

Uncertainty in travel demand forecasting models: Literature review and research agenda

ABSTRACT: Reasoning why uncertainty analysis will become important in years to come, this paper reviews prior work on uncertainty analysis in travel demand forecasting. Different sources of uncertainty are discussed. Studies examining these various sources of uncertainty are summarized differentiating between four step models, discrete choice models and activity-based models of travel demand. Next, gaps in the literature and avenues of future research are systematically discussed with a special focus on complex activity-based models. The paper is completed with some concluding comments.

KEYWORDS: Uncertainty analysis, travel demand forecasting

BACKGROUND AND MOTIVATION

Travel demand analysis and forecasting belong to the core of the transportation discipline. The topic continues to receive substantial attention, both in academic research and applied transportation planning. Annually, hundreds of papers on travel behavior appear in journals and conference proceedings, while outcomes of model applications are routinely used to support transportation policy decisions. These studies have contributed to the development of a rich body of accumulated knowledge about the variates and co-variates of travel decisions, and differences and commonalities in travel behaviour related to socio-economic, cultural, environmental, spatial and institutional contexts. Models of travel demand have been used to predict future demand, either endogenously or exogenously, and to assess the impact of various kinds of policies on mobility indicators and traffic flows. Recent trends evidence expanding spheres of policy domains. Traditional travel demand forecasts are increasingly augmented with performance indicators related to emissions, energy consumption, and exposure.

Considering the vast amount of research on travel demand forecasting, the concept of uncertainty has received scant attention at best. Given the lack of systematic research on this topic, one can only speculate why scholars and consultants have spent relatively little effort in

¹ Eindhoven University of Technology, Urban Planning Group, PO Box 513, 5600MB Eindhoven, Netherlands. Email: s.rasouli@tue.nl; h.j.p.timmermans@tue.nl

addressing the uncertainty that is inherently associated with their models and schemes of analyses. Analyses of travel demand have been predominantly, at least implicitly, driven by the methodological principle of hypothesis testing. Although very few authors in transportation research explicitly formulate hypotheses, which are subsequently accepted/rejected using appropriate statistical tests, virtually all papers do contain a discussion of the significance of estimated coefficients. Assessment of the significance of estimated coefficients is often seen as one of the goals of the analysis. Similarly, modellers tend to focus on the goodness-of fit of models and face validity. Uncertainty analysis, in contrast, is not a standard topic of concern in papers on travel demand forecasting.

One would expect that the concept of uncertainty is even more relevant in applied transportation planning settings, but in general the state-of-practice does not seem to differ very much from academic research in its (lack of) attention to uncertainty. It seems that the interpretation of impact assessments and forecasts, often involving multiple performance indicators and multiple scales of spatial and temporal resolution, for different policy scenarios is already complicated and demanding enough. Adding uncertainty would further complicate matters, although some authors have suggested ways of incorporating risk analysis and uncertainty in transportation planning practice (e.g., Jeon, Chang and Amekudzi, 2010; Matas, Raymond and Ruiz, 2011; Mishra, Khasnabis and Swain, 2011; Bang Saling and Leleur, 2011). It may induce a discussion on the uncertainty of the uncertainty analysis. Often, it seems more efficient and effective for the policy development process to ignore the issue of uncertainty altogether. Our experience in transportation and other planning contexts teaches that a discussion on uncertainty becomes relevant if (i) political parties hold strongly diverging views on the topic/solutions and model results favour one particular view, (ii) the risks, either financially, politically or societal, are very high, (iii) the policy is controversial, both in terms of costs and benefits, and (iv) there are some concerns about the limitations of the model.

This situation is not unique to transportation. Uncertainty analysis has never received much attention in disciplines such as urban planning, perhaps with the exception of integrated land use transportation models (e.g. Pradhan and Kockelman, 2002; Pontius Jr. and Spencer, 2005; Clay and Johnston, 2006; Krisnamurthi and Kockelman, 2006; Ševčíková, Raftery and Waddell, 2007) and marketing. On the other hand, the recent rapid increase in uncertainty analysis in environmental sciences (e.g., Borgonova *et al.*, 2011; Margvelashvili and Campbell, 2011) can be understood as a reaction to increasingly divergent views, shifting

political and societal priorities, and the realization that analyses of model uncertainty are at least equally relevant for policy and academic discussions as analyses of forecasted trends.

Contending that these circumstances, stimulating the use of uncertainty analysis, will become increasingly prevalent in transportation policy in years to come, the goal of the present article is to systematically discuss the limited existing literature on uncertainty analysis as it has evolved in transportation research. Our purpose is to summarize earlier findings, identify gaps in existing knowledge and develop an agenda for future research. Notably absent in previous work on uncertainty analyses is the latest generation of complex, stochastic activity-based models of travel demand. Hence, the agenda for future research will be articulated with this new generation of travel forecasting models in mind.

The remainder of this article is organised as follows. First, we will start discussing the various types of uncertainty and their underlying causes. It serves as the basis for the next section, which is concerned with the design and results of previous studies on uncertainty analysis. In this section, a distinction is made between the various types of models used in travel demand forecasting. Type of error, type of outputs, aim of the analyses, details of the studies and main findings will be systematically summarized and discussed. In the section that follows gaps in our knowledge, relatively under-explored research questions and methodological issues will be identified to articulate a research agenda on uncertainty analysis in travel demand forecasting models. The paper is concluded with some final reflections.

