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Systematic bias in transport model calibration arising from the variability of linear data projection

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A R T I C L E I N F O

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A B S T R A C T

In transportation and traffic planning studies, accurate traffic data are required for reliable model calibration to accurately predict transportation system performance and ensure better traffic planning. However, it is impractical to gather data from an entire population for such estimations because the widely used loop detectors and other more advanced wireless sensors may be limited by various factors. Thus, making data inferences based on smaller populations is generally inevitable. Linear data projection is a commonly and intuitively adopted method for inferring population traffic characteristics. It projects a sample of observable traffic quantities such as traffic count based on a set of scaling factors. However, scaling factors are subject to different types of variability such as spatial variability. Models calibrated based on linearly projected data that do not account for variability may introduce a systematic bias into their parameters. Such a bias is surprisingly often ignored. This paper reveals the existence of a systematic bias in model calibration caused by variability in the linear data projection. A generalized multivariate polynomial model is applied to examine the effect of this variability on model parameters. Adjustment factors are derived and methods are proposed for detecting and removing the embedded systematic bias. A simulation is used to demonstrate the effectiveness of the proposed method. To illustrate the applicability of the method, case studies are conducted using real-world global positioning system data obtained from taxis. These data calibrate the Macroscopic Bureau of Public Road function for six 1×1 km regions in Hong Kong.

1. Introduction

Reliable model calibration is crucial in transportation studies as it helps to establish a better understanding of the interactions between transportation infrastructure, vehicles and road users. Accurate model calibration leads to better urban and traffic planning and the implementation of traffic management and control measures. Consequently, it helps to develop a less congested and more efficient network, keeps a city more economically competitive and decreases traffic emissions. In addition, due to the irreversible patterns of development restricted by infrastructures and the critical role of infrastructure in promoting economic growth (Carlsson et al., 2013), careful planning with the support of reliable model calibration is essential for preventing the misuse of the public budget and resources.

The accurate measurement and estimation of traffic quantities result in reliable model calibration. Technological advancements have improved the accuracy and efficiency of traffic data collection methods over the past decades. Hand tally measurement has gradually been replaced by automatic systems such as inductive loop sensors, radar and television

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cameras. In addition to point measurement, methods for measuring along a length of road and the collection of data by a moving observer have also been developed. The rapid development of intelligent transportation systems has made it possible to conduct measurements over a wide area at a relatively low cost.

On-road fixed detectors such as inductive loop sensors are still the most commonly adopted means of collecting traffic data for important roadways, as such methods provide an acceptable level of accuracy with minimal effort. However, high installation and maintenance costs sometimes make it impractical or economically unviable to ubiquitously deploy these sensors on all highways and the entire arterial network (Herrera and Bayen, 2010; Herrera et al., 2010). Hence, the coverage is normally limited to a subset of links (Caceres et al., 2012).

Given that vehicle movement can be interrupted by signals, the travel time estimates of loop detectors could be inaccurate. In principle, a vehicle re-identification system can improve the accuracy as follows. Sensors installed at the two ends of a selected arterial link record the times when a vehicle passes by and measure its signature. The travel time of the vehicle is calculated when the signature is matched at the two consecutive locations of the link (Kwong et al., 2009). The radio frequency identification (RFID) transponders (Wright and Dahlgren, 2001; Ban et al., 2010), license plate recognition (LPR) systems (Herrera et al., 2010) and other unique tags are readily available utilities for this scheme. However, in addition to raising privacy concerns, these systems are similarly limited by the cost of sensor deployment over the entire arterial network, thus restricting coverage. Kwong et al. (2009) presented a scheme based on matching signatures measured by wireless magnetic sensors installed at the two ends of the arterial link. Although this scheme is able to avoid the risk of privacy issues, it fails to resolve cost and coverage problems. More recently, the Bluetooth Media Access Control Scanner (BMS) was proposed as a complementary traffic data source (Bhaskar and Chung, 2013). However, Jie et al. (2011) identified the poor quality of its data and the uncertainty surrounding its identification of Bluetooth device carriers (i.e., whether a carrier belongs to a vehicle, a cyclist or a pedestrian).

