Transportation Research Part C 63 (2016) 147–169

Contents lists available at ScienceDirect

Transportation Research Part C

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

A cross-entropy method and probabilistic sensitivity analysis framework for calibrating microscopic traffic models

R.X. Zhong [a,b], K.Y. Fu [a,b], A. Sumalee [c], D. Ngoduy [d,*], W.H.K. Lam [e]

[a] School of Engineering, Sun Yat-Sen University, Guangzhou, China
[b] Guangdong Provincial Key Laboratory of Intelligent Transportation Systems, Guangzhou, China
[c] Department of Civil Engineering, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand
[d] Institute for Transport Studies, University of Leeds, Leeds LS2 9JT, United Kingdom
[e] Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hong Kong Special Administrative Region

ARTICLE INFO

Article history:
Received 18 August 2015
Received in revised form 5 December 2015
Accepted 8 December 2015
Available online 30 December 2015

Keywords:
Car-following model
Model calibration
Cross-entropy method
Probabilistic sensitivity analysis
Relative entropy
Kullback–Leibler distance

ABSTRACT

Car following modeling framework seeks for a more realistic representation of car following behavior in complex driving situations to improve traffic safety and to better understand several puzzling traffic flow phenomena, such as stop-and-go oscillations. Calibration and validation techniques pave the way towards the descriptive power of car-following models and their applicability for analyzing traffic flow. However, calibrating these models is never a trivial task. This is caused by the fact that some parameters, such as reaction time, are generally not directly observable from traffic data. On the other hand, traffic data might be subject to various errors and noises. This contribution puts forward a Cross-Entropy Method (CEM) based approach to identify parameters of deterministic car-following models under noisy data by formulating it as a stochastic optimization problem. This approach allows for statistical analysis of the parameter estimations. Another challenge arising in the calibration of car following models concerns the selection of the most important parameters. This paper introduces a relative entropy based Probabilistic Sensitivity Analysis (PSA) algorithm to identify the important parameters so as to reduce the complexity, data requirement and computational effort of the calibration process. Since the CEM and the PSA are based on the Kullback–Leibler (K–L) distance, they can be simultaneously integrated into a unified framework to further reduce the computational burden. The proposed framework is applied to calibrate the intelligent driving model using vehicle trajectories data from the NGSIM project. Results confirm the great potential of this approach.

1. Introduction

For most planning and operational applications, accurate representation of realistic driving behaviors offers a great help to transportation analysts. Along this stream, microscopic traffic models especially Car Following (CF) models are widely adopted to simulate complex traffic scenarios such as traffic incident, signal control, public transport priority wherein analytical methods are unlikely to work due to the complexity. A large number of CF models have been developed to describe CF

* Corresponding author. Tel.: +44 (0)113 34 35345.
E-mail addresses: zhrenxin@mail.sysu.edu.cn (R.X. Zhong), asumalee@gmail.com (A. Sumalee), D.Ngoduy@leeds.ac.uk (D. Ngoduy), cehklam@polyu.edu.hk (W.H.K. Lam).

http://dx.doi.org/10.1016/j.trc.2015.12.006

behavior under a wide range of traffic conditions in the past decades, see e.g. Barceló (2010) and Saifuzzaman and Zheng (2014) for a review. Model calibration would heavily affect the reliability of the results achieved by using the underlying model as well as its applicability in traffic engineering practice. Calibration is vital for microscopic traffic models, yet it can be rather difficult since these models often contain a wide range of variables. Moreover, some parameters, such as reaction time, desired spacing, desired time headway, desired speed, are generally not directly observable from traffic data, and this makes them hard to be identified. Nonetheless, the parameters are scenario specific, i.e. they are not transferable to other situations (different locations, periods of the day such as morning rush hours and evening rush hours, etc.). On the other hand, driving behavior and local traffic rules, which the microscopic traffic flow models intend to describe, are variable in time and space, etc. (Hoogendoorn and Hoogendoorn, 2010; Treiber and Kesting, 2014). Therefore, many of the microscopic traffic models were neither empirically calibrated nor validated using real traffic data until recently, a considerable amount of research have been devoted to the calibration and validation of microscopic models, see e.g., Ossen and Hoogendoorn (2008), Kesting and Treiber (2008), Hoogendoorn and Hoogendoorn (2010) and Treiber and Kesting (2014). However, guidance on the systematic and rigorous calibration and validation of traffic flow models is still lacking (Ngoduy and Maher, 2012; Saifuzzaman and Zheng, 2014). Nevertheless, traffic data might be subject to various errors and noises. The calibration of stochastic microscopic models is more complicated as they will require multiple runs to reduce the noise in the objective function (Ngoduy and Maher, 2012). To tackle these difficulties, this paper aims to develop a new framework for calibrating microscopic traffic models with various uncertainties to maximize the model's descriptive power based on representative traffic data.

