17th Meeting of the EURO Working Group on Transportation, EWGT2014, 2-4 July 2014, Sevilla, Spain

Calibration Framework based on Bluetooth Sensors for Traffic State Estimation using a Velocity based Cell Transmission Model

Andreas Allström\textsuperscript{a,b}, Alexandre M. Bayen\textsuperscript{c}, Magnus Fransson\textsuperscript{a,b}, David Gundlegård\textsuperscript{a,b,*}, Anthony D. Patire\textsuperscript{c}, Clas Rydergren\textsuperscript{a}, Mats Sandin\textsuperscript{a}

\textsuperscript{a} Linköping University, Department of Science and Technology, SE-601 74 Norrköping Sweden
\textsuperscript{b} Sweco TransportSystem, Box 34044, SE-100 26 Stockholm, Sweden
\textsuperscript{c} University of California Berkeley, 642 Sutardja Hall, CA 94720-1710, USA

Abstract

The velocity based cell transmission model (CTM-v) is a discrete time dynamical model that mimics the evolution of the traffic velocity field on highways. In this paper the CTM-v model is used together with an ensemble Kalman filter (EnKF) for the purpose of velocity sensor data assimilation. We present a calibration framework for the CTM-v and EnKF. The framework consists of two separate phases. The first phase is the calibration of the parameters of the fundamental diagram and the second phase is the calibration of demand and filter parameters. Results from the calibrated model are presented for a highway stretch north of Stockholm, Sweden.

© 2014 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/3.0/).
Selection and peer-review under responsibility of the Scientific Committee of EWGT2014

Keywords: Highway traffic modelling; calibration;

1. Introduction

To have a good knowledge of the current and future traffic state is essential both for traffic management and traffic information purposes. Today's traffic sociaty has numerous methods available for estimating the traffic state on a highway. The methods can be based on different theories and approaches e.g. kinematic wave theory, statistical theory or queuing theory. The methods based on kinematic wave theory are often derived from Lighthill-Whitham-Richards partial differential equitation (the LWR PDE) (Lighthill and Whitham, 1955 and Richards, 1956) which is

* Corresponding author. Tel.: +46 (0)11 36 33 16, fax +46 (0)11 36 32 70
E-mail address: david.gundlegard@liu.se
solved with the cell transmission model (CTM) introduced by Daganzo (1994). Macroscopic models usually have numerous parameters and to produce as accurate results as possible, these parameters need to be calibrated. One of the projects where the traffic state on highways has been estimated based on the kinematic wave theory is the Mobile Millennium project at UC Berkeley (Bayen et al., 2011). What distinguish this project from others is that the estimation is done in real-time and the cell transmission model is modified to handle velocity observations from different sources, such as stationary sensors and probes. However, during the development of this traffic state estimation model, the only calibration that was made was made manually and based on previous experience. During the last couple of years the Mobile Millennium highway traffic estimation model has been adapted to also handle traffic data collected in the greater Stockholm area and estimate the traffic state on the main roads (Allström et al., 2011). The extension of the model to another area further highlights the need for a calibration framework. Therefore, a general calibration framework has been developed. This framework could be applied to other models than the highway model implemented in the Mobile Millennium project and the calibrations procedures used are exchangeable in the framework.

The purpose of this paper is to introduce the calibration framework and the calibration methods that have been implemented in this first stage. The results from the initial calibration and the effect of different parameter settings will also be presented, together with a discussion on how the highway model implemented in Stockholm can be improved. The paper is structured as follows. Firstly, an overview of the highway traffic state estimation model is presented together with previous work on calibration of such models. In the following section the calibration framework is introduced, followed by a description of the calibration methods used. Thereafter the experimental setup and the results are presented followed by conclusions and future work.

