Transportation Research Part C 59 (2015) 358–374

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

21st International Symposium on Transportation and Traffic Theory

Robust calibration of macroscopic traffic simulation models using stochastic collocation ☆

Sandeep Mudigonda [a,*], Kaan Ozbay [b,1]

[a] Department of Civil and Urban Engineering, New York University, Six Metrotech Center, 4th Floor, Brooklyn, NY 11201, USA
[b] Center for Urban Science + Progress (CUSP), Department of Civil & Urban Engineering, New York University (NYU), One MetroTech Center, 19th Floor, Brooklyn, NY 11201, USA

ARTICLE INFO

Article history:
Received 21 April 2015
Received in revised form 21 July 2015
Accepted 29 July 2015
Available online 24 August 2015

Keywords:
Calibration
Stochastic collocation
Macroscopic traffic flow

ABSTRACT

The predictions of a well-calibrated traffic simulation model are much more valid if made for various conditions. Variation in traffic can arise due to many factors such as time of day, work zones and weather. Calibration of traffic simulation models for traffic conditions requires larger datasets to capture the stochasticity in traffic conditions. In this study we use datasets spanning large time periods to incorporate variability in traffic flow, speed for various time periods. However, large data poses a challenge in terms of computational effort. With the increase in number of stochastic factors, the numerical methods suffer from the curse of dimensionality. In this study, we propose a novel methodology to address the computational complexity due to the need for the calibration of simulation models under highly stochastic traffic conditions. This methodology is based on sparse grid stochastic collocation, which, treats each stochastic factor as a different dimension and uses a limited number of points where simulation and calibration are performed. A computationally efficient interpolant is constructed to generate the full distribution of the simulated flow output. We use real-world examples to calibrate for different times of day and conditions and show that this methodology is much more efficient that the traditional Monte Carlo-type sampling. We validate the model using a hold out dataset and also show the drawback of using limited data for the calibration of a macroscopic simulation model. We also discuss the drawbacks of the predictive ability of a single calibrated model for all the conditions.

1. Introduction

Traffic simulation models are mathematical abstractions of the transportation system in which output is derived from a particular set of mathematical equations and relationships given a specific input data. The input data consists of two main groups of data sets: physical input data I_s (e.g., volume counts, capacity and physical features of roadway sections) and driver specific parameters C_s (i.e., adjustable components of driver behavior such as free flow speed, reaction time and mean

☆ Part of the work presented in this study was performed when the author was finishing his graduate studies at Rutgers University, Piscataway, New Jersey, USA.

* Corresponding author.
E-mail addresses: sandeep.mudigonda@nyu.edu (S. Mudigonda), kaan.ozbay@nyu.edu (K. Ozbay).
[1] Tel.: +1 (646) 997 0552; fax: +1 (646) 997 0560.

http://dx.doi.org/10.1016/j.trc.2015.07.015
0968-090X/

headway). Output from a simulation model can be expressed as shown in Eq. (1). The process of calibration entails adjusting the calibration parameters (C_s) so that the error between the output from simulation and field observations is minimized.

$$\begin{aligned} &O_{obs} : f(I_s, C_s) \rightarrow O_{sim}|I_s, C_s + \varepsilon \\ &f(I_s, C_s) = \text{functional specification of the internal models in a simulation system} \\ &O_{sim} = \text{simulation output data given the input data and calibrated parameters,} \\ &\varepsilon = \text{margin of error between simulation output and observed field data, and,} \\ &O_{obs} = \text{observed field data.} \end{aligned} \tag{1}$$

Traditionally traffic simulation models are used to study scenarios for a certain time period of a so called ‘‘typical day’’. However, as shown in Ozbay et al. (2014), the determination of a typical day is not a trivial task or a typical day may not even exist in reality. In fact, the typical day scenario might not also be the best scenario to test the effectiveness of operational strategies. Moreover, there is an increasing trend for using well-calibrated simulation models as predictive tools for real-time traffic control (Vasudevan and Wunderlich, 2013; Yelchuru et al., 2013, US DOT ICM Initiative (2014), Olyai, 2011; Dion et al., 2009). Clearly, these simulation models have to work under a combination of conditions that will considerably deviate from the typical day scenario.

