Traffic Simulation Model Calibration Framework using Aggregate Data

Ramachandran Balakrishna* Moshe E. Ben-Akiva* Haris N. Koutsopoulos†
Tomer Toledo*

*Department of Civil and Environmental Engineering
Massachusetts Institute of Technology
77 Massachusetts Avenue, Cambridge, MA 02139, USA
{rama, mba, toledo}@mit.edu

†Department of Civil and Environmental Engineering
Northeastern University
360 Huntington Avenue, Boston, MA 02115, USA
haris@coe.neu.edu

1 Introduction

A number of traffic simulation models have been developed to date, ranging from detailed microscopic to mesoscopic models. These models are being used to support a variety of traffic operations applications, such as the evaluation of infrastructure design, traffic control systems and ITS deployment strategies. However, the effectiveness of such models hinges on how field conditions are replicated by the parameters in the simulation model. Calibration of the simulation model is required in order to achieve the best reproducibility of field conditions.

Model parameters include parameters that capture travel behavior (such as route and departure time choice) as well as those that affect traffic dynamics. Microscopic simulation models typically employ acceleration, lane-changing and intersection models to capture traffic dynamics. Mesoscopic models, on the other hand, rely on capacities and speed-density functions to capture queues and spillback. In addition, origin-destination (OD) flows are an important input to simulation models. However, because of the spatial extent of the applications, OD matrices, let alone accurate, dynamic ones, are not readily available. Hence input OD flows need to be estimated as part of the calibration process.

Calibration of traffic simulation tools is not a trivial task. The source of the difficulty is that the available field data usually consists of aggregate traffic measurements (such as flows, speeds and occupancies at sensor locations, queue lengths and point-to-point travel times), which are the emergent results of the interactions between various behaviors of individual drivers. Therefore, this type of data does not support independent calibration of the various models the traffic simulator consists of.

A number of papers have been published on the subject of traffic simulation model calibration (see, for example, Ben-Akiva *et al* 2004, Park and Schneeberger 2003, Hourdakis *et al* 2003 and Yang *et al* 2001). However, a majority of the work has focused on the calibration of individual simulation model components (such as OD demand or driving behavior models), thus ignoring the complex interactions between them. For example, while the OD estimation problem has received considerable attention, it has rarely been combined with the calibration of other models that affect the mapping of OD flows onto the aggregate traffic measurements. Solution approaches for the calibration problem have largely been based on ad hoc formulations of the problem, and utilize heuristic algorithms. The objective of this paper is to present a systematic procedure for joint calibration of model parameters and dynamic OD flows using aggregate data.

2 Calibration methodology

The general calibration framework (Figure 1) consists of two steps: initially, the individual models (such as the route choice and driving behavior models and speed-density functions) are estimated independently using disaggregate data. Route choice model parameters, for example, can be estimated using detailed survey data. Similarly, driver behavior information such as vehicle trajectories can be used to calibrate microscopic car following or lane changing models. Time-dependent sensor speed and density records can be used to identify the parameters in speed-density functions used by mesoscopic models. The estimated models may also be tested independently, for example, using holdout samples.

In the second step, the simulation model as a whole is calibrated and validated using aggregate data. Aggregate calibration ensures that the interactions between the individual models within the simulator are captured correctly, and allows for the refining of the independently estimated parameter values for the specific site being studied.

While this two-step approach is desirable, data availability often dictates the feasibility of the steps outlined above. Most often, only aggregate data collected through loop detectors is available and therefore only aggregate calibration and validation are possible. Section 3 provides a rigorous mathematical formulation of the aggregate calibration problem.

3 Aggregate calibration formulation

The aggregate calibration step can be formulated as an optimization problem which seeks to minimize a measure of the deviation between observed measurements and corresponding predictions from a model:

$$\underset{\mathcal{X}_N,\boldsymbol{\theta}_N}{\text{minimize}} \sum_{i=1}^{N} \left[z_1(\mathbf{M}_i^{obs}, \widehat{\mathbf{M}}_i) + z_2(\mathbf{x}_i, \mathbf{x}_i^0) + z_3(\boldsymbol{\theta}_i, \boldsymbol{\theta}_i^0) \right] \tag{1}$$

$$\text{s.t. } \widehat{\mathbf{M}}_i = f(\mathbf{x}_i, \boldsymbol{\theta}_i, \mathbf{TT}_i^{hab}, G_i) \tag{2}$$