2. Background

The implemented highway traffic estimation model is based on a first order traffic model, the Lighthill-Whitham-Richards for velocity (LWR–v). It is a velocity based partial differential equation consistent with the classical LWR PDE, first presented in Lighthill and Whitham (1955) and Richards (1956). The traffic state is discretized into cells of approximately 300 meters and at every time step, the discretized partial differential equation is solved numerically using the velocity based cell transmission model (CTM–v). Since the state variable is velocity it is straightforward to combine different types of speed measurements such as aggregated data from fixed detectors and single point speed measurements from probe vehicles. Currently, data from fixed sensors are available in the Stockholm area and are used as input. This data is pre-processed and assimilated into the highway model every 60 seconds. The assimilation is made using the ensemble Kalman filter, the EnKF (Evensen, 2003). The ensemble Kalman filter is an extension of the classical Kalman filter that involves representing the state estimate distribution as a set of ensembles. This allows optimality guarantees even in the case of non-linear dynamics. The output of the filter is a minimal variance estimate given the traffic model and the measurements. For a more detailed description of the model see Work et al. (2010).

The pre-processing filter, the CTM–v, and the EnKF all include parameters that needs to be calibrated. The EnKF includes parameters describing the noise and error from the model and the measurements. The highway model also contains parameters describing the capacity of the sinks, the demand of the sources and allocation parameters for each junction, also entitled split ratios. Finally, the pre-processing filter and CTM–v include link specific parameters related to the hyperbolic-linear version of the fundamental diagram for traffic.

Before a traffic model can be used for analysis or other applications it must be proven that the model is a good enough representation of the infrastructure and the traffic dynamics. An important step towards a valid model is model calibration.

In the literature, the definition of calibration varies but in general it can be described as an iterative process where the model parameters are adjusted in such a way that the model output matches field observations (Fransson and Sandin, 2012). If possible it would be preferable if this iterative change in model parameters was managed by an automated algorithm (Ngoduy and Maher (2012), Munoz, et al. (2004), Cremer and Papageorgiou (1981). Therefore, an automatic calibration framework has been implemented where the calibrations procedures used are exchangeable. The framework is further described in section 3.
The Complex algorithm is one of the methods that have been used for solving parameter estimation problems related to macroscopic traffic modelling, see for instance Cremer and Papageorgiou (1981) and Kotsialos et al. (2002). Hence, the Complex algorithm was the first calibration method to be implemented in the developed calibration framework. The Complex algorithm is used to calibrate the parameters related to the sinks, sources, split ratios and EnKF. The calibration of the parameters related to the fundamental diagram is performed using the Compass search algorithm (Kolda et al., 2003). Both calibration algorithms are described in section 4.

Once the model is calibrated it has to be validated. The validation is made by comparing the output from the calibrated model field observations, for a time period different from the one used in the calibration, see for example Braban-Ledoux (2000), Ngoduy and Maher (2012) and Cremer and Papageorgiou (1981) for a discussion of validation techniques.

By the proposed framework for calibrating the highway travel time estimation model, we will show the viability of using an automatic calibration procedure for the proposed CTM-v based highway traffic model.

3. Calibration framework

The calibration framework enables calibration of parameters in a traffic flow model based on travel time measurements and stationary sensors. The flow model can be used for traffic state assimilation using multiple sensors as well as short term prediction. The main motive for using travel time measurements for the calibration process is that there are several cost efficient options to measure travel times available, e.g. mobile Bluetooth detectors and floating car data. Another motive is that travel times can fully capture the aggregated traffic state over a given spatial domain. In this paper we focus on travel time measurements from Bluetooth detectors. The main parameters of the flow model are the traffic sources (traffic demand), traffic sinks (end node capacities), split ratios (distributed route choice) and fundamental diagrams (link capacities). It is possible to calibrate all parameters of the model using only travel times. However, to reduce the risk of ending up with parameters that has little connection to the physical system and to reduce the number of parameters to calibrate in each process, we have divided the calibration into two phases: calibration of fundamental diagrams and calibration of sources, sinks and split ratios.

The first phase is currently performed using measurements from stationary sensors whereas the second phase is performed using the travel time measurements. The calibration methods currently implemented for the two phases are described in detail in Section 4. The second phase requires preprocessing of both stationary sensors and travel time detectors, as well as aggregation in time and space related to the placement of the travel time detectors. The preprocessing and the iterative calibration framework are illustrated in Figure 1. The spatiotemporal aggregation process is described in Figure 2a, whereas the performance assessment of the calibration process is visualized in Figure 2b.

