Transportation Research Part C 58 (2015) 395–412

Contents lists available at ScienceDirect

Transportation Research Part C

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

Dealing with uncertainty in detailed calibration of traffic simulation models for safety assessment

Carlos Lima Azevedo [a,*], Biagio Ciuffo [b,1], João Lourenço Cardoso [c,2], Moshe E. Ben-Akiva [d,3]

[a] Singapore MIT Alliance for Research and Technology, 1 Create Way, 138602 Singapore, Singapore
[b] Institute for Energy and Transport, Joint Research Centre, 2749 Via Enrico Fermi, 21027 Ispra, Italy
[c] National Laboratory for Civil Engineering, 101 Av. Do Brasil, 1700-066 Lisbon, Portugal
[d] Massachusetts Institute of Technology, Cambridge, MA 02139, USA

ARTICLE INFO

Article history:
Received 30 April 2014
Received in revised form 2 January 2015
Accepted 30 January 2015
Available online 11 April 2015

Keywords:
Road safety
Traffic simulation
Uncertainty management
Sensitivity analysis
Calibration

ABSTRACT

With the increasing level of detail of traffic simulation models, the need for a consistent understanding of simulators' performance and the adequate calibration and validation procedures to control uncertainty is crucial, particularly in applications focusing on complex driving behaviour and detailed outputs, such as road safety analysis.

In this work the calibration of traffic microscopic simulation models for safety analysis is analyzed considering four different key uncertainty sources: the input data, the calibration methodology, the model structure and its parameters, and the output data. The use of a multi-step sensitivity analysis (SA) framework is proposed and applied to the simulation of an urban motorway scenario, using a complex traffic simulation model with more than one hundred parameters. A three-level analysis is presented: (1) different advanced SA and calibration methods are described, compared and integrated in a multi-step global SA framework; (2) the proposed method is tested using both vehicle trajectory and aggregated traffic data to assess the impact of model parameters uncertainty and different types of input data on relevant outputs; and (3) accident and non-accident scenario-specific calibrations are performed to test the capacity of the simulator in replicating changes in detailed traffic and safety related measurements. Different techniques are adopted in each phase of the global SA and calibration method, attending to the problem complexity, the dimensionality of the experiment, and minimizing the necessary number of model evaluations.

The proposed method successfully identified the role played by all parameters and by the model stochasticity on different safety outputs. The final model calibration, carried out by explicitly considering the presence of uncertainty at different levels, confirmed the potential of advanced microscopic traffic models to adequately replicate detailed traffic and safety measurements, shedding light on different aspects of the interaction between road safety and traffic dynamics.

* Corresponding author. Tel.: +65 66011547; fax: +65 66842118.
E-mail addresses: cami@smart.mit.edu (C. Lima Azevedo), biagio.ciuffo@jrc.ec.europa.eu (B. Ciuffo), jpcardoso@lnec.pt (J.L. Cardoso), mba@mit.edu (M.E. Ben-Akiva).
[1] Tel.: +39 0332 789732; fax: +39 0332 786627.
[2] Tel.: +351 218443661; fax: +351 218443029.
[3] Tel.: +1 6172535324; fax: +1 6172531130.

http://dx.doi.org/10.1016/j.trc.2015.01.029

1. Introduction

Traffic micro-simulation tools have been developed and enhanced based on an increasing level of modelling complexity. It is becoming recognized the crucial importance of analyzing these models, understanding how they work and, in particular, what influences their capability to reproduce the socio-physical phenomena they are intended to simulate. Global sensitivity analysis (SA) is the family of tools to be used with this aim. Together with uncertainty analysis, SA studies how the uncertainties in model inputs affect the model response (Saltelli et al., 2008). These analyses are of high importance in reducing the complexity of the calibration task and minimizing the burden of non-influential parameters in such optimization process.