Conventionally, deterministic search methods which aim to minimize the discrepancy between the model prediction and observed data are common approaches to access model calibration for both microscopic and macroscopic traffic models. As a consensus in the literature, such kind of methods will result in a large number of local optima due to the complex structure of the optimization problem and different combinations of the set of parameters, see e.g., Ngoduy et al. (2003), Ngoduy and Maher (2012), Ciuffo and Punzo (2014) and Zhong et al. (2015). For this reason, gradient-based solution algorithms are not considered as a popular option (Kontorinaki et al., 2015). Therefore, a popular and convenient approach to compensate this is to use random search techniques (Ciuffo and Punzo, 2014; Hale et al., 2015). The basic idea behind such methods is to systematically partition the feasible region into smaller subregions and then to move from one subregion to another based on information obtained by random search (Ciuffo and Punzo, 2014; Ngoduy and Maher, 2012). Well-known examples include simulated annealing, genetic algorithms, tabu search, and ant colony methods. All these methods are reported to find a good local optimal solution (while some also claimed global optimal solution can be obtained) but there is not as yet a fully accepted method. Noticing the optimization nature of the calibration problem, remarkably, Ciuffo and Punzo (2014) applied the No Free Lunch (NFL) theorems to the calibration problem of microscopic traffic models to access the performance of various algorithms ranging from heuristic optimization methods to meta heuristic searching methods. To be more specific, the simultaneous perturbation stochastic approximation method, simulated annealing, Genetic Algorithm (GA), and OptQuest/Multistart heuristic methods are evaluated and compared in Ciuffo and Punzo (2014). It is found that the performance of different algorithms over the 42 experiments considerably differ, which confirms the validity of NFL theorems in the calibration problem, i.e., the dependence of the performance from the parameters to be calibrated, from the GoF measure, and from the quality of the data. Remarkably, the analysis reveals that the GA, which is probably the most widely used algorithm type for the calibration of microscopic traffic models, outperforms the others globally while the OptQuest results the best algorithm in the sense of convergent time and optimization performance indicator. As a contrast, the simulated annealing results the worst algorithm for the tested cases in Ciuffo and Punzo (2014).

It is known that the GA is generally computationally intensive and of no convergence proof. Moreover, the presence of random noise would affect the optimization procedures. Ngoduy and Maher (2012) applied the Cross Entropy Method (CEM), which is a generic monte carlo technique with importance sampling for reducing the computational burden, to the calibration purposes of a second order macroscopic model. The empirical results have verified several merits of such method, e.g. attaining a set of parameters that are close to the global known optimal set, computational efficiency and convergence. Maher et al. (2013) extended this CEM framework for signal optimization to consider the effect of noise in the evaluation process.

Noting that single data source may be not sufficient for calibrating a microscopic traffic model, Hollander and Liu (2008) summarized an exhaustive list of both Goodness-of-Fit (GoF) measures and optimization algorithms used in the calibration of microscopic traffic models with some tips for their usage. However, a thorough investigation still lacks while this has been further pursued by Ciuffo and Punzo (2014). To compensate the drawbacks of a single data source, Hoogendoorn and Hoogendoorn (2010) proposed a data fusing framework to calibrate the parameters of CF models based on several data sources. Treiber and Kesting (2014) also applied several (GoF) measures to assess descriptive quality of CF models and provided comparative calibration results using different optimization methods and data sources under the umbrella of maximum-likelihood and least squared errors.

Because of the unobservable parameters of the CF models, inherent noise of traffic data, complicated human factors to be modeled and traffic scenarios to be simulated, one of the main challenges arising in the calibration process concerns the selection of the most important parameters and the identification of their probabilistic characteristics. Selecting the most important parameters also helps guiding data collection by limiting the number of input parameters to be observed rather than the whole parameter set (Saifuzzaman and Zheng, 2014). However, there is usually no formal procedure for selecting these parameters other than the experiences of the participating engineers. Such a prior selection of relative parameters