4. Calibration methods

4.1. Fundamental diagrams

Each link in the network has its own fundamental diagram and each fundamental diagram is defined by the four parameters free flow speed, shockwave speed, critical density and critical speed. The parameters in each of the fundamental diagram are individually calibrated using one month of radar sensor speed and flow data from March 2013. Optimal parameter values are found using a Compass Search (Kolda et al., 2003) using the objective:

\[
\min \left\{ \sum_{i=1}^{n} (\hat{\rho}_i - \bar{\rho}_i)^2 + \sum_{i=1}^{n} (\hat{v} - \bar{v})^2 \right\}
\]

where \( \hat{\rho} \) is the density computed from the speed and flow observations, \( \hat{v} \) is the observed speed, and \( \bar{\rho} \) and \( \bar{v} \) are the corresponding values computed from the fundamental diagram, implicitly given by the parameter values.
The relations in the fundamental diagram used, are given by
\[ \bar{v}(\rho) = \begin{cases} v_{\text{max}} \left( 1 - \frac{\bar{\rho}}{\rho_{\text{max}}} \right), & \text{if } \bar{\rho} \leq \rho_{\text{cr}} \\ -w_f \left( 1 - \frac{\rho_{\text{max}}}{\rho} \right), & \text{otherwise} \end{cases} \]  

(2a)

and

\[ \frac{\rho_{\text{cr}}}{\rho_{\text{max}}} = \frac{w_f}{v_{\text{max}}} \]  

(2b)

where \( \rho_{\text{max}} \) is the maximal density parameter for the link, \( \rho_{\text{cr}} \) is the critical density parameter for the link, \( w_f \) is the shockwave speed parameter for the link and \( v_{\text{max}} \) is the free flow speed parameter for the link.

4.2. Demand, splits and filter parameters

Apart from the links the network also consists of sources and sinks. Sources and sinks are considered to be ghost cells that post the boundary conditions at the network edges. They both have a parameter given in vehicles per second per lane that states the number of vehicles entering the network at each source, or the number of vehicle that can leave the network at each sink. At each off ramp a split ratio needs to be set, a parameter used to determine the proportion of vehicles of the major stream that wishes to leave the main line via the off ramp, and how many that wishes to continue forward. Finally there is a set of parameters that are part of the EnKF-filter, i.e. the model and measurement noise mean and standard deviation.

Thus, the number of parameters depends on network size (the number of on- and off ramps) and the number of data sources. All with values that are treated as unknowns during the calibration process, and in contrast to the fundamental diagram, we do not have any observations to estimate their values upon.

The gradient free search algorithm of Box (1965) is used to calibrate these parameters. The method is used to solve problems on the form

\[ \min \quad f(x_1, \ldots, x_N) \]

s.t. \[ x_i^L \leq x_i \leq x_i^U, \quad i = 1, \ldots, N \]

where \( x_i^L \) and \( x_i^U \) denote the lower and upper bound for variable \( i \), respectively. When the search algorithm is instantiated, several different, but admissible, random parameter values, or points, are created. Each point has \( N \) dimensions and there are usually at least \( K > (N + 1) \) different points in order to ensure that the dimensionality is kept during the search. The objective function is evaluated for each of the \( K \) points. The iterative procedure used follows the description in Box (1965). Here, one iteration in the procedure includes the running the highway model, compute travel times and compare the travel times to measured travel times. The travel times are computed by simulating vehicles in the velocity field between each Bluetooth sensor pair. The estimated and measured travel times are, in the objective function, compared by

\[ \frac{1}{|J||T|} \sum_{j \in J} \left( \sum_{t \in T} \frac{\|\hat{y}_{jt} - y_{jt}\|}{\hat{y}_{jt}} \right) \]  

(3)

where \( J \) is the set of Bluetooth routes, \( T \) is the set of time intervals over which the travel times are aggregated, \( \hat{y}_{jt} \) is the observed and aggregated travel time over Bluetooth route \( j \) at time interval \( t \) and \( y_{jt} \) is the estimated travel time, dependent on the parameters \( x \). The metric is the mean absolute percentage error (MAPE). A convergence criterion is checked, if it is satisfied, the search is completed and the point with the best performance is chosen as the model parameter set. But as long as the criterion is unsatisfied the worst point will be moved over the centroid of all the other points in the domain, where it is once again evaluated.

