DATA FUSION TECHNIQUES FOR ADAPTIVE TRAFFIC SIGNAL CONTROL

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Abstract: Adaptive online traffic control in urban road networks requires information on the present and future traffic state. This information needs to be as complete and precise as possible. This paper introduces on the one hand a new method for online queue length determination based on data fusion technique (Mueck, 2002) and investigates on the other hand the performance gains that can be achieved employing this determination module as a quasi measurement with Kalman filtering technique in queuing theory models (e. g. Markovian chains). Both, the theoretical approach of the respective models as well as the results of simulation studies are presented. Copyright © 2002 IFAC

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1. INTRODUCTION

Adaptive online traffic control in urban road networks requires information on the present and future traffic state. This information needs to be as complete and precise as possible. For this reason, advanced control methods involve respective traffic models in order to complement local measurements and to derive criteria on the traffic state that cannot be measured. As criterion to be optimised, most models calculate either the queue length (Hunt et al., 1981; Henry et al., 1983; Donati et al., 1984; Friedrich and Keller, 1994) or the number of vehicles per link (Diaakaki, 1999). It is therefore the precise determination and short term forecast of the mentioned criteria which is a crucial prerequisite for any adaptive control strategy. However, given the standard supply for detection, with inductive loops located close to the stop lines, traffic state modelling in saturated conditions is particularly difficult.

Most adaptive control methods are using vehicle counts from detectors that are located some 100 m upstream from the stop line in order to determine the inflowing traffic. The vehicles leaving the link are generally calculated assuming fixed saturation flow conditions during green time. The evolution of the queue lengths over time and according to the signal timing is either modelled with microscopic deterministic car following models (e. g. SCOOT) or by the help of stochastic queuing theory (e. g. BALANCE). Independent from the modelling approach, most known methods suffer from a missing feedback algorithm, which compares calculated traffic state variables against measured values (an exception is TUC (Diaakaki, 1999)). Systematic errors in the calculations may be the consequence of that shortcoming
as for instance Robertson (1987) reports for an evaluation of SCOOT in the city of Bingley, UK. Apart from that, a major problem for adaptive control methods in practice is that traffic-dependent signal control systems are usually operated with the vehicle-actuation method, which allows the green time to be varied between preset limits in small extension steps. Controllers are therefore mostly equipped with detectors 10 m - 50 m upstream of the stop-line.

Some recent research concentrated on the direct determination of congestions and queue lengths through measured data. For instance Bernhard and Riedel (1999) introduced a method for the detection of congestions between the stop-line of a traffic light and an upstream detector that is based on balancing entering and leaving flows. Henninger 1999 developed a model-based method to estimate the traffic state in a road network where optimum results require the detectors to be placed approximately 100 m - 150 m upstream of the traffic signal. Chang et al. (2000) also developed a method to estimate queue lengths using detectors in this position, using among other data of kinematic properties of vehicles and (as with Henninger) knowledge of the varying signal state of the downstream and upstream controllers. Mück (2002) introduced a model that determines queue length on the basis of vehicle counts from detectors located close to the stop line and on the basis of signal timings.

First studies proofed this online model to calculate rather reasonable results using vehicle-actuated detectors already present. It allows estimating lengths up to distances five or ten times longer than the distance between detector and stop-line. Further on the ensuing delays and travel times can be computed. The model of Mück can be used with "short" detectors with a spatial extension of 1m in the direction of traffic and is furthermore suitable for determining saturation traffic rates and to recognise disturbances in the outflow of signalised intersections. These properties allow for completely new possibilities for developing local and network control methods, for the online monitoring of road networks and the gathering of planning data. The kernel of the combined estimation algorithm is a method for measuring maximum queue lengths.

2. STABILISATION OF THE CONTROL LOOP FOR ADAPTIVE METHODS

The Mück (2002) method for determining the lengths of queue is based upon the a relationship that is connected with fill-up time. The fill-up time is defined as the time passed from the beginning of the red time of a signal until continuous occupancy of a detector. According to Mück, empirical data shows that the frequency with which the fill-up time falls short of the reference period is correlated up to a certain degree with the length of congestion. The event “falling short of the reference period” can be described by a congestion characteristic $\delta$ (between 0 and 1). Using a correlation calculation, a relation between the congestion characteristic $\delta_n$ and the maximum back-up length $L_{n\max}$ can be constructed with the aid of manually retrieved measuring data.

