive Control System Design and Implementation Using MATLAB, London: Springer Verlag, 2009.

[15] Forschungsgesellschaft für Straßen- und Verkehrswesen (FGSV), *Richtlinien für Lichtsignalanlagen,* Köln: FGSV Verlag, 2010.

[16] D. Krajzewicz, J. Erdmann, M. Behrisch and L. Bieker, "Recent Development and Applications of SUMO - Simulation of Urban MObility," *International Journal On Advances in Systems and Measurements,* pp. 128-138, December 2012.

[17] S. Krauß, "Microscopic Modeling of Traffic Flow: Investigation of Collision Free Vehicle Dynamics (Diss.)," Köln, 1998.

[18] Forschungsgesellschaft für Straßen- und Verkehrswesen (FGSV), *Handbuch für die Bemessung von Straßenverkehrsanlagen,* Köln: FGSV Verlag, 2010.

[19] Forschungsgesellschaft für Straßen- und Verkehrswesen (FGSV), *Hinweise zur mikroskopischen Verkehrssimulation,* Köln: FGSV Verlag, 2006.

[20] B. Potočnik, G. Mušič, I. Škrjanc and B. Zupančič, "Model-based Predictive Control of Hybrid Systems: A Probabilistic Neural-network Approach to Real-time Control," *Journal of Intelligent & Robotic Systems,* pp. 45-63, January 2008.

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