$$\mathbf{TT}_i^{hab} = g[\mathbf{TT}_{i-1}^{hab}, \mathcal{TT}_{i-1}] \tag{3}$$

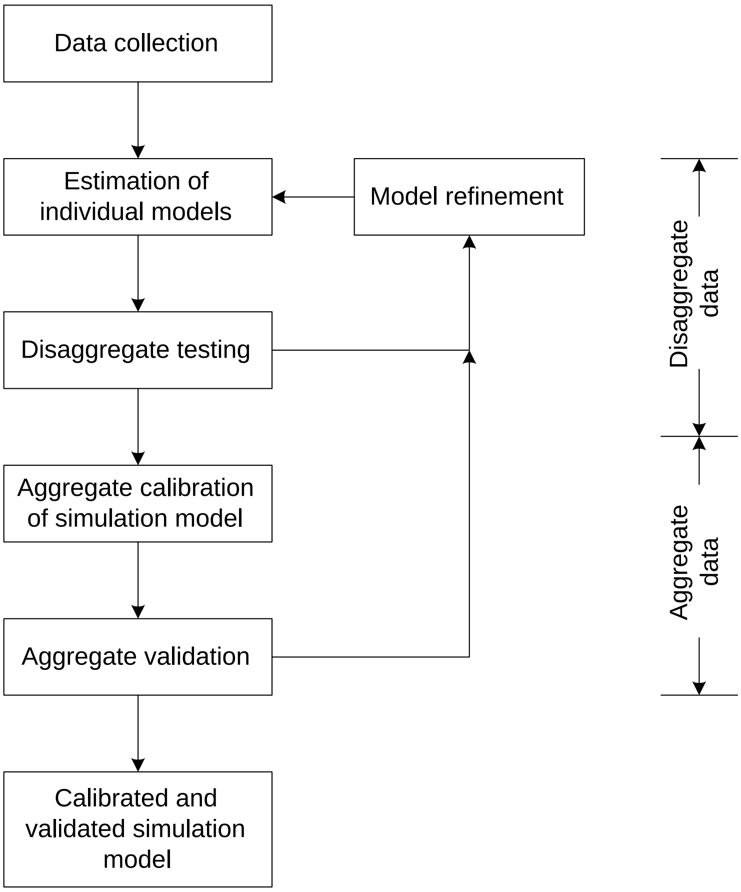

Figure 1: General Calibration Framework

The objective function in Equation (1) captures the deviations of mean model measurements $\widehat{\mathbf{M}}_i$, OD flows $\mathbf{x}_i$ and model parameters $\boldsymbol{\theta}_i$ for day i, from their observed or a priori estimates $\mathbf{M}_i^{obs}$, $\mathbf{x}_i^0$ and $\boldsymbol{\theta}_i^0$ respectively. The minimization is performed across all N days, so that $\mathcal{X}_N = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}$ and $\Theta_N = \{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, \ldots, \boldsymbol{\theta}_N\}$. The mean model measurements (which could include link counts and speeds as well as point-to-point travel times) are a function of habitual travel times $\mathbf{TT}_i^{hab}$ and the network G_i in addition to OD flows and model parameters, as denoted by Equation (2). Further, each realization of the simulator output (represented by the subscript w) is modeled as a noisy measurement of the corresponding mean quantity:

$$\mathbf{M}_{iw} = \widehat{\mathbf{M}}_i + \epsilon_{iw}$$

where ϵ_{iw} is a zero-mean error term. The stochasticity of the simulator is represented through the variance of the error term, which vanishes for deterministic models. The habitual travel times $\mathbf{TT}_i^{hab}$ perceived by drivers on day i are modeled, in the general case, through a learning model (Equation (3)) that updates previous perceptions $\mathbf{TT}_{i-1}^{hab}$ with the latest experiences. $\mathcal{TT}_{i-1}$ represents the set of all experienced travel times upto and including day $(i-1)$. Network travel times, which are inputs to the learning model, are often not measured. Mean simulated travel times $\widehat{\mathcal{TT}}_{i-1}$ can then be used instead of $\mathcal{TT}_{i-1}$ in Equation (3).The network G_i captures all factors that affect the capacity of the network, such as link closures and incidents.

While the specification of a learning model to capture day-to-day variations in drivers' travel time perceptions is intuitive, it requires data from a sufficiently long sequence of consecutive days. The recursive nature of the learning model also requires knowledge of the habitual travel times on the first day of the sequence. An assumption that perceived travel times are constant during the days for which data was collected is a practical alternative for many applications, while still allowing the experienced travel times to be different for each day. Further, the available data can be classified based on factors such as day of the week, weather conditions and special events, with constant habitual travel times and model parameters in each class. OD flows, however, can still vary from day to day. The remainder of this paper focuses on solving for the OD flows $\mathcal{X}_N$, model parameters $\boldsymbol{\theta}$ and habitual travel times $\mathbf{TT}^{hab}$ for one class containing N days of observations.