If the congestion characteristics $\delta_n$ is known from measurements, the back-up length can be deduced. Applying this method for determining back-up length showed good results in the field test. An example done by Mück showed good agreement between the real queue length and the determined one using this method with a confidence measure of 0.76.

To overcome the problem of systematic instability as explained above and to exploit the potential of adaptive network control methods, a feedback procedure using directly estimated queue lengths could be introduced in order to stabilise the control loop. To do so, we consider determined queues by Mück (2002) for the present stage as quasi-measured data and feed this information (for the future stage) back to the control loop via an extended Kalman filter as it is shown in figure 1.

The time-discrete, non-linear and time-variant process model of the system describes the state $\dot{x}$ of the system using the variables inflowing traffic volume $q_{n+1}^{in}$, average queue length $L_{n+1}^{avg}$ and maximum queue length $L_{n+1}^{max}$:

$$\dot{x}_{n+1} = \begin{pmatrix} q_{n+1}^{in} \\ L_{n+1}^{avg} \\ L_{n+1}^{max} \\ L_{n+1}^{max} \end{pmatrix}$$

Fig. 1. Time sequence of estimation and control (Papageorgiou, 1991)
Using the input: data green time, cycle time and average time required per vehicle, combined in
\[ u_n = (t_{n}^2, t_{n}^3, t_{n}^4) \]  
and the measurable output values
\[ y_n = \left( \frac{q_{n}^{in}}{L_{n}^{avg} + z_{avg}}, \frac{q_{n}^{in}}{L_{n}^{avg} + z_{avg}}, u_n \right) \]  
\[ \text{max} \left( L_{n}^{avg} + z_{avg}, q_{n}^{in} + z_q, u_n \right) + z_{L_{max}} \]  
(1)

\[ \begin{align*}
&= \left( q_{n}^{in} + z_q \\
&\mathcal{I} \left( L_{n}^{avg} + z_{avg}, q_{n}^{in} + z_q, u_n \right) \right) \\
&\mathcal{I} \left( L_{n}^{avg} + z_{avg}, q_{n}^{in} + z_q, u_n \right) + z_{L_{max}} \right)
\end{align*} \]  
(1)

3. RESULTS AND EVALUATION

To analyse the new feedback approach, some tests using a microscopic simulation are done. In addition, some well-known models e. g. (Akcelik, 1980; Webster, 1958; Kimber and Hollis, 1981; Miller, 1986), Markovian chains by Friedrich (2000) of queue lengths estimation are also studied and compared to the performance of the feedback models. To assume realistic detection equipment, the detector was located in a distance of 30 m from the stop line, which corresponds to a normal position in urban roads.

Table 1. Scenarios and corresponding degrees of saturation x

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Degree of Saturation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>x = 0.5</td>
</tr>
<tr>
<td>2</td>
<td>x = 1.2</td>
</tr>
<tr>
<td>3</td>
<td>x = 0.5/0.8/1.0/1.2</td>
</tr>
<tr>
<td>4</td>
<td>x = 0.5/1.2/0.5/1.2</td>
</tr>
<tr>
<td>5</td>
<td>x = 0.5/0.8/1.0/0.8/0.5</td>
</tr>
<tr>
<td>6</td>
<td>x = 0.05/0.1/0.2/0.35/0.5/0.65/0.8/0.9/1.0</td>
</tr>
<tr>
<td></td>
<td>1.1/1.25/1.4</td>
</tr>
</tbody>
</table>

To be sure to reproduce realistic traffic situation, an existing four-way intersection was modelled. The test network was calibrated on the basis of flow data, queue length data and heavy vehicle fraction (2%), which were collected in a field study. The simulated intersection is fixed time controlled by a 90 second cycle and the green time of the access lane, on which the analysis is focused, is 32 seconds.

Different scenarios, with respect to various traffic demand, were considered to test the performance of the queuing models under various conditions. The flow was generated by OD-matrices, which were either non-varying over time or varying in intervals of 90 seconds (= cycle time), the flow counted by the detector (and some further data if they are needed, e. g. the detector occupancy by the model of Mück) was recorded and used as input data for the different queuing models. The queue lengths resulted from the simulation, which were supposed to be the real ones, were used to evaluate and to compare them to the values of the estimation. The simulation time is at least one hour corresponding to the scenarios.

The saturation flow, which is also needed for most of the models (not for Mück, the calculation is integrated in the model), is calculated by using the equation 16-4 of the HCM (2000) and found to be a fixed value of 1669 vehicles/hour over time.