SOURCES OF UNCERTAINTY

Uncertainty analysis is concerned with the amount and nature of uncertainty in the outcomes of model and the results of particular analyses. The topic should not be confused with the literature on choice behaviour and decision making under uncertainty (e.g., Circella, Dell'Orco and Sassanelli, 2005). Uncertainty in forecasting can be attributed to two basic sources: input uncertainty and model uncertainty. *Input uncertainty* concerns the fact that data are not necessarily error-free; i.e., data are bound to include error, due to sampling bias, survey design, reporting and/or coding mistakes, and incomplete information. The practice of developing models of travel demand involves estimating or deriving the functional relationship between particular choice facets underlying activity-travel patterns and a set of socio-demographic, land use and service-level variables. Behavioral and socio-demographic data commonly stem from travel surveys, while land use and service level data are commonly based on generally available statistics and/or field work. Both these data sources are

potentially sensitive to a multitude of errors. We will identify some general sources of error that seem to apply to all travel surveys and land use statistics.

Travel surveys are prone to *sampling bias*: the travel behaviour of the non-response group may significantly differ from the behaviour of the respondents. If this happens, the data used to express the relationship between socio-demographic and particular facets of travel behaviour may not be representative of the larger population and the model may pick up a biased relation. *Survey design* may also cause errors in data, some random others more systematic. For example, if the survey does recruit individuals as opposed to households, reported behaviour may not sufficiently capture household-level activities/travel and task allocation. Another source of error concerns the fact that in most travel surveys respondents are requested to report their (activities and) travel for a single day. Activity-travel episodes are manifestations of underlying temporal processes, some of which are more regular others less. Activity-travel patterns are characterized by context-dependent rhythms and reflect certain repertoires, with fluctuations due to irregularly occurring events. Hence, an ideal sample would be a random sample from these underlying processes, with known or measured initial conditions. However, a random sample of individuals/households is not necessarily the same as a random sample of such processes. Moreover, intrapersonal variability is not captured in the data collection, although there is evidence that it is larger than interpersonal variability (e.g. Pas and Sundar, 1995). Also, Schlich and Axhausen (2005) found for their MobiDrive data that similar activity-travel patterns do not exhibit strong associations with socio-demographics or average travel behaviour. Similarly, survey design sometimes imposes thresholds on activity and travel episodes that should be reported (e.g. walking trips less than a certain distance may be skipped or certain stages may not be reported). Respondents may also not report certain trips to reduce respondent burden or because they believe that the trip is not important for the purpose of the study. *Reporting error* may be caused by simple mistakes and this may also happen at the coding stage (*coding error*). It is, for example, well known that the correct coding of destinations of trips represents a challenge because respondents often use their own labels and mental representation.

As for land use and level of service attributes, a common issue is the *inherent variability* of such data. For example, travel times, congestion, time to find a parking space, availability of a seat, to name a few vary from day-to-day and from hour-to-hour. Even if time of day, day of the week and season are incorporated in the model of travel demand, still some within-person-variability is left. Similarly, land use data and general data sources sometimes contain errors due to insufficient maintenance, the fact that they are based on a sample rather

than the full relevant population and coding errors. Moreover, the classifications in existing general-purpose data bases do not necessarily match the classification in activity types/travel purpose, implying that the modeller needs to decide which data to use. By definition, this will lead to imprecision, even if the data themselves would be perfect. Interesting discussions on the estimation of unknown model parameters in the presence of measurement error can be found in, for example, Bhatta and Larson (2007), and Walker *et al.* (2010).

These possible errors in input pertain to the data used to estimate the model of travel demand. When used for forecasting or policy assessment, another type of input uncertainty may arise: policy scenarios need to be translated into the explanatory variables and parameters estimates of the model of travel demand. The literature on scenarios development differentiates between different types of scenarios (e.g. Wilson and Rallston Jr., 2006; Brail, 2008), but all by definition are uncertain, even those that attempt to express the most likely future developments (e.g., Geenhuizen *et al.*, 1998; Brunel, 2004). Experts are thus faced with the problem how to translate such uncertain scenarios into the explanatory variables of the model. Usually the parameters of the model are left unchanged because otherwise there is no longer any proof that the model specification has been successful in reproducing observed activity-travel patterns. However, travellers may become less sensitive to travel time, or policy may go beyond currently observed conditions and hence certain parameter values may need to be changed, adding further uncertainty in the process. The scenarios themselves may also relate to an uncertain future, and therefore running a model for slightly different scenarios has been applied a lot in applied transportation planning research. Sometimes this practice has been referred to as sensitivity analysis. Moreover, non-policy variables such as fuel price and income distribution may also be uncertain, and may be hard to predict. If a model directly or indirectly relies heavily on such variables then considerable error will be introduced into a forecast because the forecast inputs cannot be predicted with any reasonable degree of (un)certainty.

