Calibration of mesoscopic simulation models for urban corridors based on the macroscopic fundamental diagram

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1. Introduction

Dynamic traffic models i.e. analytical and simulation-based models are an effective tool for development and assessment of traffic management and information systems. Most of real-time applications such as dynamic traffic management and traffic predictions use the dynamic traffic assignment (DTA) framework. Traditionally, to avoid mathematical intractability researchers have employed simulation-based DTA. However, to capture the stochastic behavior of traffic it is necessary to make multiple runs to generate statistically robust results. This typically involves a large set of parameters that need to be calibrated, especially on a network scale. Due to computational costs of microscopic models, most of the developed DTA frameworks (Ben-Akiva et al., 2002; Zhou et al., 2003) use mesoscopic traffic models. Such models represent the individual vehicles or vehicle packets in the network using macroscopic traffic dynamics. The application of mesoscopic simulation is not limited to DTA. Agent based modelling approaches such as in MATSim (Horni et al., 2016) employ similar traffic flow models as well.

In order to represent the traffic states accurately, calibration of the parameters is necessary. Generally, the calibration task can be divided into two sub-tasks. First calibration of demand - time-varying origin-destination (OD) pairs - and second, calibration of supply which usually involves calibration of fundamental diagram of traffic flow theory. The focus of this paper is on calibration of supply side and therefore, estimation of OD demand is not discussed further.

Due to their computational speed, event-driven queue-based mesoscopic traffic simulation models have become more popular than other approaches such as cellular automata (CA). However, with the advances in cloud computation one may argue that and revisit the application of CA models. In queue-based models, a road network is modeled as directed graph consisting of edges representing streets and nodes representing intersections. Each edge consists of a free-flow segment and a congested segment where the movement of vehicles is regulated by using a speed-density relationship. The main task is to calibrate the

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parameters of the fundamental diagram (FD) for each link. Since these models are a numerical solutions of first order kinematic wave theory (KWT) problem assuming a triangular FD, only 6 parameters need to be calibrated, namely segment capacities and speed-density relationship parameters in Equation 1.

$$v = v_{max}[1 - (\frac{k - k_{min}}{k_{jam}})^{\beta}]^{\alpha} \tag{1}$$

Where v_{max} is the free-flow speed, k_{min} and k_{jam} are the critical and jam density respectively and α and β are segment coefficients. Calibration of such a speed-density function on uninterrupted links has been widely studied and is a trivial task in comparison to OD demand estimation. However, the existence of a smooth relationship between speed-density on urban links is not guaranteed and thus, such a function cannot accurately represent the traffic dynamics. Another limitation of this method is that it will result into immediate transfer of disruptions from the downstream front of the queue to the upstream end (infinite-wave speed) which is not realistic for modelling shockwaves and spillbacks.

To overcome such limitations some studies (see e.g. Yildirimoglu and Geroliminis (2014); Mariotte and Leclercq (2018)) have proposed an alternative approach based on the concept of macroscopic fundamental diagram (MFD). The MFD by its current definition was introduced by Geroliminis and Daganzo (2008); Daganzo and Geroliminis (2008) which relates the space-mean flow and density in a homogeneously congested network. Many empirical and simulation studies have shown that it represents the dynamics of traffic flow in urban networks well and enables to design efficient traffic control (Ambühl et al., 2018; Yildirimoglu et al., 2015; Wu et al., 2011). Initially, the multi-reservoir representation of an urban network was used where each subnetwork is modeled according to a single-reservoir model of Daganzo (2007). To rectify the problem of infinite-wave speed, a trip-based model was proposed by Arnott (2013). This approach is in early stage of development and despite the possibility to consider several trip lengths, congestion propagation inside the reservoir remains a challenge (Mariotte and Leclercq, 2017).

Therefore, using mesoscopic simulation models which can capture the wave-speed and allow to model traffic signal settings i.e. g/C-ratio and coordination are the most efficient methods. For calibration of these models, traditionally, travel time along a route (or locally measured speed) is used. However, this approach cannot ensure that the empirical MFD can be reproduced. Moreover, local authorities have usually only access to loop detector data (LDD). Therefore, a calibration procedure based on this data type is highly beneficial for practitioners.