An overview of the different scenarios and the corresponding degrees of saturation are given in table 1. But it should be marked that the degree of saturation is calculated by the comparison of the simulated flow given by the OD-matrix and the saturation flow. Therefore the real degree of saturation in each evaluated 90-second interval varies a bit form the denoted one because the
simulated flow is generated randomly on the basis of the OD-matrix.

To evaluate the estimated queue lengths $L_{\text{est}}$, they are compared to the real ones $L_{\text{real}}$ using three indicators. These indicators are determination coefficient $R^2$ [-], root mean square error RMSE [veh] and relative root mean square error PRMSE [%] are used. Table 2 and Table 3 report the values of these indicators for the different used queuing models.

By analysing the scenarios, it could be ascertained that the Kimber-Hollis (KH) and the Markov chains method for estimating the average queue length give good results for relatively low degree of saturation. For example, scenarios 1 and 3 for Kimber and Hollis gives $R^2$ of 0.62 and 0.95 respectively. However, when the degree of saturation increases, the mentioned two methods extremely overestimate and the systematic errors continue to increase as shown in Figure 2 of scenario 6. This problem is managed when employing Mück module as a quasi measurement with Kalman filtering technique in those two methods. For example, scenarios 6 for Kimber and Hollis gives RMSE of 31.9 while it gives RMSE = 3.3 when Mück is used with Kimber-Hollis.

This improvement is clear in almost all scenarios as shown in the tables of different indicators and also in the figures presented. Even under varying situation of degrees of saturation (e.g. scenario 5), the employed Mück-method stabilises, the queue estimation as shown in Figure 3. Especially under those conditions, the feedback method contributes the improvement of the control strategy. Only in scenarios (1 and 3) in which a large interval of the studied period is low, the feedback method does not give better results because of the determination problem of low maximum queue lengths in the Mück-model which is described in the following paragraph.

The comparison shows that for relative low degree of saturation (e.g. scenario 1, $x = 0.5$) most of the well-known models achieve quite good result for the estimation of the average queue length (e.g. Miller: $R^2 = 0.66$, Kimber-Hollis: $R^2 = 0.62$) or the maximum queue length (e.g. Webster: $R^2 = 0.77$, Akcelik: $R^2 = 0.79$). In that case, the combination with the Mück-model could not improve the estimation. This is because of that Mück (2002) determines zero queue length at the conditions of low saturation, at which low queue length are existed between the stop line and the detector. However, the degrees of saturation less than about 0.6 don’t cause problematic traffic situations and therefore they are not very important to be considered in the control strategy.

Akcelik (1980) method for estimating the maximum queue length gives good results for relatively low degree of saturation as shown in Figure 3 of scenario 2. However when the degree of saturation increases, the method extremely underestimates and the error continues to increase. One can also see how much the Mück method integrated with Kimber-Hollis is better than Akcelik method in almost all scenarios.

To investigate how much the position of the detector influences the estimation quality, some more studies are made with a distance of 130 meters
Fig. 2. Estimated average queue lengths. Sector of Scenario 6

Fig. 3. Estimated average queue lengths. Scenario 5

Fig. 4. Estimated average queue lengths. Scenario 2
from the detector to the stop line, which is said to be more optimal for the well-known models but which of course does not correspond to a normal measurement position. In this case, almost all scenarios and all well known models resulted relatively better results. One should say that the method of Mück is not practicable for such a long distance because a queue length less than the distance from the stop line to the detector could not be determined, as mentioned before. However the improvement made at 130 m distance of the detector is not as high as by employing the model of Mück as a feedback at distance 30 m. For example, at 130 m distance, Kimber-Hollis gives $R^2$ of 0.69 in scenario 2 while at 30 m distance Kimber-Hollis with Mück gives $R^2$ of 0.93 in the same scenario.

In total, it can be said that a high performance gain could be achieved employing the Mück determination method as a quasi measurement in queue theory models. Especially in cases of high and varying degree of saturation the combined method could stabilise and improve the queue estimation.

4. CONCLUSION

In this paper, a new method for real time queue length determination based on data fusion technique is evaluated and compared to well known models of queue length estimation. This determination module as a quasi measurement with Kalman filtering technique is employed in queueing theory models (Kimber-Hollis and Markovian chains model). Simulation studies documented high effects of introducing the new module in order to stabilise the calculation of the real time queue estimation.

REFERENCES