While input uncertainty pertains to the effects of various sources of random or systematic measurement errors or to scenario uncertainty on ultimate model forecasts, in contrast, model uncertainty pertains to two types of errors: specification error and calibration (or estimation) error. Specification error results from a failure of the researcher to identify the true model, a simplification of the model or from the statistical distribution of random components. Estimation error pertains to error in estimating the values of various constants and parameters of the model. In this context, it is critical to articulate that a model is nothing but an expression of the researcher's beliefs about the relationship between theoretical

constructs. These relationships may be inherently probabilistic and the researcher cannot be sure that the true relationship has been depicted. A researcher may try alternative model formulations (e.g. a context-dependent choice model rather than a multinomial model may be used), but general goodness-of-fit statistics may not convincingly discriminate between such competing model alternatives, although specific forecasts will differ. Moreover, in travel demand forecasting, researchers are usually restricted by existing data sources, implying that they often can only include variables for which data are available. Finally, modellers always have to decide on the boundaries of their model: some processes are modeled, others are not and are implicitly or explicitly assumed to represent white noise.

In addition, for various reasons, models are often simplified. Methodological principles lead us to believe that simple models should be the hallmark of academic research. Although we do not necessarily agree with this principle in applied travel demand forecasting as travel behaviour may be highly context-dependent and the need to predict the likely impact of specific policies may induce modellers to use a large set of variables to operationalize the policy at hand (Timmermans, 2009), researchers may decide not to use all variables at their disposal and use simplified models. Deleting one or more variables will increase model uncertainty from a statistical perspective.

Finally, the latest generation of travel demand forecasting models is probabilistic in nature. Many activity-based models of travel demand rely on random utility theory. The utility of a choice option, according to this theory, includes an error term, which has various interpretations. In the early stage of development of this approach, when computing power was limited, rigorous assumptions about these error terms were often made to arrive at closed form expressions to calculate choice probabilities. Although marginal and conditional probability matrices of such closed form choice models can still be used to predict activity-travel behaviour, recently researchers seem to prefer the use of micro-simulation techniques as it gives them considerably more flexibility in addressing complicated dependencies and feedbacks in the model building process, even though this involves additional, often ad hoc and untested assumptions, which are not part of the estimation process. Vovsha, Peterson and Donnelly (2002) argued that micro-simulation has the technical advantage of computational savings in the calculation and storage of large multi-dimensional probability arrays, can explicitly model various decision-making chains and time-space constraints on individual travel, and allows variability of micro-simulation outcomes that can yield full information of the distributions of the travel demand statistics of interest rather than single deterministic estimates or average values. Moreover, in situations where the choice frequency of the

behaviour under investigation is low and/or the number of choice options is very high, discrete realizations of the underlying continuous probably distributions are required, resulting in *micro-simulation error*: successive runs of the model will result in different choice outcomes.

Of special interest in travel demand forecasting is the notion of *error propagation*. In case the ultimate forecast involves a series of successive submodels in which the output of the previous submodel in the model chain is used as input to the next submodel, errors in any submodel may be amplified or reduced in the next submodels. The field of travel demand forecasting has many such model chains. The conventional four-step model involves the chain trip generation, destination choice, transport model choice and route assignment. Activity-based models such as CEMDAP (Bhat *et al.*, 2004), FAMOS (Pendyala *et al.*, 2005), TASHA (Miller and Roorda, 2003) and typical activity-based models applied in the United States (e.g. Vovsha *et al.*, 2004) add activity generation to these facets. For example, the 2004 version of CEMDAP is a suite of 36 advanced econometric models to predict activity generation of workers and non-workers and schedule these at the pattern, tour and stop level. Similarly, Albatross (Arentze and Timmermans, 2000, 2004, 2005) consist of 27 decision trees, representing a priority-based scheduling process.

ACCUMULATED KNOWLEDGE

Because the various types of travel demand models that have been developed over the years differ fundamentally in their design and approach, and consequently the kind of uncertainty analysis that can be conducted also differs, the discussion of previous research findings in this article is organised by differentiating between different modelling approaches. It should be explicated from the outset that the allocation of a specific model to a specific approach is sometimes rather arbitrary and debatable. Our focus will be on the demand generating effects; we will not discuss the emerging literature on uncertainty in network assignment models (e.g. Clark and Waitling, 2005; Lam *et al.*, 2008; Zheng and van Zuylen, 2010), nor on very specific models (e.g., Cheung and Polak, 2009; Matas *et al.*, 2010; Duru *et al.*, 2010). Table 1 gives a summary of key previous research on uncertainty analysis in travel demand forecasting.

Evidence for Four Step Models of Travel Demand

Four step models of travel demand consist of 4 loosely-coupled aggregate models that predict respectively trip generation, trip distribution, modal split and trip assignment. The unit of

analysis of these models is a trip, conducted by individuals. Models have a low degree of spatial and temporal resolution. Trip generation is usually predicted using regression analysis with socio-demographic and land use variables as explanatory variables. Spatial interaction models are commonly used to predict trip distribution (OD-matrices). Modal split is obtained by factoring the OD-matrices. In early years, this step was often combined with trip distribution, estimating trip distribution by various transport modes for various travel purposes. More recently, this step is commonly modelled by using (nested) logit models, although sometimes still at the aggregate level. The assignment step involves loading the O-D matrices onto the transportation network and applying some assignment algorithm to predict traffic flows. Further details about the four-step modelling approach can be found in McNally (2007).