To the best knowledge of the authors, no work is existing on investigating the calibration of mesoscopic simulation models based on empirically derived MFDs. Thus, this paper aims to fill this gap. The calibration is based on empirical data from loop detectors from a main corridor in Munich, Germany. SUMO Lopez et al. (2018) is used as a simulation environment, as it is open-source and offers microscopic and mesoscopic models. The results from the mesoscopic simulation are compared to a calibrated microscopic simulation.

The paper is structured as follows. Section 2 explains the methodology of the study. This includes the cleaning of the empirical data, the structure, calibration and validation of both the microscopic and mesoscopic simulation, as well as used comparison metrics. Section 4 shows preliminary results of this study, and discusses them. Eventually, Section 5 draws conclusions, states limitations and outlines future work.

2. Methodology

The proposed methodology in this paper is composed of a mesoscopic simulation, which is calibrated based on a reference MFD. This reference MFD can be derived either from a previously established microscopic simulation or adjusted empirical data. The calibration procedure takes a metric which minimizes the difference between the reference MFD and the one resulting from the mesoscopic simulation. First, we describe the mesoscopic simulation environment. Then the generation of the reference MFD is explained. Eventually, we describe the metric on which the calibration is based on.

2.1. Mesoscopic simulation

For the purpose of calibration, the traditional speed-density based models cannot be applied. It is necessary to be able to take in to account the signal timings and wave-speed. These require to add a delay time at signalized intersection. Moreover, the possibility to divide each edge into smaller segments has to be provided. Each segment has its own independent service rate function depending on its traffic state and is dependent on the traffic state of the downstream segment. Among the existing tools, the open-source simulator SUMO provides these possibilities.

The mesoscopic model of SUMO has been developed by Eissfeldt (2004) and follows a similar principle of the cell transmission model of Daganzo (1995). Each link with a finite length of L_l is divide into $i = 0, 1, ..., I$ segments with equal lengths of L^i. In segment i at time t^k, a leaving time t^k_{min} is assigned to each vehicle v according to:

$$t^k_{min} = t^k + t_r(n^i, L^i, v^i_{max}, ...) \tag{2}$$

where v^i_{max} is the maximum speed on the segment, and $t_r()$ is a travel time function that depends on the density of the segment. If the maximum capacity of the downstream segment is reached the vehicles are not allowed to enter it. In addition, vehicles are forced to obey flow constraints to reasonably model traffic flow including the propagation of shock waves. If Q^i_s is the maximum flow that segment i can sustain in situation s, then the average headway between two vehicles is derived by $\tau^i_s = 1/Q^i_s$. The principals are illustrated in Figure 1. Assuming a triangular FD, only four different combinations of traffic states between two consecutive segments exist which are translated into four different headways. In addition, there are parameters to set the segment length and the "tls-penalty" which is a ratio that reflects the quality of signal coordination along the corridor. A value of 1.0 corresponds to uncoordinated traffic lights, a value of 0.0 to perfect coordination). Since computation time on a corridor is trivial a short segment length is selected to increase the accuracy of the simulation. Hence, the only parameter that is calibrated in this paper is the tls-penalty. This is perhaps important, since traffic signal data are difficult to collect and, additionally, modelling them in the simulation is tiresome. As a result, the modelling of correct signal plans is often ignored.

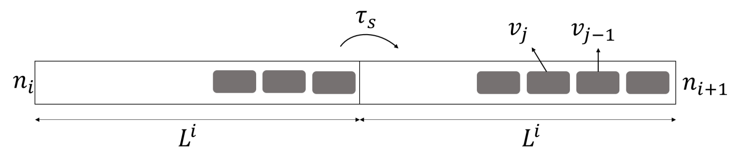

Figure 1: Sketch of two consecutive segments and their parameters on SUMO adapted from Eissfeldt (2004)

2.2. Reference MFD

We obtain the reference MFD by applying Edie's definition over a link which determines the relationship between flow and density of a corridor without any bias. This is essential, as Leclercq et al. (2014); Wu et al. (2011) show that the position and number of loop detectors significantly influence the shape of the obtained MFD. Moreover, one can argue that punctual observations cannot properly reflect the spatial average of speed or density within edges. However, for our case, these data can only be recorded based on detailed vehicle trajectories from a microscopic simulation and not from field data collection. Therefore, this step involves calibration of a microscopic simulation as well. The procedure is explained in the description of the case study in Section 3.