It has been noted by Andersson (2001) that this kind of search algorithm can get stuck around a local optimum. The algorithm was implemented in a way that moves the same point gradually as long as it continues to be the worst
point. A random value is added to the point in order to avoid a situation where the trial point ends up to close to another point. This also increases the search effort compared to a reflection through the centroid.

5. Experimental setup

To analyze the impact of the calibration framework and different parameter settings, data collected along the main highway in Stockholm has been used. In this section the available data and the test site are presented together with the setup of the analyzed calibration scenarios.

5.1. Test site

The test site is a 5 km long segment of the southbound part of the highway just north of Stockholm city. This particular site was chosen since both radar and Bluetooth data was collected during one week in March 2013. See Figure 3 for an overview of the placement of the two detector types.

![Figure 3: Each dot in the figure represent a radar detector, only the nine stations that are marked in the figure collected data during the field trial. Each Bluetooth sensor is illustrated with a Bluetooth symbol.](image)

The radar detectors were mounted over each lane of the highway and collected speed and traffic flow aggregated at one-minute intervals. The Bluetooth sensors were placed every 500-1000 m and collected travel times from all active Bluetooth devices that passed two sensors. Not all radar stations were active during the field trial, only the nine stations that are marked in the figure collected data during the field trial. In the middle of the test site the speed limit changes from 90 km/h to 70 km/h while the number of lanes varies between two, three and four along the road stretch. There are three on-ramps and three off-ramps on the chosen segment and adding the start and end of the network there are in total four sinks and four sources in the network.

5.2. Analyzed scenarios

Four different sets of parameters that could be calibrated have been identified: the capacity of sinks and the demand of sources, parameters related to the fundamental diagram, split ratios and parameters related to the Ensemble Kalman Filter. To analyze which sets of parameters that are most critical to calibrate, six different scenarios have been set up. Two of the scenarios, Scenario 1 for the time interval of 06:00 to 22:00, and Scenario 4 for 07:00 to 09:00, corresponds to “default values”, which are the values that the model system defaults to if no parameter values are given as input. In Scenario 2 and Scenario 5 only the parameters for the link fundamental diagrams are calibrated for the two time intervals. Scenario 3 and Scenario 6 corresponds to the situation where all available parameters are calibrated. Scenario 1 and 4 can be used for analyzing the improvement of the traffic state estimation that the calibration process result in, and, compared to Scenario 2 and 5 and Scenario 3 and 6, the effect of only calibrating the fundamental diagrams.
The sinks, sources and split ratios are static in the current implementation of the model. To analyze the possible improvement that a more dynamic set of parameters could imply, these parameters have been calibrated both against one day of data, but also against data only from the morning peak, 7am to 9am.

Table 1: Description of scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Time period</th>
<th>Fundamental diagram</th>
<th>Sinks/sources</th>
<th>Split ratios</th>
<th>EnKF</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>06-22 21st of March 2013</td>
<td>Default values</td>
<td>Default values</td>
<td>Default values</td>
<td>Default values</td>
</tr>
<tr>
<td>2</td>
<td>06-22 21st of March 2013</td>
<td>Calibrated</td>
<td>Default values</td>
<td>Default values</td>
<td>Default values</td>
</tr>
<tr>
<td>3</td>
<td>06-22 21st of March 2013</td>
<td>Calibrated</td>
<td>Calibrated</td>
<td>Calibrated</td>
<td>Calibrated</td>
</tr>
<tr>
<td>4</td>
<td>07-09 21st of March 2013</td>
<td>Default values</td>
<td>Default values</td>
<td>Default values</td>
<td>Default values</td>
</tr>
<tr>
<td>5</td>
<td>07-09 21st of March 2013</td>
<td>Calibrated</td>
<td>Default values</td>
<td>Default values</td>
<td>Default values</td>
</tr>
<tr>
<td>6</td>
<td>07-09 21st of March 2013</td>
<td>Calibrated</td>
<td>Calibrated</td>
<td>Calibrated</td>
<td>Calibrated</td>
</tr>
</tbody>
</table>

6. Results

Figure 4 a) shows the results of the calibration of the fundamental diagram for one of the links. The data points are speed and flow observations for the whole month of March 2013, for the times 06:00 to 23:00. Figure 4b) shows the result of travel time estimation during one day (06:00 to 22:00) using the CTM-v model before and after calibration of the fundamental diagram (Scenario 1 and Scenario 2), using default parameters of the source, sink, and split ratio parameters, and the travel times from the model when all parameters are calibrated (Scenario 3). Bluetooth measurements are shown as reference. From Figure 4 b) we can conclude that the results in terms of match the travel times from the Bluetooth sensors improves significantly when the parameters are calibrated.

