Dynamic OD Estimation Using Additional Information from Traffic Signal Lights Timing

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1. Context

Changing public awareness with respect to the impacts of car traffic in combination with the increasing traffic demand has caused a new orientation of transport and traffic policies in metropolitan areas. In order to minimise negative impacts of car traffic as pollutant emissions and in order to preserve mobility in a sustainable way most cities start implementing strategies to optimise car traffic flow while improving public transport at the same time. Due to this focus traffic control aims to influence the traffic situation not only on the local level but by a co-ordinated approach on the network level.

Co-ordinated online control in the network context requires a as complete as possible knowledge on the present traffic state and in particular on the OD streams. For this reason many advanced control methods involve a model for OD estimation. However, as a prerequisite most of the known OD estimators need historical offline information. Especially the age and the static character of historical information has a strong influence on the quality of the estimated OD streams. Simulation studies show that the accuracy of respective OD estimators does not really cope with the requirements of online control and thus a strong need for a more accurate estimation is given.

2. State of the Art

The well known existing models for OD estimation (e.g. WILLUMSEN, 1981) originally were designed for offline calculations:

\[ f_{kl} = w_{kl} \cdot X_0 \cdot \prod_a \left( \frac{q_a^{\text{est}}}{q_a^{\text{real}}} \right) \]

where \( w_{kl} \) weights indicating the relative significance of the OD relation between \( k \) and \( l \),

\[ X_0 = \frac{\sum_k \sum_l w_{kl}}{F} \]

normalising factor,

\[ g_{kl} = \sum p_{kl}^a \]

and

\[ X_a^{n+1} = X_a^n \cdot \frac{q_a^{\text{real}}}{q_a^{\text{gesch}}} \]

factors for the iterative solution of the equation using observed and estimated traffic volumes \( q_a^{\text{real}} \) and \( q_a^{\text{est}} \) respectively for the adjustment.

The estimated traffic volumes \( q_a^{\text{est}} \) are calculated in conjunction with the relation

\[ q_a = \sum_k \sum_l p_{kl}^a \cdot f_{kl} \]

and thus \( f_{kl} \) can be determined iteratively.

However, at present these models are used in online control methods for road networks in order to obtain information on the network streams. Apart from traffic counts \( q_a^{\text{real}} \) at cross
sections that may be gathered online the approach of maximising entropy needs additional, historical information $w_{kl}$. Since this static historical information frequently does not represent the changing traffic demand pattern the online OD estimation tends to perform poorly and thus directly influences also the performance of any control method. For this reason CREMER AND KELLER [1981] proposed an approach for the dynamic determination of the weights $w_{kl}$ by comparison of flow profiles in entries and exits of the considered system. This approach was further extended by KELLER AND PLOSS [1987] introducing the analysis of correlation. PLOSS [1993] later showed by field observation that the precision of the online estimation could be improved significantly applying dynamically determined weights. But in particular he found that a rather high degree of determination ($r^2 = 0.88$) could be achieved when the turning movements at intersections are estimated in a first step applying dynamic weights $w_{mn}$ and the resulting volumes of the movements $f_{mn}$ are then used in the maximising entropy model.

<table>
<thead>
<tr>
<th>Coefficient of determination $r^2$</th>
<th>Weights $w_{kl}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Only information from traffic counts</td>
<td>none</td>
</tr>
<tr>
<td></td>
<td>0.53</td>
</tr>
<tr>
<td>Additional information on turning movements $f_{mn}$</td>
<td>0.88</td>
</tr>
</tbody>
</table>

*Table 1: Excerpt of the sensitivity analysis by PLOSS [1993] with respect to the influence of the weights $w_{kl}$ and $f_{mn}$ on the performance of the OD estimation in a network.*

The results of this work suggest that there is some potential using dynamic weights ($r^2 = 0.72$) according to the approach of CREMER and KELLER. But moreover, this work outlines that there is a particular relevance to provide additional information in form of turning movements $f_{mn}$ at intersections. Given these outcome the following hypothesis could be put:

The better the estimation of movements at intersections the better the OD estimation for the respective road network.

