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How uncertainty in input and parameters influences transport model : output A four-stage model case-study

Stefano Manzo, Otto Anker Nielsen, Carlo Giacomo Prato *

Technical University of Denmark, Department of Transport, Bygningstorvet 116B, 2800 Kgs. Lyngby, Denmark

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ABSTRACT

If not properly quantified, the uncertainty inherent to transport models makes analyses based on their output highly unreliable. This study investigated uncertainty in four-stage transport models by analysing a Danish case-study: the Næstved model. The model describes the demand of transport in the municipality of Næstved, located in the southern part of Zealand. The municipality has about 80,000 inhabitants and covers an area of around 681 km^2. The study was implemented by using Monte Carlo simulation and scenario analysis and it focused on how model input and parameter uncertainty affect the base-year model outputs uncertainty. More precisely, this study contributes to the existing literature on the topic by investigating the effects on model outputs uncertainty deriving from the use of (i) different probability distributions in the sampling process, (ii) different assignment algorithms, and (iii) different levels of network congestion. The choice of the probability distributions shows a low impact on the model output uncertainty, quantified in terms of coefficient of variation. Instead, with respect to the choice of different assignment algorithms, the link flow uncertainty, expressed in terms of coefficient of variation, resulting from stochastic user equilibrium and user equilibrium is, respectively, of 0.425 and 0.468. Finally, network congestion does not show a high effect on model output uncertainty at the network level. However, the final uncertainty of links with higher volume/capacity ratio showed a lower dispersion around the base uncertainty value.

Results are also obtained from the implementation of the analysis on a real case involving the finalization of a ring road around Næstved. Three different scenarios were tested. The resulting uncertainty in the travel time savings from the comparison of the three scenarios expressed in terms of coefficient of variation, turned out to be between 0.133 and 0.145, thus confirming the importance of uncertainty analysis in transport policy assessment.

1. Introduction

The literature on urban planning and transport planning has demonstrated that there is considerable inaccuracy between forecasted and observed traffic flows (e.g., Bain, 2003; Bain and Plantagie, 2004; Bain and Polakovic, 2005; Flyvbjerg, 2005; Flyvbjerg et al., 2006; Parthasarathi and Levison, 2010; Welte and Odeck, 2011). The list of potential sources of such inaccuracy originates from the complexity of the systems generating traffic flows (Van Zuylen et al., 1999). Complex systems are systems whose components interact in a way that is difficult to understand, thus making their output unpredictable. As a consequence, whenever a model is created to reproduce a complex system, its output will invariably be affected by uncertainty. Uncertainty pertains everything the modeller does not know to a full extent due to limited knowledge (e.g., statistical sampling) or stochasticity (e.g., parameter calibration) of some model components (Walker et al., 2003). Any of the model components can be affected by uncertainty: context, structure, inputs, parameters and final output.

The main consequence of such uncertainty is that the point estimates of modelled traffic flows, and their derived measures, only represent one of the possible outputs generated by the models. Instead, modelled traffic flows are better expressed as a central estimate and an overall range of uncertainty margins articulated in terms of output values and likelihood of occurrence (Boyce, 1999). In fact, analyses based on point estimates invariably produce unreliable results and decisions taken relying on them may easily lead to unexpected consequences. Thus, it is essential to assess transport model uncertainty by producing uncertainty measures. This can be done by investigating where the uncertainty

* Corresponding author. Fax: +45 45936533.
E-mail addresses: stman@transport.dtu.dk (S. Manzo), oan@transport.dtu.dk (O.A. Nielsen), cgp@transport.dtu.dk (C.G. Prato).

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originates, which are its main drivers and how it propagates throughout the model, especially for sequential iterative analytic frameworks such as the commonly used four-stage model.

Previous studies addressed uncertainty propagation throughout four-stage sequential transport model frameworks, such as Zhao and Kockelman (2002), Zhang et al. (2011) and Yang et al. (2013). They all found a common uncertainty propagation pattern, where uncertainty increases throughout the first three model steps, i.e. trip generation, trip distribution and mode choice, to finally reduce in the assignment model. Zhao and Kockelman (2002) argued that this reduction might be due to the network congestion effects on the trip assignment equilibrium procedure, implying that capacity constraints might reduce the variability of the results on the link flows. However, they also pointed out that the reduction of uncertainty in the assignment step might also be the consequence of the accumulation on the same links of independent trips related to different origin–destination pairs. In their analysis of the Dutch national model, De Jong et al. (2007) found that congestion reduced final model output uncertainty but only to a minor degree. Zhang et al. (2011) investigated model output uncertainty for different levels of congestion. The results from their analysis showed that the higher the level of congestion, the lower the capacity of the assignment model to reduce the overall uncertainty. Rasouli and Timmermans (2013), when investigating uncertainty of origin–destination matrix tables using the Dutch national transport model “Albatross”, found that higher levels of traffic volumes (at zone level) result in lower levels of uncertainty for different model output. Thus, it can be said that there is no consensus on how network congestion affects final model uncertainty. Nevertheless, as pointed out by Volosin et al. (2010), it is reasonable to expect that model output variability can be somehow sensitive to the level of congestion in the network.