In Figure 5, the space-time diagrams are shown. Figure 5a) shows the space-time diagram of the radar sensor data only. Figure 5b) show the space-time diagram for scenario 2, and Figure 5c) shows the results of the calibration (Scenario 3) in a space-time diagram.

The fact that our model uses a static demand limits the possibility for the calibration to adapt for change in traffic demand. In Figure 6 a) the source flow for one source is shown. From the figure it can be noted that the demand is not static, which indicate that the model might be improved if dynamic modelling of the demand is used. This is further analyzed by evaluating the model for a shorter time interval. Figure 6 b) shows the result when we run the model during the morning peak hour for the calibration scenarios 4, 5 and 6, and the corresponding Bluetooth travel time measurements.

![Figure 4a](image1.png)  
Figure 4a: Plot of speed and density for one lane for one month of data, and the corresponding calibrated fundamental diagram.

![Figure 4b](image2.png)  
Figure 4b: Estimated travel times on the 21th of March for Scenario 1, 2 and 3, and travel times from Bluetooth detectors.
In Table 2, one example of the default and calibrated parameters for a fundamental diagram of a specific link is shown. Further, Table 2 shows the demand parameter values for the sources, the sink parameters, the split ratios (the proportion of the traffic continuing on the modelled highway at each intersection), and the values used for the EnKF filter. The computed MAPE values for the Scenarios 1 to 6 are given in Table 3.

Since there are several parameters to adjust in the model, it is reasonable that it is possible to get a good fit with the Bluetooth travel times. However, to make sure we don’t over fit the model we would also like to see how the model performs on new data sets. In Table 3, the MAPE value when the parameter values found in Scenario 6 (for the time period 06:00 to 09:00 for the 21st of March) is applied to observed data for the time period 06:00 to 09:00 the 25th of March.

Figure 5a: Space-time plot for sensor data only. Black indicates no sensor data.

Figure 5b: Space-time plot for Scenario 1.

Figure 5c: Space-time plot for Scenario 3.

Figure 6a: Observed flow for one source over time.

Figure 6b: Travel times for Scenario 4, 5 and 6 and Bluetooth detectors.
7. Conclusions and future work

In this paper, a framework for calibrating a highway travel time estimation model, based on a two-stage process is presented. In the first stage, the fundamental diagrams of links are calibrated, and in the second stage, a search method is applied to the problem of finding the best possible model parameters. The fundamental diagram parameters are relatively important to achieve good results, where the capacity of the link is critical in order to capture the shockwaves correctly. For the estimation problem, when calibrating the parameters in a two-stage process, errors in the fundamental diagram parameters can be compensated with fictive changes in the demand. This is not a major problem for travel time estimation, but becomes much more important when using the model for travel time prediction.

Future work includes several challenges to enable wide area deployment of travel time predictions for the Stockholm highway network. For the calibration of the fundamental diagram parameters, it is possible to use the method presented in this paper, but to install Bluetooth sensors over the entire network for calibration of the remaining parameters is not a good option. A model parameter calibration method where travel times calculated by a subset of the fixed sensor covering the highway network or based on floating car data could be an option for wide area deployment.

The aim for the next step is to use the model for travel time prediction by running the model forward in time, without sensor input, or with historic sensor input. For this to be successful, both the demand of the sources and the split ratios have to be dynamic. The parameters of the fundamental diagram should also be adapted for different weather conditions and incidents to enable use of the model in a more generic setting.

Acknowledgements

The authors would like to acknowledge the contribution of Viktor Bernhardsson, Rasmus Ringdahl and Christoph Seybold.
References