Generally, previous SA on micro-simulation models refers to applications to a sub-model with few parameters, with a clear focus in car-following (CF) behaviour. In fact, when dealing with complex traffic simulation models, it is common practice to make a selection of the parameters to involve in the sensitivity analysis and calibration. On top of this, simplified approaches such as the one-at-time (OAT) approach remain the most adopted method when dealing with microscopic simulation models (see for example Mathew and Radhakrishnan, 2010 or Kesting and Treiber, 2008). OAT approaches are based on the estimation of partial derivatives, and assess how uncertainty in one factor affects the model output keeping the other factors fixed at a nominal value. The main drawback of this approach is that interactions among factors cannot be assessed, since they require inputs to be changed simultaneously for several variables. Furthermore, this method restricts the analysis of the model response to the proximity of a certain point, rather than allowing for exploring its full input space (Daamen et al., 2014). Multi-factor analysis of variance (ANOVA) has also been used in the SA of traffic simulation models (see for example Park and Qi, 2005). It allows analyzing the effect of two or more parameters on a response variable and it is used to determine both the first-order and the interaction effects between parameters and a response variable. Further to using the standard definition of ANOVA, a more efficient method based on variance decomposition can be used in model SA. This method consists in evaluating two types of sensitivity indices and represents the most advanced and conceptually sound way of performing model SA (Saltelli et al., 2008). It can accommodate parameters interactions and a comprehensive analysis of their input space. However, this method may still require a large number, ($N \cdot [k+2]$, being k the number of parameters and N the dimension of the Monte Carlo experiment) of model evaluations when dealing with complex traffic models. This approach was successfully applied by for the SA of two CF models (Punzo and Ciuffo, 2009).

More recently, Ciuffo and Lima Azevedo (2014) proposed a multi-step approach to the use of variance-decomposition SA on computationally expensive and high-dimensional traffic simulation models. At each step, a variance-decomposition-based analysis is applied to groups of parameters, selected on the basis of their possible common features, allowing for the reduction of the number of evaluations and focusing at each step on more sensitive parameters. When applying it to a complex driving behaviour model with 101 parameters (Toledo et al., 2007) using aggregated data from loop sensors, the multi-step approach required 80% less model evaluations, when compared with a full SA technique.

While the large majority of these calibration studies focused on aggregated traffic variables as measures of performance (MoP), simulation studies focusing on road safety depend on detailed calibrated outputs such as accelerations, headways and lane changing decisions. Indeed, the importance of using trajectories when analyzing detailed driving behaviour and interaction outputs has been pointed out in recent studies (Cunto and Saccomanno, 2008; Jie et al., 2013; Ciuffo and Lima Azevedo, 2014). Focusing in rear-end crashes at signalized intersections, Cunto and Saccomanno (2008) used a multi-step approach to identify the most sensible parameters of the CF, lane-changing and stochasticity models of VISSIM (PTV, 2009) using real trajectory data. The measure of performance was the crash potential index (CPI) a surrogate safety assessment measure based on the acceleration differential and exogenous conditions. From 13 initial parameters, a first ANOVA reduced the number of sensitive parameters to 6 and a subsequent fractional factorial analysis reduced it to 3. A final genetic algorithm (GA) for calibration estimated the final values of the parameters. Duong et al. (2009) then extended this framework to a multi-criteria optimization, where the CPI was coupled with traffic volume and speed during the optimization of the GA.

In Jie et al. (2013) trajectories were used to calibrate a subset of VISSIM parameters (PTV, 2009) regarding MoP based on speeds and accelerations. After fine tuning a few driver heterogeneity parameters individually, a local (individual and group) OAT SA was carried out on the parameters related to the car-following behaviour. Although focusing in emissions modelling, this study also showed the different detailed kinematic outputs, when using trajectories or aggregated data in the calibration process. Vieira da Rocha et al. (2015) demonstrated that car-following models calibrated with trajectory data can replicate fuel consumption and NOx and PM emissions at the aggregate level. A variance-based global sensitivity analysis was also performed but, similarly to the work presented in Jie et al. (2013), the scope was limited to a small number of parameters (less than 10) and a single driving behavior (car-following).

Ge et al. (2014) presented a comparison between the variance-decomposition method and a Kriging-based approach (Ciuffo et al., 2013) coupled with the quasi-Optimized Trajectories Elementary Effects (quasi-OTEE) screening technique (Ge and Menendez, 2013) regarding the identification of sensitive parameters of the Wiedemann-74 CF model (PTV, 2009) using trajectory data. The quasi-OTEE SA was used to identify the whole sub-set of influential parameters from the initial 25 set, and the Kriging-based SA was then used to refine the analysis and correctly rank the most influential parameters in a more reliable way, using 40 times less model evaluations. Along with Ciuffo and Lima Azevedo (2014), this study revealed the potential of coupling and replacing variance-decomposition methods with less demanding ones. Furthermore, it has been demonstrated in several studies (Toledo and Koutsopoulos, 2004; Cunto and Saccomanno, 2008; Ciuffo and Lima Azevedo, 2014) that coupling advanced SA techniques with metamodels may significantly reduce the computational burden