2.3. Calibration procedure

The last component is a calibration of mesoscopic model parameters. The problem is formulated as an optimization problem which tries to calibrate the parameters in a way that the mesoscopic model reveals the same MFD as Edie's link definition. The curves are generated by applying a LOESS regression method on the scatter data which is extracted from the simulation models. Consequently, the objective function is to minimize the distance between the two curves. To achieve that, we choose the Fréchet distance (Fréchet, 1906). It is a metric for the similarity between two continuous curves, P and Q. The Fréchet distance equals the minimum length between two points travelling along P and Q. The rate of travel along the curves does not have to be uniform. Additionally, the curves do not have to be of the same length. The discrete Fréchet distance (Eiter and Mannila, 1994) is an approximation for the case of non-continuous data. It acts only on the endpoints of each polygon of the total curve. Thus, the latter one is applied to the flow-occupancy tuples recorded in the mesoscopic and microscopic simulation and serves thereby as similarity measure for both curves.

3. Case study

3.1. Empirical Data

The data used in this paper are collected from loop detectors for a typical weekday on Leopoldstraße which is a corridor in the center of Munich, Germany. Its length is 2.7 km and consists of two lanes with an additional turning lane at intersections. In total, there are 8 signalized intersections from which LDD are available. It is a highly frequented corridor with actuated traffic signal control and transit signal prioritization. The studied part of the corridor is shown in Figure 2. After performing data cleaning, the raw data (flow and occupancy) are aggregated to 5-minute intervals to obtain the empirical MFD of the corridor. Detailed descriptive statistics on the data and discussion on the existence of the MFD for this corridor has been presented in Tilg et al. (2019). In addition to LDD, a small sample of travel time data during peak and off-peak hour using a single vehicle traveling along the corridor has been collected to calibrate the microscopic simulation. Furthermore, turning rates at the intersections have been extracted. The OD demand estimation is based on these measurements.

Figure 2: Layout of the Leopoldstraße in SUMO.

3.2. Microscopic simulation

The corridor has been modeled in SUMO for microscopic simulation as well. The virtual loop detectors are placed 35m upstream from each stop line. This assembles the positions of loop detectors on the actual Leoplodstraße. In total, 129 OD pairs are defined and the route choice is designed based on the collected turning rates at each intersection. Since the data were collected only for two hours, the demand is scaled by using constant factors across all OD pairs to cover more traffic conditions. The calibration of the microscopic simulation parameters of Krauss car-following model Krauß (1998) is based on the measured travel times. More details on the calibration of microscopic model are described in Grigoropoulos et al. (2018).

Two different types of data are extracted from the simulation. First, 5-minute aggregated occupancy and flow from the virtual loop detectors and second, occupancy and flow across the link which is identical to Edie's link definition. The obtained MFDs from each data source are presented in Section 4.

3.3. Mesoscopic simulation

As described earlier, the mesoscopic model of SUMO is used to reproduce the same scenario as in the microscopic simulation. For the mesoscopic simulation, the average occupancy and flow for each edge are provided and are converted into lane-specific values. For the calibration of the selected parameter, i.e. the tls-penalty, a step size of 0.1 is selected and for each value the Fréchet distance between the obtained MFD and the Edie's definition MFD is calculated.

4. Preliminary results and discussion

The results shown and discussed in this section focus on two plots. First, we present the relation of the empirically derived as well as the simulation-based MFDs. Subsequently, we show preliminary results from the calibration procedure.