4 Solution approach

The formulation in Section 3 lends itself to various iterative solution approaches. The evaluation of the objective function, however, involves costly simulation runs. Furthermore, the dimensionality of the calibration parameters, in particularly the OD flows, can be very high even for networks of modest size. We therefore propose an approach based on the decomposition of the problem by parameter group (i.e. OD flows $\mathcal{X}_N$, and model parameters $\boldsymbol{\theta}$). This strategy creates two sub-problems: an OD estimation problem for which existing efficient solution methods may be used, and a parameter calibration problem which typically has a much lower dimensionality. Algorithm 1 outlines the steps in the general iterative solution approach.

$k = 0$, $\hat{\mathbf{x}}_i^k = \mathbf{x}_i^0 \; \forall i$, $\hat{\boldsymbol{\theta}}_k = \boldsymbol{\theta}^0$
repeat
  Calculate $\widehat{\mathbf{TT}}_k^{hab}(\hat{\mathcal{X}}_N^k, \hat{\boldsymbol{\theta}}_k)$
  Solve for $\hat{\mathcal{X}}_N^{k+1}(\hat{\boldsymbol{\theta}}_k, \widehat{\mathbf{TT}}_k^{hab})$
  Solve for $\hat{\boldsymbol{\theta}}_{k+1}(\hat{\mathcal{X}}_N^{k+1}, \widehat{\mathbf{TT}}_k^{hab})$
  $k = k + 1$
until $\|\hat{\mathbf{x}}_i^k - \hat{\mathbf{x}}_i^{k-1}\| < \epsilon_{\mathbf{x}} \; \forall i$ and $\|\hat{\boldsymbol{\theta}}_k - \hat{\boldsymbol{\theta}}_{k-1}\| < \epsilon_{\boldsymbol{\theta}}$ for successive iterations.

Algorithm 1: Solution Steps

The starting point for the algorithm is denoted by $\mathbf{x}_i^0$ and $\boldsymbol{\theta}^0$, representing the best a priori estimates of OD flows and model parameters available. Each iteration k of the solution process consists of several steps. At every step a set of parameters are calibrated, while the remaining parameters are fixed at their previous values. OD estimation is a critical calibration step and requires the generation of assignment matrices, which itself depends on route choice behavior and experienced travel times. Habitual travel times are important explanatory variables in route choice models. Hence habitual travel times are calculated based on the current estimates of OD flows and simulation model parameters. These travel times along with the current route choice parameters are used to generate assignment matrices. OD estimation can be performed using the calculated assignment matrices. The new OD flows are then used to re-calibrate route choice and traffic dynamics parameters, before moving to the next iteration. The algorithm terminates when the deviations of parameter estimates from estimates in past iterations fall

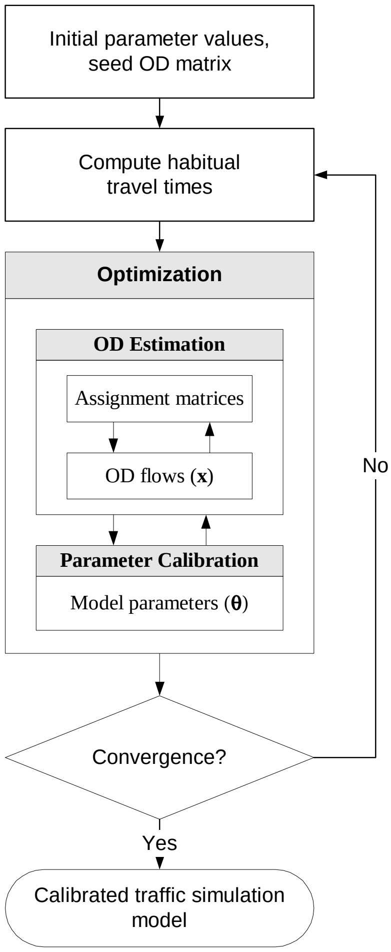

Figure 2: Solution Approach

within pre-defined thresholds (denoted by $\epsilon_{\mathbf{x}}$ for OD flows, and $\epsilon_{\boldsymbol{\theta}}$ for model parameters). The proposed approach is illustrated in Figure 2.

Several variations of the basic solution approach are possible. For example, habitual travel times may be re-calculated following the updating of each subset of variables (i.e. OD flows, route choice parameters and traffic dynamics parameters) or only after all variables have been updated. Moreover, the order in which the three sets of parameters are calibrated may be modified. Another variation, considering the closer inter-dependency between OD flows and route choice parameters, is to perform several iterations of these two steps before updating the traffic dynamics parameters. In this case, the calibration of route choice and traffic dynamics parameters will be performed in two separate steps, using similar mathematical formulations.

5 Ongoing research: case study

The formulation and solution approach outlined thus far are currently being demonstrated through a case study using a freeway network in Hampton Roads, Virginia.

6 Conclusion

A framework for the calibration of traffic simulation models using aggregate data was presented. The framework takes into account the interactions between the various model parameters and the OD flows by estimating OD flows jointly with the model parameters. An iterative solution framework is proposed based on the fact that parameter estimates depend on the OD flows, and vice versa.

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