

Investigating uncertainty in transport modelling: a four-stage model case study

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1 Background and purpose

The literature has demonstrated that often there is a considerable and almost systematic difference between forecasted and observed traffic flows, e.g. Flyvbjerg [1,2], Bain and Plantagie [3,4], Bain and Polakovic [5]. The reasons for this difference have been frequently searched in political/decision-process related issues or in inefficiencies of the modelling methods. However, the list of potential sources of such inaccuracy should also include the complexity of the systems generating traffic flows, as suggested by van Zuylen et al.[6]. In fact, by modelling complex systems, transport models are subject to uncertainty which can affect all model components, i.e. context, model structure and methodology, input and parameters to finally propagate to the model output.

The main consequence of this inherent uncertainty is that modelled traffic flows cannot be expressed as a point estimate, because this would only represent one of the possible outputs generated by the model. In other words, transport models do not provide reliable point estimates of modelled traffic flows and derived measures. 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, as suggested by Boyce [7]. Uncertainty analysis relates to how uncertainty in each model component propagates to the model output and how to express the model output as a distribution, so reflecting the overall uncertainty within the model.

The research described in this paper investigated uncertainty in transport models by using as a case study the four-stage model based on the Danish town of Næstved. The

analysis focused on model output (traffic flows) uncertainty propagated from model input, parameters and methodology uncertainty, and was carried out using sensitivity analysis. Specific attention was given to issues related to the choice of input and parameter distribution and the number of model runs required.

2 Methods

The studies on modelled traffic flows uncertainty mainly investigated input and parameter uncertainty while context, structure and methodology uncertainty were not extensively considered. Overall, input uncertainty seems to have a higher effect than parameter uncertainty on the model output, such as in De Jong et al. [8]. Moreover, as shown in Matas et al. [9], when the model is used for forecasting purposes, the relative influence of parameters uncertainty on model output uncertainty is higher in the short-run whilst input uncertainty prevails in the long-run.

For quantifying input and parameters uncertainty, the prevalent method applied is stochastic simulation, for instance Monte Carlo simulation as in Krishnamurthy and Kockelman [10]. However, parameters uncertainty has also been analysed using random re-sampling techniques like Bootstrap, for instance by Hugosson [11]. Only Zhao and Kockelman [12] investigated how uncertainty propagates through the different steps of a four-stage model. They found that uncertainty increases while propagating through the first three sub models, trip generation, trip distribution and mode choice, to finally reduce in the assignment model, possibly due to congestion effects on the assignment equilibrium procedure.

The analysis carried for this study was based on sensitivity analysis approach. The output analysed were (i) total number of trips, (ii) travel resistance within the network, and (iii) traffic flows and speed on single links. The main sources of uncertainty within the model were identified and classified using the uncertainty matrix tool shown in Walker et al. [13]. Based on that, the effect on the model output deriving from uncertainty in model input, parameters and methodology was investigated using sensitivity analyses. For quantifying input and parameters uncertainty, the approach applied was a stochastic simulation based on the Latin hypercube sampling method. The analysis mainly focused on the selection of the distributions for the simulation to test how different distributions affect the final output uncertainty. With respect to the methodology, the required number of model runs was investigated by using a multiple model simulation technique.

3 Preliminary results and discussion

This study found that input uncertainty, despite the fact that it is assumed low, has a higher influence than parameters uncertainty on the model output propagated uncertainty. These results are consistent with the outcome from existing literature, such as in the aforementioned De Jong et al. [8] and Zhao and Kockelman [12]. The model however was not tested for forecasting purposes, thus the output uncertainty was not investigated in its temporal dynamics.

The analysis on the variables distributions provides new insights for the methodology applied to examine uncertainty in model outputs. The different scenarios, based on the combination of different variables distributions, proved to produce model output significantly different. This suggests that attention should be used in selecting the more realistic variables distributions and thus that the time consumed in the identification process must be taken into account.

Also, the propagation pattern through the four sub-models was investigated. The analysis confirmed that while propagated uncertainty increases through the first three stages, the assignment procedure seems to reduce it. This again was consistent with the findings from Zhao and Kockelman [12]. The assumption which relates this observed effect with high congestion levels was tested by comparing results from different selected links. Results seem to confirm the assumption. However, the overall congestion level in the network analysed is not high; this partially reduces the reliability of this test.

The multiple model simulation technique demonstrated that a low number of model runs, focusing on mean and quartiles values, can provide a sufficient amount of information on model output uncertainty thus saving computational time without losing accuracy.

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