4.1. Empirical and simulation-based MFDs

As described in Section 3.1, an MFD was derived from empirical data (E-LDD). Additionally, V-LDD were modeled in the calibrated microscopic simulation, and a corresponding MFD was obtained. Also, the MFD based on Edie's definition was constructed. The corresponding curves plus the empirical scattered data are shown in Figure 3.

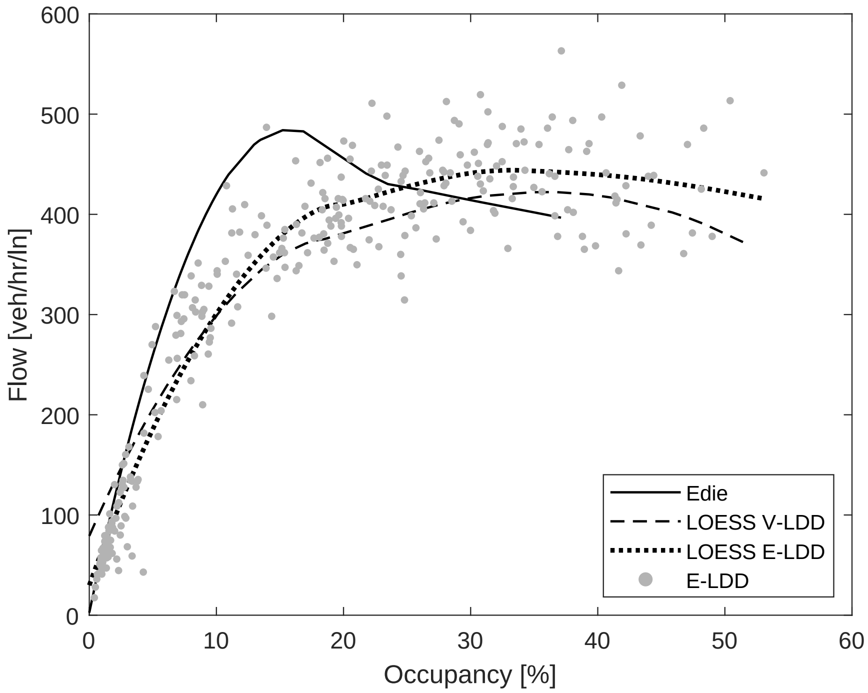

Figure 3: Edie's definition based MFd, LOESS regression MFD for virtual and empirical LDD, and scattered empirical LDD based MFD

The ordinate and the abscissa display the average flow and the average occupancy in the corridor, respectively. Each point of the empirical scattered LDD (E-LDD) represents the average traffic state during a 5-minute interval. The dotted curve represents the corresponding fitted curve, based on the LOESS regression method (LOESS E-LDD). The dashed curve shows the LOESS regression based curve for the virtual LDD (LOESS V-LDD). The solid curve displays the MFD based on Edie's definition which was derived from trajectories from the microscopic simulation.

The empirical MFD shows a clear capacity at a flow of ca. 450 veh/hr/ln. The data related to free flow states shows a lower amount of scatter. At higher congestion the scatter increases. Likely reasons which lead to these observations might by the adaptive signal control and the transit signal priority. The resulting variations in the supply side could lead to larger scatter in the empirical MFD. Interestingly, it can be seen that the microscopic simulation-based MFD derived from virtual loop detectors assembles the empirical one very well. However, the one based on Edie's definition shows a clearly higher free flow speed and also slightly higher capacity. This finding shows the influence of the loop detector position on the MFD, and is in line with Leclercq et al. (2014); Wu et al. (2011). Thus, we take the MFD based on Edie's definition as reference MFD for the calibration of the mesoscopic simulation.

4.2. Calibration

In the next step, the mesoscopic simulation was calibrated based on the Edie's definition based MFD. For this purpose, the mesoscopic simulation was run with several different tls-penalty values. For each run, the MFD was derived and the Fréchet distance with regard to the Edie's definition based MFD was calculated. The results are shown in Table 1.

Table 1: Preliminary calibration results

tls-penalty	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Fréchet distance	102	188	185	163	122	31	45	94	131	151	181

The results presented in the table show that a tls-penalty value of 0.5 leads to the lowest Fréchet distance and thus to the best fit of the mesoscopic MFD to the reference MFD.