As mentioned above PLOSS proposed for the determination of the turning movements at intersections the correlation analysis. However, this method does not consider additional information which can be obtained from traffic signal light control. This paper on the one hand introduces an new model to determine turning movements using online data not only from traffic counts but also from traffic light controllers. On the other hand the paper presents results from a comprehensive simulation study where different approaches for OD estimation were tested and compared under constant external conditions.

### 3. Methodology of the New Approach

The new method to identify turning movements at signalised intersections was developed in the light of the existing methods and in view of the potential knowledge obtainable from vehicle movements. The method combines signal phase timing information and detected
flow data by probability functions for each particular movement over time. Flow data are collected in the exit legs of the intersection. Following major components characterise the new model:

- Classification of priority types for different movements
- Identification of combinations of movements that may pass exit detectors during the same green time of a stage
- With respect to travel time within an intersection determination of lower and upper limits as constraints for the assignment of detection data to specific movements
- Definition of probability functions for each time interval within the cycle time for the assignment of detection data to movements. The figure below shows a sketch of the respective proceeding.

![Figure 1: Assignment of probabilities for detected data to specific movements (signal groups)](image)

4. Simulation Results

Both models, the new one as well as the model using the correlation analysis for estimating the movements at one intersection $f_{mn}$ were tested by the microscopic simulation AIMSUN2. The discrete time interval considered for both traffic flow detection and signal timing was one second. In defined intervals the volumes of the turning movements were estimated and compared to the simulated flows which were supposed to be the real ones. Different scenarios with respect to traffic demand, demand pattern and intersection design were considered.

The scenario that was tested first simulated low traffic flow of all turning movements. The estimation rate resulted in a high determination coefficient of 0.97. Scenario 2 also simulated equal traffic flow of all turning movements but higher volumes. The statistical analysis showed a determination coefficient of 0.98. One now may suppose that the model only
achieves a high quality of estimation if flow at all turning movements will be as well constant over time as equal.

In order to investigate the model’s performance for the mentioned more realistic demand pattern three further scenarios were defined and analysed. In scenario 3 traffic flow of the through passing streams is twice as much as the of the other streams, in scenario 4 flow of the left turning streams is the highest and in scenario 5 demand varied over time. The analysis by simulation showed that the performance for scenario 3 and 4 is as good as for equally distributed traffic volumes (determination coefficient of 0.99 and 0.98 respectively). In scenario 5 the new model performed with a determination coefficient of 0.93 nearly as good as in the cases with constant demand.

In summary the statistical analysis resulted in a determination coefficient that varies for the new model between 0.93 and 0.99. In contrast the model using the correlation analysis achieved a determination coefficient that varies between 0.46 and 0.81.

<table>
<thead>
<tr>
<th>Coefficient of determination $r^2$</th>
<th>New model using additional information from traffic signal lights</th>
<th>Model using the correlation analysis (PLOSS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>0.97</td>
<td>0.81</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>0.98</td>
<td>0.81</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>0.99</td>
<td>0.57</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>0.98</td>
<td>0.47</td>
</tr>
<tr>
<td>Scenario 5</td>
<td>0.93</td>
<td>0.46</td>
</tr>
</tbody>
</table>

*Table 2: Statistical analysis of the estimation results*

Apart from the excellent estimation results it may be emphasized that the new model requires minimal detection equipment since only the exit lanes of the intersections need to be detected. Because of the location in the exit area queues blocking the detection sites and leading to wrong measures of demand are avoided.

5. Conclusions

Finally, for the OD estimation in road networks the model was extended due to the methodology described above. In a first stage the intersection movements $f_{mn}$ are estimated applying the new model and are then used in a second step as additional information in the maximising entropy approach. In this second step explicitly no historical information is further used and all weights $w_{kl}$ of valid OD relations are set equal. Simulation trials are just under process ad will be finalised within the next months. However, the first simulation results which were already yielded do not yet reflect the results of PLOSS [1993] and thus do not confirm the hypothesis that was stated above.

References