As four step models are aggregate deterministic models, primarily input uncertainty is of interest. Of course, it is possible to investigate some forms of model uncertainty such as uncertain parameters but such studies have been less common. The focus has been on input uncertainty and error propagation. Early uncertainty analyses in the context of the four step approaches have been rather ad hoc (e.g., Bonsall, *et al.*, 1977; Robbins, 1978; Ashley, 1980; Boyce, 1999; Boyce and Bright, 2003). Later, more systematic approaches have been conducted. Usually, no distinction has been made between different sources of input uncertainty. Rather, point values for input variables have been replaced by probability distributions (often the normal distribution), with the standard deviation of the distribution capturing the amount of uncertainty. Monte Carlo draws of these probability distributions then generated different configurations of input values used in different runs of the model of travel demand. Some measure of variability in the outcomes of the model has then been used to quantify the degree of uncertainty in model outcomes as a function of uncertain model input.

Rodier and Johnston (2002), for example, examined the effects of changes in model input to percentage change in some key output variables of the SACMET96 model. More specifically, plausible errors in population, employment, fuel price, and income projections were specified, and using the travel demand and emissions models of the Sacramento region their effects were simulated. Results indicated that plausible error ranges for population and employment projections were significantly contributing to travel demand and emissions projections, while plausible error ranges for household income and fuel prices were not.

Armoogum (2003), only concerned with travel demand generation and therefore not a full-fledged four-step model, examined input and model uncertainty of a simple analysis of

variance model for the city of Paris. Input uncertainty was studied in the context of possible errors in population forecasts, while model uncertainty was confined to the question whether the model picks up trends in the data. Jackknifing was used to construct different samples and estimate the variance and confidence intervals of the forecasts of trip frequency and daily distance traveled. Input uncertainty was investigated using different scenarios for the population forecasts. Results indicated that confidence intervals increased with increasing time horizons. Errors increased from roughly 10% to 30% for trip frequency, with differences between zones and segments, and from 3% to 10% for distance traveled. Estimates for trip frequency varied between -5% and +15% for the different population forecasts, while variation in estimates for distance traveled again were less sensitive to uncertain population forecasts.

While many studies assumed univariate normal distributions for the input variables, ignoring correlations between inputs, more realistic estimates of input uncertainty should also account for correlations between input variables. A good example is Zhao and Kockelman (2002). Arguing that only point estimates and not variances and covariances are commonly carried forward through travel demand models, they investigated input uncertainty and error propagation of a conventional four-step model based on an 818-link network covering 25 zones in the Dallas-Fort Worth metropolitan region. Input uncertainty was investigated by setting the coefficients of variation for two demographic inputs (number of households and different employment types) to respectively 0.1, 0.3 and 0.5. These inputs were assumed to be multivariate normally distributed with a correlation of + 0.3 across all variables. The four-step model was run 100 times with different input values, drawn randomly from the assumed multivariate distributions. Results showed that the coefficients of variation of two link flows were larger than the 0.3 input uncertainty. Variability was smaller for VMT (vehicle miles traveled) than VHT (vehicle hours traveled).

As for error propagation, they found evidence that average uncertainty is amplified in the first three sub-models of the model chain (trip generation, destination choice, mode route, route assignment), and somewhat reduced in the final, route assignment model step, but not below the input uncertainty.

Because model specification in traditional four step models is not uniquely derived from a set of underlying theoretical assumptions, many studies compared on an ad hoc basis different definitions and operationalisations of attraction and distance deterrence. However, results have typically been assessed and expressed in terms of goodness-of-fit and not in terms of model uncertainty. Hence, we will not discuss these studies in this paper.

Evidence for Discrete Choice Models of Travel Demand

The class of discrete choice models of travel demand is somewhat difficult to describe. Discrete choice models predict the choice of discrete responses (mode choice, destination choice, etc.), usually based in random utility theory. According to this theory, a choice alternative can be described in terms of a utility function with a deterministic and random component. By assuming utility-maximizing behavior, the probability of a choice alternative being chosen then depends on the form of the distribution of the random components and assumptions with respect to the variance-covariance matrix. Most operational, applied models of travel demand involve the multinomial or nested logit model. The problem of correctly characterizing the class of discrete choice models stems from the fact that conventional four-step models were sometimes gradually transformed into utility-based approaches by replacing the aggregate mode and/or destination model with a discrete choice model. Sometimes this was accompanied by a shift from a trip to a tour-based model, which some academics and professionals called an activity-based model. As the classification in this article is only meant to order the studies, we leave the issue as is, but readers should realize that sometimes the classification is rather arbitrary and arguable.

Because the application of discrete choice models often involves the use of micro-simulation, both input uncertainty and various kinds of model uncertainty (specification, parameter uncertainty and stochastic error) of such discrete choice models have been examined in previous research. Beser Hugosson (2004, 2005) examined the impact of *sampling error* on uncertainty in different results of the Swedish SAMPERS model, a nested logit model with frequency, mode and destination choice levels. Transport modes include car, bus, train, high-speed train and air. Destination zones are defined at the national 670-zone level; the analyses, however, was based on 20 destination zones. The frequency alternatives consist of making a trip or not. She used the bootstrapping technique to study the effect of sampling on uncertainty in model outputs. This means that from the sample, used to estimate the model, 999 different samples of the same size with replacement were constructed. These bootstrap samples were then used to calculate their standard deviation and estimate the standard error and confidence levels for the population. For each sample, the SAMPERS model was applied resulting in total demand, origin–destination demand and link flows. Results indicated that the uncertainty in total demand varied between $\pm 8.5\%$ (car) and $\pm 13.3\%$ (train). To calculate uncertainties related to OD-matrices, six OD-relations with different traffic volumes were selected. The uncertainty of these OD-pairs demand varied between

$\pm 6.5\%$ and $\pm 14\%$. The standard error was larger for the larger relations. Two links were studied, one with a larger car traffic volume and one link with a lower car traffic volume. Results indicated that the uncertainty at the link level varied between $\pm 8.4\%$ and $\pm 10.8\%$. The standard error was larger for the link with the larger flow.