Additionally, Figure 4 shows the reference MFD as solid black curve as well as three example MFDs based on the mesoscopic simulation as dotted, dashed and dot-dashed grey curves. Again, the ordinate displays the average flow and the abscissa the average occupancy in the corridor.

The figure shows descriptively that the MFD with the lowest Fréchet distance, which is the grey dashed curve, fits the reference MFD best. Thus, the methodology based on the Fréchet distance let us successfully calibrate the mesoscopic simulation based on the comparison of the resulting MFD with a reference MFD.

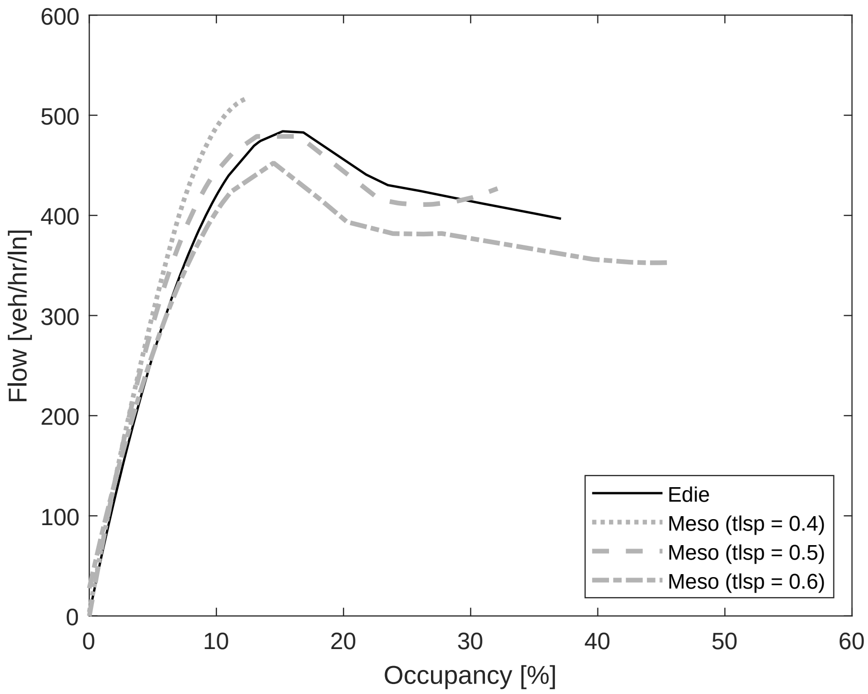

Figure 4: Reference and mesoscopic simulation-based MFDs.

5. Conclusion

This paper studies the potential of MFD-based calibration methods of mesoscopic simulation models. Based on empirical LDD from a highly frequented corridor in Munich, a microscopic simulation was built. Based on trajectories from this simulation and Edie's definition, a reference MFD was derived. Note that for the case of a network where no microscopic simulation is available, a reference MFD can be derived based on probe vehicle data. In the next step, we built a mesoscopic simulation model of the corridor by using the traffic simulator SUMO. In order to conduct calibration, we applied a similarity measure as metric to compare the MFD resulting from the mesoscopic simulation with the reference MFD. In this study, we exemplary show by calibrating only one parameter that a good fit can be achieved. This comparison suggests that mesoscopic simulation models are able to catch traffic dynamics described by the MFD for this urban corridor.

Given a reference MFD, we thus conclude that mesoscopic simulation is superior to microscopic simulation as it shows the same accuracy while needing less calibration effort and having a lower computational cost. This opens the door to network wide modeling based on mesoscopic simulation models.

The preliminary calibration results seem to be promising, but the applicability of the Fréchet distance needs be further investigated in a more sophisticated calibration procedure. Furthermore, only one corridor was investigated in this paper. The studied corridor consists of several intersections with adaptive signal control and transit signal prioritization and therefore has complex traffic dynamics. Thus, the next steps include an extension of the analysis to networks in order to prove the suitability of MFD-based calibrated mesoscopic simulation models.

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