Thus, calibration parameters estimated using limited sample data are not always representative of all possible conditions of the simulated system and might thus result in inaccurate predictions. In other words, models that are not adequately calibrated cannot accurately capture time-varying conditions of traffic. Traditional sources of traffic data used in the calibration of traffic models are either limited by the availability of the data that only cover typical conditions or may not be reliable enough. However, with the advent of new information technologies, unprecedented wealth of calibration data is on the fingertips of users by means of connected vehicles, smart phones, GPS-equipped devices, RFID readers among others. This, in turn, has led to massive amount of passively collected location and event data for various time periods. These data provide an opportunity to validate and calibrate traffic simulation models for a variety of spatiotemporal conditions.

Variability can be incorporated within *inputs* (demands) I_s and *calibration parameter set* (supply) C_s during different periods of the day, weather conditions, driver population composition, highway geometry, etc. There were previous studies that captured traffic variability (Li et al., 2009; Ngoduy, 2011; Jabbari and Liu, 2012; Sumalee et al., 2011; Lee and Ozbay, 2009) to name a few. However, the increase in the number of factors affecting stochasticity increases the dimensionality of the calibration process. This in turn results in increased computational effort required in calibrating traffic simulation models for different conditions such as variability within weekday/weekend, seasonal variability, special situations including adverse weather and work zones.

In this study, we propose a novel calibration methodology to address the computational complexity due to the need for the calibration of simulation models under highly stochastic traffic conditions. We show the utility of larger datasets to capture variability in traffic flow and speed for various time periods.

2. Literature review and motivation

Typically, accurate modeling traffic flow requires three types of data: model inputs, model parameters and observed outputs. Model inputs involve the demand-side data for which the traffic simulation is performed. Model parameters involve different types of supply-side parameters used in the traffic simulation depending on the level of complexity in modeling. The output data observed in real-world is required to compare model outputs and evaluate the accuracy of the models.

There are myriad of studies that deal with the calibration of traffic simulation models using various types of input and output data. Due to space constraint, we show a selected sample of them in Table 1.

Studies from other fields indicate that bias and variance in simulation output results are due to the bias and variance in the input models used, after simulation error is eliminated; the input models consist of simulation model inputs and parameters (Barton and Schrubenm, 2001; Henderson, 2003). The effect of data and parameter uncertainty in traffic simulation models has received considerable attention recently (Henclewood et al., 2013; Punzo et al., 2013; Ge and Menendez, 2013).

Federal Highway Administration (FHWA)’s Traffic Analysis Toolbox (Dowling et al., 2008) recommends that if George E. Haver’s statistic, GEH < 4 ($GEH = \sqrt{\frac{\frac{1}{T}\sum_{i=1}^{T}(O_{sim,i}-O_{obs,i})^2}{\frac{1}{2T}\sum_{i=1}^{T}(O_{sim,i}+O_{obs,i})}}$) for link volumes for 85% of the links and average travel times are within 15% of observed values, then it is considered as a satisfactorily calibrated model (Dowling et al., 2008). In order to achieve this level of calibration for various conditions (peak, off-peak, weekends, normal and inclement weather, under accident, and other events), detailed level of data is required.

Table 1 also shows the data used in each study for the calibrating process. It can be seen that in most studies data used for calibration is a small set of traffic conditions and/or time periods no more than a few days. Thus, the data captures only a few specific conditions, or is a dilute sample of different conditions. As depicted in Fig. 1, using only smaller samples of data will not accurately capture variation in traffic data. Hence, it is expected that the model predictions will only be accurate for those specific conditions. Using these models for conditions other than the ones for which calibration data was available for would not yield accurate results.