While most other studies assumed some degree of input uncertainty, De Jong *et al.* (2005) in their uncertainty analysis of the Dutch national and regional travel demand model used the standard deviations and correlations of 20-year moving averages of some input data to extract values from a multivariate normal distribution. The Choleski decomposition was used to generate a multivariate normal distribution with the correlation based on uncorrelated univariate normal draws. Bootstrapping was used to estimate the variance-covariance matrix for coefficients of the tour frequency and commuting mode-destination submodels of the model system, while the original estimates were used for the other mode-destination submodels. In total, they implemented 100 runs of the model, 50 for a reference scenario and 50 for a new infrastructure project. For each of these 50 runs, 20 were made for varying input variables, 20 with varying model coefficients and 10 in which input variables were combined with model coefficients. Uncertainty of the LMS (the National Model System) forecasts was studied both at the national level (number of tours and passenger kilometres by mode and purpose) and link level (traffic flows in passenger car equivalents, travel times and vehicle hours lost on a number of selected links). Results indicated that standard deviations that result from model uncertainty are clearly smaller than for input uncertainty for all modes and the total across modes. In most cases standard deviations for input and model uncertainty were slightly higher than those for input uncertainty alone. Similar results were obtained for the reference scenario and the project. Uncertainty in the number of tours was the same with and without congestion feedback, while with congestion feedback variation in kilometres was slightly smaller. Standard deviations of the link flows were between 4% and 9% for input uncertainty, and around 1% for model uncertainty. Results for the number of hours traveled were in the same magnitude.

This study is the only one that systematically varied various sources of error. Most studies focused on a single aspect. Castiglione, Freedman and Bradley (2003), for example, investigated stochastic error of the San Francisco SFCTA model, focusing on the effect of different seeds for the pseudo-random number generator on the robustness of model outputs. It should be realised that random number generators generate reproducible sequences of numbers. Differences can thus occur due to different seeds. The model system was run 100 times, changing the sequence of random numbers in each run. The extent of random

variability in the model results was explored primarily as a function of the type of model (vehicle availability, tour generation, destination choice and mode choice) and level of spatial aggregation (zone (TAZ), neighbourhood and county-wide). The study area included 766 TAZs in San Francisco and 1,740 in the region, 26 neighborhoods. Outcomes were more stable for lower levels of spatial aggregation. They also found that results for the models with many alternatives, such as destination choice, show more random variability than the results of models with fewer alternatives, such as vehicle availability and tour generation.

Walker (2005) investigated simulation error for the Southern Nevada implementation of a trip-based, microsimulation model with a step towards a tour-based implementation. The microsimulator was run 10 times each for four different sample sizes (500, 5000, 50000, 50000). The impact was studied for the range of the VMT and number of transit trips indices as well as an estimate of the standard deviation. Results indicated that simulation error was negligible with 500,000 households. As expected, the size of the sampling error was proportional to the inverse of the square root of the sample size.

One of the most elaborate studies on this line of research was conducted by Yang and Chen (2010, 2011), who investigated uncertainty and error propagation in the combined travel demand model, originally proposed by Oppenheim (1995). Because this model can be formulated as a nonlinear programming problem and the uniqueness of its solution can be guaranteed, they could derive sensitivity expressions of the output variables with respect to perturbations from various input variables and parameters in the combined travel demand model. They considered multi-dimensional travel demands, traffic flows, and travel costs as output variables. Uncertainty analysis of the model was investigated for the Sioux Falls network, consisting of 24 nodes and 76 links, reduced to two modes (car and transit). Both input uncertainty, parameter uncertainty and the combination of these were studied. As for input uncertainty, inputs were assumed independently and normally distributed, while the coefficient of variation was set at 0.3 for all inputs. Results indicated that the CV of travel demand and traffic flows was almost identical to input uncertainty. On the other hand, uncertainty in link flows dropped in the assignment step. In contrast, the CV's of *TTT* (total travel time) and *TVM* (total vehicle miles) are lower than the CV of inputs. As for parameter uncertainty, the results at each choice step except for the travel choice step, indicated that the impact of parameter uncertainty on outputs is higher than that of input uncertainty. Finally, as for the combination of these two types of uncertainty, the authors found that the uncertainty of outputs is not simply the sum of uncertainties from inputs and parameters individually.

The same network and embedded nested logit model were investigated by Zhang, Chie and Waller (2011). Monte Carlo simulations were used to simulate uncertainty due to 3 different travel demand or traffic congestion levels (0.5, 1.0 and 1.5 times the mean values of the maximum number of potential travellers), 3 different degrees of uncertainty (coefficient of variation values of 0.1, 0.2 and 0.3), and 3 different uncertainty sources (demand, supply and parameter uncertainties). For each combination, 300 simulation runs were conducted. Uncertainty was assessed in terms of error propagation in the various modelling steps. Consistent with Zhao and Kockelman (2002), they found errors to increase in the first three modelling steps, while the assignment step reduced error propagation. The coefficient of variation of VHT was higher than that of VMT under both the demand and supply uncertainty scenarios. As for OD-pairs, results indicated that uncertainty is higher for a larger maximum number of potential travellers, reflecting the fact that trip rates are directly influenced by demand uncertainty. In contrast, parameter and supply uncertainty had relatively little effect variation in trip rates. Finally, results indicated that the distributions of the link flow rates were diverse. With increasing parameter uncertainties, the variance of the distribution of link flow rates centred around the middle, compared to the production and O-D trip rates.

Another interesting, older study on model uncertainty was conducted by Brundell-Freij (1997). She studied model misspecification, estimation and use in the context of high correlation and low variations in revealed preference data. An estimated multinomial logit model of transport mode choice was the starting point. For different sample sizes, the deterministic utility of the choice alternatives was calculated, an error term were added and based on the principle of utility-maximization, the alternative with the highest utility was selected. Next, several model specification were made, including deliberately misspecified models and the logit models were estimated. Sample sizes were 85, 210 and 850. For each, sample size the model(s) were run 500 times. Results indicated that especially at smaller sample sizes, some parameters might be systematically biased: absolute values of all parameters were systematically overestimated, and, consequently any effect of policy measures will be over-predicted. Estimated asymptotic variances in parameters were systematically underestimated, and the standard deviation increased with smaller samples (for N=85, the true standard deviation seemed 10-15% higher than estimated). Similar effects were found for well-specified models and clear-cut choice situations and considerable taste variation in specific variables within the population. In a sequel (Brundell-Freij, 2000), she used bootstrapping and Monte Carlo simulations to analyze the effect of resampling of random model components under a specified model to investigate the influence of such

variation on estimation output and model selection. Results suggested that substantial bias, and increased variability, may be introduced already by quite restricted model searches.

Evidence for Activity-Based Models of Travel Demand

Activity-based models of travel demand are based on the contention that travel is derived from and should therefore be understood in the context of activity participation. Travel is the result from the way in which individuals and household organize their daily life in time and space. A major difference between four step and activity-based models therefore is the consideration of activity participation. A full activity-based model of travel demand predicts which activities (activity participation) are conducted where (destination choice), when (timing), for how long (duration), which chain of transport modes is involved (mode choice), travel party (travel arrangements and joint activity participation) and which route is chosen (route choice), subject to personal, household, spatial, temporal, institutional and space-time constraints. In addition, advanced activity-based models consider household (e.g., Timmermans and Zhang, 2009) and group (social networks) decision making (e.g. Kuwano, Zhang and Fujiwara, 2011) as opposed to individual decision making, and also model the relationship between physical and virtual travel. Reviews of activity-based models can be found in Bhat and Koppelman (1999, 2000), Arentze and Timmermans (2000) and Hensen, Goulias and Golledge (2010).

The literature on activity-based analysis can be divided into analytical studies which analyze/model one or more of the choice facets mentioned above or focus on special topics such as scheduling behaviour (e.g., Joh, Arentze and Timmermans, 2004; Mohammadian and Doherty, 2005, 2006; Auld, Mohammadian and Doherty, 2008; Ruiz and Roorda, 2011) and space-time prisms and accessibility (e.g. Yoon and Goulias, 2010). In contrast, comprehensive activity-based models capture the majority of these choice facets. Recent examples of analytical studies are Paez and Farber (2011-activity participation), Habib and Carrasco (2011-start time and duration), Mitra *et al.* (2010-choice of transport mode), Roorda, Miller and Knuchten (2006-travel arrangement), Mosa (2011-joint activity participation), and Wang and Li (2011-physical versus virtual travel). Comprehensive activity-based models, based on different modelling approaches have been formulated, include:

1. Daily activity schedules (Bowman and Ben-Akiva, 1999). This approach can be best viewed as an extension of nested logit model structures from two choice facets to multiple choice facets, incrementally expanding tour-based models to activity-based models.

Variants and elaborations of this model have been applied in several US cities and regions (Vovsha *et al.*, 2004).

2. CEMDAP (Bhat *et al.*, 2004). This is a suite of advanced largely independent econometric models of different kind for workers and non-workers and different times of the day, which can be linked in a micro-simulation framework to simulate daily activity-travel patterns.
3. FAMOS (Pendyala *et al.*, 2005), a micro-simulation which determines the time-space prism boundaries of individuals and then simulates activity-travel behaviour using a series of submodels (nested logit) of activity type, activity duration, destination and mode choice.
4. ALBATROSS (Arentze and Timmermans, 2000, 2004a,b, 2005; Angrainni *et al.*, 2009), a strongly linked rule-based process model of individual and household activity-travel decisions, developed for the Dutch Ministry of Transportation, which results in emerging individual activity-travel trajectories of high spatial and temporal resolution. The model has also been developed for Flanders, Belgium in the context of the FEATHERS platform (Janssens *et al.*, 2007; Bellemans *et al.*, 2010)
5. TASHA (Miller and Roorda, 2003; Roorda, *et al.*, 2007), a scheduling model in which individual and household tasks related to projects are scheduled in agendas and conflicts are eliminated, based on a set of ad hoc rules. Other components of the model, such as activity generation and location choice are based on sampling from distributions of observed data and simple discrete choice models.
6. ADAPTS (Auld and Mohammadian, 2009), a discrete event simulator system, which shows some resemblance with TASHA in that it focuses on the planning, scheduling and rescheduling of activities, but differs from TASHA in that no priority in the scheduling process is assumed.

In general, activity-based models focus on activity-travel generation and activity scheduling decisions. If traffic flows need to be simulated, time-dependent origin-destination tables are derived and loaded onto the network, using conventional assignment algorithms. In addition to these models, macro- and microscopic traffic simulation models have been extended to include concepts of activity-travel generation. Examples are TRANSIMS (Smith *et al.*, 1995), MATSIM (e.g. Nagel, 2004; Meister *et al.*, 2010) and RAMBLAS (Veldhuisen, Timmermans and Kapoen, 2000). Compared to the above models, these simulators primarily focus on traffic and are strongly data-driven, sampling directly from observed probability distributions, without a major attempt of generalising or explaining these distributions.

In recent years, the momentum of developing these cross-sectional activity-based models of travel demand has slowed down or seems in some cases have come to a stop. The international research agenda has moved to the next generation of activity-based models: *dynamic* activity based models (e.g. Han *et al.* 2008, 2009, 2010, 2011; Arentze and Timmermans, 2009, 2011; Habib and Miller, 2009). A review of these developments is given in Arentze and Timmermans (2008).

Because activity-based models of travel demand use agent-based or micro-simulation either because these models are fundamentally developed from such principles or because micro-simulation is used to link the suite of independent or loosely-coupled models in an integrated framework, these models are sensitive to both input and model uncertainty (stochastic error). This explains the focus on input uncertainty related to these models.

The topic of micro-simulation error has been picked up first in the context of the true micro-simulation models. Veldhuisen, Timmermans and Kapoen (2000) examined model uncertainty of their Ramblas model. The possible effect of Monte Carlo draws was investigated at several levels: (i) origin-destination matrices at the municipal level across the Netherlands, excluding intra-municipal trips and zero cells, (ii) origin-destination matrices at the level of traffic zones for the Eindhoven region, and (iii) traffic intensities at the link level for the Eindhoven region. R-square and Robinson's agreement measures were calculated for pairs of 5 model runs. Results indicated that the consistency between pairs of model runs was extremely high, slightly lower but still very high for higher scales of spatial resolution. The lowest value obtained was .96 for the agreement measure for links, but in general measures were higher than .99. Similar findings were obtained by Gibbs and Bowman (2007). They studied convergence properties of an activity-travel simulator and a traffic assignment model and found that the system can converge close to equilibrium by running the activity-based model upon small samples of the population during early iterations, progressing to larger samples in later iterations. They also concluded that a constant step size of one-half converged more rapidly than the customary $1/(\text{iteration number})$ step size, and that the common "preloading" option of assignment requires significantly fewer assignment iterations. For this review paper, more relevant is the finding that robust results are obtained after a few runs.

Lawe, Lobb, Sadek and Huang (2009) in a similar vein examined some aspects of model uncertainty of TRANSIMS for Chittenden County, USA. In order to gauge the extent to which the TRANSIMS model results varied with the seed number, they performed 5 different runs with 5 different seed numbers, and analyzed the variation in traffic volumes and average speeds along 10 links for each hour of the day. The results showed very little

variation as evidence by CV values, ranging between 0 and 2.59%. A very similar, but slightly more elaborate study was completed by Ziems, Sana, Plotz and Pendyala (2011). The goal of their study also was to determine the effects on various traffic characteristics resulting from the random number seed in respectively the router, the microsimulator, and in both these modules of TRANSIMS. This was accomplished by implementing 60 model runs based on a base simulation, each with a different random number seed. One set of 20 runs involved varying the random number seed of the router module, keeping constant the random number seed of the microsimulator module; another set of 20 runs varied the random number seed of the microsimulator module, keeping constant that in the router module, while a final set of 20 runs involved varying both random number seeds. This process also involved 12 iterations of the router stabilization process and 8 iterations of the microsimulator stabilization process. To reduce computing times, only those trips planned to start between 6 AM and 7 AM on an average weekday were included. Performance indicators examined included traffic volumes, travel times, average travel speeds, and density. Results indicated that the effect of stochastic variation is small for all sets of runs as reflected in a small coefficient of variation. They also found that the coefficient of variation is larger for the router than for the microsimulator module.