Cellular systems were introduced a decade ago (Bolla and Davoli, 2000; Ygnace and Drane, 2001,Zhao, 2000) to overcome the limitations imposed by expensive implementation costs and the limited coverage of stationary roadside equipment (Herrera et al., 2010) in systems such as loop detectors and vehicle re-identification systems. However, because the use of cell phones while driving disrupts drivers' attention (Liang et al., 2007), it is prohibited or discouraged in many countries, thus limiting the application of the proposed models. Moreover, flow measurements from cellular systems follow an aggregate format for each group of links intercepting the corresponding inter-cell boundary (Caceres et al., 2012), making it impossible to estimate traffic flow for any individual link.

Advancements in global positioning systems (GPSs) have made it possible to collect data from GPS-equipped vehicles. These systems have been widely adopted to extend the coverage of data collected from stationary roadside equipment to almost the entire network at a relatively low cost (Miwa et al., 2013). Many recent travel time estimation studies have been based on GPS probe vehicle data (Nanthawichit et al., 2003; Hofleitner et al., 2012; Peer et al., 2013; Herring et al., 2010; Jenelius and Koutsopoulos, 2013; Zheng and Van Zuylen, 2013; Zhan et al., 2013). Although they lend potential to future global coverage, these probe vehicle data come from various sources that present specific challenges. First, fleet data (FedEx, UPS, taxis, etc.) (Moore et al., 2001; Schwarzenegger et al., 2008; Bertini and Tantiyanugulchai, 2004; Wong et al., 2014) pose bias problems due to the operational constraints and specific travel patterns involved. Second, participatory sensing data taken from industry models (INRIX, Waze, etc.) are unpredictable, and no single company has ubiquitous coverage (Hofleitner et al., 2012). Moreover, the added cost of equipping every vehicle with GPS trackers coupled with potential privacy issues prevent this system from being applied on a global scale, making direct measurement of total traffic flows implausible.

Despite the advancement of technologies, the collection of traffic data via different devices remains limited by various factors. Mathematical techniques used for traffic data estimations, such as sampling methods, filtering algorithms and data scaling, offer possible solutions to the problems presented by data acquisition. Linear data projection is a prevalent data scaling method that infers population traffic characteristics by projecting the observable traffic characteristics of a smaller population via the mean of a set of scaling factors.

The scaling factors used in linear data projections vary by situation. Example scaling factors include traffic composition ratios and passenger car units (PCUs). The factor is usually a random variable that is subject to variability and assumed to follow a distribution, rather than a constant. Depending on the sampling method used, the variance of the sampled scaling factor measures different types of variability, such as spatial and temporal variability. If traffic composition ratios are sampled across a network, then the variance measures spatial variability. Contrary to the usual assumption, a PCU is not essentially static (Chandra et al., 1995). Thus, if it is selected as the scaling factor, its variance during different time points at the same site measures temporal variability. Because the mean of the distribution is the most probable observed scaling factor, it is usually adopted in linear data projections.

Linear data projections are especially useful for traffic data estimations in situations where direct measurement is not possible such as the lack of spatial coverage of sensors. For instance, a linear data projection can be adopted to estimate an hourly total traffic flow on a link where on-road fixed detectors are not installed. Assuming that occupied taxi flow is observable on every roadway in a network and that total traffic flow is only observable on a subset of links outfitted with detectors in the network, the total traffic-to-occupied-taxi ratio can be the chosen scaling factor, and is assumed to follow a distribution over a region due to geographical proximity. Scaling factors can be sampled at sites outfitted with detectors. The mean of the sampled scaling factors is the expected total traffic-to-occupied-taxi ratio across that region in the long run. The variance of the sampled scaling factors measures the spatial variability of the total traffic-to-occupied-taxi ratio within