The present study investigates uncertainty deriving from input (i.e. collected data) and parameters (i.e. calibrated parameters) in a four-stage transport model using Monte Carlo Simulation (MCS) performed by means of Latin Hypercube Sampling (LHS). The literature reviews by De Jong et al. (2007) and Rasouli and Timmermans (2012) showed that MCS is also used by Ashley (1980), Kroes (1996), Zhao and Kockelman (2002), Pradhan and Kockelman (2002), Krishnamurthy and Kockelman (2003), De Jong et al. (2007) and Zhang et al. (2011). The MCS approach has also been used more recently, e.g. in Rasouli et al. (2012) and Rasouli and Timmermans (2013). However, none of these studies explored the uncertainty deriving from the choice of the probability distribution function to be used in the sampling procedure.

The current study contributes to the stream of the existing literature primarily by (i) investigating the impact on model uncertainty deriving from using different probability distributions in the sampling procedure, (ii) analysing the effect of assignment procedures leading to different equilibrium conditions, and (iii) examining uncertainty for different levels of congestion. The following section of this paper introduces the four-stage transport model used as case-study followed by a section that illustrates the methodology applied in this study. Results and conclusions are discussed in the last two sections of the paper.

2. Case-study

The uncertainty analysis was implemented on the four-stage Næstved model. The four-stage transport model is an analytic framework that combines trip generation, trip distribution, mode choice and trip assignment (see, e.g., Ortuzar and Willumsen, 2011). Each model output is used as input for the model that follows, and the link flows from the trip assignment are used as feedback for the previous stages of the framework. The model is solved with an iterative procedure that concludes when the link flows reach equilibrium, which usually corresponds to the state of either deterministic User Equilibrium (UE) or Stochastic User Equilibrium (SUE) (see, e.g., Sheffi, 1985; Ortuzar and Willumsen, 2011). Given the wide use of the four-stage transport model framework, results from this study are straightforward to interpret and to compare with other literature and project results.

The Næstved model describes the demand of transport in the municipality of Næstved, located in the southern part of Zealand. The municipality has about 80,000 inhabitants and covers an area of around 681 km^2. In the Næstved model, the area of interest is divided into 106 zones. The road network, graphically described in Fig. 1, is composed by 315 links classified as “small”, “large” and “highway” which represent around 92%, 5% and 3% of the number of links, respectively. The network contains all the roads present in the modelled area – including residential roads – and it is only roads in closed (dead end) residential areas that are not coded, as well as very small rural secondary roads. Basically the modelled network consists of the city of Næstved, where there is congestion, and then a large uncongested hinterland. The traffic, modelled over a single 24-h time interval, is divided into two modes, private and public transport, with the first absorbing around 85% of the demand, and into two categories, home/work and business. The model's final output is based on 3 model's iterations only involving trip distribution, mode choice and trip assignment stages; in other words after the first model run the trip generation output is kept constant and is not influenced by the travel impedance of the network. In the Næstved model, the four stages are specified as follows.

2.1. Trip generation

The trip generation stage uses a cross-classification approach to calculate the number of trips produced and attracted by each zone. Trip production and trip attraction, respectively, are specified as

$$P_i = \beta_{wp} WP_i + \beta_w W_i \tag{1}$$

$$A_j = \beta_{wpp} WPP_j + \beta_{wps} WPS_j \tag{2}$$

where P_i is the number of trips produced in zone i, A_j is the number of trips attracted to zone j, WP_i and W_i are the number of workplaces and workers in zone i, WPP_j and WPS_j are the number of primary work places and secondary work places in zone j, and the respective β's are the trip production and attraction rates, based on national statistics. To balance trips generated and attracted a balancing tool is then applied as follows:

$$P_i = zP_{0i} + (1-z)P_{0i}\frac{\sum A_0}{\sum P_0} \tag{3}$$

$$A_i = (1-z)A_{0i} + zA_{0i}\frac{\sum P_0}{\sum A_0} \tag{4}$$

where z is the balancing factor having values between 0 (production adjusted based on attraction) and 1 (attraction adjusted based on production). For the present study, the balancing tool was implemented with z having the value of 1.

2.2. Trip distribution

The trip distribution stage is based on a double constrained gravity model: