Transportation Research Part B 92 (2016) 22–34

Contents lists available at ScienceDirect

Transportation Research Part B

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

Statistical methods for comparison of day-to-day traffic models

Martin L. Hazelton[a,*], Katharina Parry[b]

[a] Massey University, New Zealand
[b] Auckland University of Technology, New Zealand

ARTICLE INFO

Article history:
Received 23 February 2015
Revised 4 July 2015
Accepted 8 August 2015
Available online 29 August 2015

Keywords:
Bayesian
DIC
MCMC
Network
Route choice

ABSTRACT

Day-to-day dynamic traffic models have considerable potential as tools for transport network management and planning, and also for the study of traveller behaviour. However, their efficacy for these purposes is dependent on appropriate model selection. In particular, while it can be tempting to incorporate sophisticated and intricate representations of traveller learning in day-to-day models, it is important to ask whether the available data are able to support such a level of model complexity. To this end, our overall aim is to investigate the extent to which it is possible to learn about day-to-day traveller behaviour from observations on traffic counts collected over a sequence of days. The paper makes two specific contributions. The first is the development of a principled Bayesian methodology for comparing day-to-day models using link count data, and a description of how it may be implemented in practice using Markov chain Monte Carlo methods. The second contribution is a suite of simulation studies that examine whether these techniques can select the correct model within a set of alternatives with a variety of complexities of behavioural representation. We find that successful model choice based on link count data is often possible when travellers are relatively sensitive to differences in route utilities.

1. Introduction

The use of day-to-day dynamic models can be regarded as a pragmatic approach to the study of traffic networks. Such models eschew a detailed representation of the highly complex interactions between travellers in the course of a journey, seeking instead to focus on the manner in which travellers adapt their behaviours in response to past experiences. As such, day-to-day models aim to reach a balance between ease of implementation and mathematical tractability on the one hand, and flexibility to represent a wide variety of properties of a traffic system on the other hand (Watling and Hazelton, 2003).

Day-to-day dynamic traffic models can be employed for a variety of intents and purposes. One such use is for prediction of future traffic flows. In that context, a critical advantage of stochastic day-to-day models over classical deterministic equilibrium models is that the former naturally generate a range of predicted flow patterns, and hence provide insight not only into an average future day but also into potential extremes. Another important use of day-to-day models is for examining how different types of behaviour manifest themselves in terms of macroscopic properties of the traffic network. A myriad of applications ensue, from studying how systems are likely to behave following major changes to the network (e.g. He and Liu, 2012) to designing more effective means of network control. A third use of day-to-day models is for estimation of behavioural parameters, such as the scale parameter in a logit random utility route choice model. While this type of

* Corresponding author.
E-mail addresses: m.hazelton@massey.ac.nz (M.L. Hazelton), katharina.parry@aut.ac.nz (K. Parry).

http://dx.doi.org/10.1016/j.trb.2015.08.005

parameter might in some cases be estimable within the context of an equilibrium model, for example by using methods for statistical linear inverse problems (e.g. Hazelton, 2010) or reverse assignment techniques (e.g. Russo and Vitetta, 2011), it is natural to expect more precise estimation to be possible through dynamic models where we see the route choice updating in action.

One of the attractions of day-to-day modelling has been the relative ease with which one can develop models that admit a wide range of traveller behaviours. For example, the seminal class of Markov models described by Cascetta (1989) have a relatively simple structure, but nonetheless can represent processes in which travellers combine experiences from an arbitrarily large number of previous days when making decisions about route choice. See also Cantarella and Cascetta (1995) and Hazelton and Watling (2004). However, this degree of flexibility is a double-edged sword, in that it may offer a temptation to researchers to develop models with complicated descriptions of the traveller learning and route choice processes that go well beyond what could be inferred from observable data.

Transportation science is not immune to the effects of Ockham's razor (e.g. Lazar, 2010). One may conjecture any manner of intricate models for traveller behaviour, but we can only claim tangible evidence in support of any given model if it improves on simpler ones to a statistically significant degree. If this is not the case then the simpler models should be preferred. It follows that if we are to reap the full benefits of day-to-day modelling, we must have statistical tools available for model assessment and comparison. What is more, these methods should be as powerful as possible in order to detect what might be quite subtle improvements in the model fit resulting from refined representations of traveller learning and route choice.

The implementation of methods of model assessment and comparison, and their power to distinguish between competing models, will depend intimately on the type of data that is available. Day-to-day models are typically defined in terms of the vector of traffic flows on all specified routes through the network. If the route flows can be directly measured then the application of standard tools for model comparison (e.g. likelihood ratio tests) will be straightforward, and the results highly informative. However, despite the promises of big data, comprehensive data of this type are rarely available. In part this is because of shortcomings in technology. For example, tracking vehicles through the use of GPS and/or mobile phone data does not always give reliable routing information, both because of errors in determining precise vehicle location and loss of signal in tunnels and road segments shadowed by tall buildings (the so called 'urban canyon' effect). Furthermore, by no means are all vehicles fitted with the necessary technology to be tracked. Trying to correct for this by scaling up the trips counted for tracked vehicles will usually lead to differential bias, since the probability that a vehicle is equipped for tracking will often be correlated with the types of journey undertaken and hence the routes selected. The effects on statistical inference can be profound. See Parry and Hazelton (2012), for example. Finally, even were the technology to exist to provide completely reliable information on all vehicle journeys, privacy considerations would typically prevent such data being released on a routine basis.

In contrast, link count data is relatively common, cheap and unbiased. However, such data provide only indirect information about the underlying route flows, and hence about parameters describing route choice in day-to-day modelling. The question then arises as to what extent it is possible to learn about traveller behaviour from observations on traffic counts collected over a sequence of days (or observational periods). The overall objective of this paper is to study this issue. To this end we have two specific goals. The first is to describe a methodology for comparison and assessment of day-to-day models using link count data, and to show how it may be implemented in practice. As indicated earlier, it is important that we tease as much information as possible out of the data. Working within the Bayesian statistical paradigm, this means that we need to use methods based on the full posterior distribution. We show how this can be done using very recent developments in Markov chain Monte Carlo (MCMC) methods for network tomography (Airoldi and Blocker, 2013; Hazelton, 2015). Our second specific goal is to study the capacity for link count data alone to differentiate between day-to-day models with different complexities of behavioural representation. We address this issue using a simulation study.

The paper is organised as follows. In the next section we describe the class of day-to-day models under consideration (based on Parry and Hazelton, 2013), and introduce necessary notation. In Section 3 we discuss Bayesian techniques for model comparison, and show how they may be implemented using MCMC methods in Section 4. Section 5 covers the aforementioned simulation study. Conclusions are drawn in Section 6.

2. Models

2.1. A Markovian class of day-to-day models

The class of models that we employ in this paper follows Parry and Hazelton (2013). The models are Markovian in the route flows, in that the probability distribution of the route flow vector on any given day is fully specified conditional on knowledge of the route flows over a finite number of previous days. The model class is quite general, including the seminal STODYN model of Cascetta (1989), the models studied by Hazelton and Watling (2004), and many of those considered by Cantarella and Cascetta (1995).

Let $(\mathcal{N}, \mathcal{A})$ represent a traffic network, in which $\mathcal{N}$ is the set of nodes and $\mathcal{A}$ the set of directed links. We denote the number of nodes and links by $m_0 = |\mathcal{N}|$ and $n_0 = |\mathcal{A}|$ respectively. We define $\mathcal{O} \subseteq \mathcal{N}$ and $\mathcal{D} \subseteq \mathcal{N}$ to be respectively the