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Does the decision rule matter for large-scale transport models?☆

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ABSTRACT

This paper is the first to study to what extent decision rules, embedded in disaggregate discrete choice models, matter for large-scale aggregate level mobility forecasts. Such large-scale forecasts are a crucial underpinning for many transport infrastructure investment decisions. We show, in the particular context of (linear-additive) utility maximization (RUM) and regret minimization (RRM) rules, that the decision rule matters for aggregate level mobility forecasts. We find non-trivial differences between the RUM-based and RRM-based transport model in terms of aggregate forecasts of passenger kilometers, demand elasticities, and monetary benefits of transport policies. This opens up new opportunities for policy analysts to enrich their sensitivity analysis toolbox.

1. Introduction

Large-scale transport models are typically built on disaggregate discrete choice models based on linear-additive Random Utility Maximization (RUM) decision rules (e.g. de Jong et al., 2007; Hess et al., 2007). However, despite the strong foundations of such RUM-based discrete choice models in micro-economic theory and their computational tractability there has been a rapidly growing interest in the development of non-RUM discrete choice models within the travel behavior research community. There is a growing consensus now, that these 'behavior inspired' choice models form a useful addition to the toolbox of travel demand modelers, by capturing behavioral phenomena such a boundedly rational, semi-compensatory decision-making and choice set composition effects (Chorus et al., 2008; Hess et al., 2012; Leong and Hensher, 2012; Guevara and Fukushi, 2016).

However, despite this growing interest in non-RUM choice models in the travel behavior research community these models have not yet been implemented in large-scale transport models to forecast macro-level mobility patterns. Instead, the literature has predominantly focused on comparisons between RUM and non-RUM choice models at the disaggregate level, e.g. in terms of differences in model fit in the context of a given dataset. As a consequence, at present it is unknown whether large-scale transport models based on non-RUM choice models would in fact produce different aggregate level predictions than their counterparts based on RUM models. Crucially, these aggregate level forecasts, rather than micro-level analyses, form the basis for many transport policies and infrastructure investment decisions. This implies that there is currently no empirical ground for the often voiced expectation that increasing the behavioral realism of micro-level travel behavior models via the use of non-RUM choice models would lead to different (and perhaps improved?) aggregate level mobility forecasts, and, as a consequence, to different (and perhaps better informed?) transport policy making. This lack of evidence regarding the usefulness of employing non-RUM choice models for large-scale travel demand forecasting is currently considered one of the main limitations of these models (Chorus, 2014).

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Motivated by the significant scientific and societal relevance of this 'aggregate-disaggregate gap' in the travel behavior modelling literature, we[1] have developed what we believe is the world's first discrete choice-based large-scale transport model built on a non-RUM decision rule. Specifically, we devised a Random Regret Minimization (RRM) based counterpart of the internationally renowned Dutch National Transport model (henceforth abbreviated as LMS, for 'Landelijk Model Systeem'). RRM models are non-RUM discrete choice models built on the notion that regret can be an important co-determinant of choice behavior (Chorus, 2010). RRM models are designed to accommodate for semi-compensatory and reference-dependent choice behaviours, such as the compromise effect (Chorus and Bierlaire, 2013). Since their relatively recent introduction these RRM models have found their way to leading textbooks (Hensher et al., 2015) and software packages (e.g. Greene, 2012; Vermunt and Magidson, 2014), and have been used in a wide variety of travel behavior studies during the past few years (Chorus et al., 2014).

This study presents the first aggregate level comparison of mobility forecasts produced by RUM and non-RUM (i.e., RRM) based large-scale transport models. As a case study, we investigate a fictive "High Frequency Rail" (HFR) policy scenario. In this scenario train frequencies are substantially intensified as compared to the reference scenario. In the context of this policy scenario, we analyse and compare the predictions of the RUM-based and RRM-based LMS, in terms of various relevant mobility indicators such as the predicted number of tours, the predicted tour-length, and the total passenger kilometers per mode of transport; all at the national (Dutch) level.

As a secondary, methodological contribution, we introduce a technique which allows for very substantial computation time savings when estimating so-called P-RRM models (Van Cranenburgh et al., 2015a) on data sets characterized by large choice sets, as is common in transportation (e.g., destination, route choice models).

The remaining part of this paper is organized as follows. Section 2 gives a brief description of the LMS and presents the steps taken to develop the RRM-LMS. Section 3 presents baseline year forecasts and elasticities of demand, and compares the results of the RUM-LMS with those of the RRM-LMS. Section 4 presents our case study. We analyse and compare the predictions of the RUM-LMS and the RRM-LMS in the context of a HFR policy scenario.

2. Development of the RRM-LMS

2.1. The LMS in a nutshell

The LMS is a nation-wide model system for The Netherlands. It was developed in the 1980s for long-term strategic policy analysis. Nowadays, its use is obligatory (in the Netherlands) for appraisal of large transport infrastructure. Like many national transport models developed in Europe, the LMS is a tour-based model system, although in the assignment model the tours are decomposed into unconnected trips. The model operates on a national level comprising of 1406 transport analysis zones and differentiates between 9 travel purposes: Commute, Business, Education, Shopping, Other, Work-Business, Work-Other, Child-Education, and Child-Other. Furthermore, it makes use of a detailed segmentation of the population.

Several discrete choice models are embedded in the LMS, e.g. to model Car ownership, Tour generation, Mode and destination choice, and Departure time choice. These models operate at the household level or at the person level, and differentiate between travel purposes (except the car ownership model). The assignment model is not based on discrete choice models. The discrete choice models in the LMS are estimated in a Non-Normalized Nested Logit (NL) form (Daly and Zachery, 1978; Daly, 1987). As such, inclusive values or LogSums (LS) carry information about the decisions made on the lower levels to upper levels, in a sequential procedure, see e.g. Ortúzar and Willumsen (2011) for more details on Nested Logit specifications.

The core of the LMS is the forecasting system, called SES (Sample Enumeration System). This module samples individuals from the data, and computes choice probabilities for each individual in this sample. For each Transport Analysis Zone (TAZ) the sample is reweighted. SES consists of two primary sub modules: BASMAT and GM. Module BASMAT generates the base matrices based for each time-of-day and travel motive. Module GM determines the growth in travel demand for the future year relative to the base year. A pivot-point procedure is then used to construct the forecasted OD matrices. This pivot-point procedure enhances the accuracy of the model system's forecasts as model systems are usually better in predicting changes relative to a base-year situation than in predicting absolute numbers (Daly et al., 2005).

The GM sub module consists of Tour generation and Mode-Destination-Time-of-Day (MD-ToD) discrete choice models. With the exception of the Time-of-Day choice, the choice models within the LMS are estimated on Revealed Preference (RP) data obtained by the Dutch National travel survey called MON.[2] These data are collected on a yearly basis in The Netherlands with the aim to provide insights on the daily mobility behavior. Each survey wave comprises of over 40,000 Dutch residents (CBS, 2010). To estimate the choice models data from 3 survey waves are used: 2008, 2009, and 2010. The Time-of-Day models are estimated on Stated Preference (SP) data, rather than on RP data. The SP data consist of more than 1 000 respondents which were recruited from an existing panel or from short recruitment interviews at Dutch train stations and at a petrol station beside a motorway (see de Jong et al., 2003 for more details on the survey).

[1] In close collaboration with Significance consultancy (Marits Pieters, Jaap Baak, Gerard de Jong) and The Netherlands road authority/Rijkswaterstaat (Frank Hofman).

[2] Recently, the Dutch Mobility survey is renamed into OViN.