Uncertainty analysis of complex, comprehensive activity-based models has been confined to Cools *et al.* (2011), who analysed model uncertainty of the FEATHERS model, the Albatross model based on data for Flanders. To estimate the error due to (micro-) simulation, the model was run 200 times for the same 10% fraction of the population. Uncertainty, measured in terms of the coefficient of variation, was assessed for the average daily number of trips per person and the average daily distance travelled per person. These performance indicators were calculated for the entire sample and for segments, defined by mode choice, age and gender. Calculated coefficients of variation based on the 200 runs were compared against a 1.27% threshold error rate, which corresponds to the corresponding 95% confidence bounds of a 5% deviation. Results showed that this threshold value was often exceeded for public transport. In addition, a linear regression analysis was conducted to examine the contribution of segmentation variables and complexity on variance in micro-simulation error rates. Complexity was measured as the number of cross-tabulations of the categorized variables. Gender did not have any significant impact on micro-simulation error rates. As expected, micro-simulation error increases with complexity. Age had a monotonically increasing effect on error rates.

Moons *et al.* (2001, 2005) conducted a study on model simplification in the context of the Albatross model. First, they build decision trees for each of the nine choice facets of the model by using the C4.5 algorithm. In addition to this full model, they build decision trees for a subset of the most relevant features. To that end, all irrelevant attributes were first removed from the data using the Relief-F feature selection method. Next, the C4.5 trees were built using only the remaining relevant attributes. The results of the analyses indicated that the simpler models do not necessarily perform worse: more or less the same results were obtained at the activity-pattern level and at the trip-matrix level. At the choice-facet level, one can observe that a strong reduction in the size of the trees as well as in the number of predictors was possible without adversely affecting predictive performance too much.

CONCLUSIONS AND RESEARCH AGENDA

Motivated by the expectation that uncertainty analysis will become increasingly important in the assessment and application of travel demand forecasts, the aim of this review article has been to develop a general framework for uncertainty analysis and summarize findings of the existing literature. Based on this literature review, which has been targeting at the main transportation journals and conferences, the following conclusions may be drawn. First, compared to many other topics in the transportation research community, in absolute terms the issue of uncertainty has received only minor attention. Secondly, the research effort that has been paid differs widely by kind of research. Uncertainty analyses have been concentrated on forecasting models of travel demand; there is a virtual complete lack of attention in analytical studies addressing the strength and nature of the relationship between facets of travel demand and their covariates. In line with this finding, although we immediately admit that the classification of model has been arbitrary in some cases, most studies have been concerned with the older generation of travel demand forecasting models, such as the four-step models and the discrete choice tour-based models. This is understandable in that the last generation of comprehensive activity-based models is only recently moving from academic research to transportation planning practice. Thirdly, the literature review demonstrates that the analysis of uncertainty has focused on a wide variety of sources of uncertainty, ranging from methodological reflections on the nature of choice models and model uncertainty in a fundamental statistical sense to concrete studies of a specific source of uncertainty. Most studies have been rather ad hoc in nature in the sense that often only a single source of uncertainty has been examined and not much effort has been paid to systemically vary in a

more sophisticated way the factors of interest. Thus, although these studies have articulated and illustrated the issue at hand, evidence has remained rather sketchy.

Some topics have received slightly more attention. Especially the issue how many simulation runs are required to achieve robust, stable moving averages has been studied by several authors (Veldhuisen, *et al.*, 2000; Castiglione *et al.*, 2002; Lawe *et al.*, 2010; Ziems *et al.*, 2010). They have consistently found that only a few runs are needed to get a stable average. Although these results apply to data-driven micro-simulation systems, there seems no reason why these results would not equally apply to behavioral activity-based models as all these models are based on large numbers. Several studies have been concerned with the influence of number of runs on confidence intervals surrounding these stable averages. In addition, however, the assessment of uncertain forecasts would also benefit by calculating confidence levels for the coefficient of variation at the level of the synthetic population.

Several studies have examined error propagation in especially four step models. They often found that uncertainty increases in the first 3 steps and is then reduced again at the assignment step, due to capacity constraints. It is not readily evident what to expect in the context of the advanced activity-based models. Unlike the four-step models, which are loosely coupled at best, some activity-based models are characterized by various kinds of constraints during every activity-travel scheduling step, while in addition feedback and feedforward mechanisms may be activated.

The mirror image of the conclusions set the stage for a research agenda. The focus here is the perspective of advanced activity-based models. Figure 1 provides an overview of the various sources of error that may affect the uncertainty in model outcomes. Comparing this figure against the summary results mentioned in Table 1 gives an indication of under-researched topics and research needs. Beyond the obvious need for additional, repetitive studies, more systematic and comprehensive studies seem to have a high priority, especially in the context of complex activity-based models of travel demand. Several valuable lines of future research can be mentioned. First, the literature review suggests that little attention has been paid to the various choice facets underlying activity-based models of travel demand and to individual space-time trajectories. Facets such as activity participation, timing, duration and travel party in activity-based models of travel demand add the activity and temporal dimensions to commonly addressed facets in conventional forecasting models and differentiate activity-based models from four-step models. Destination and transport mode choice are key components of non activity-based models as well, but for some reason do not seem to have drawn much attention in assessing uncertainty in travel forecasts. Uncertainty

analysis has mainly been concerned with aggregate travel indices such as VMT, OD matrices and link traffic flows/volumes.

Second, most studies have assumed univariate or multivariate probability distributions, sometimes with covariance terms to represent input uncertainty. This may be a realistic assumption for some error generating processes, but not for others. For instance, most activity-based models of travel demand will use free flow travel times as input. Under such circumstances, the actual probability distribution of travel times will likely be positively skewed. Moreover, not all output variables are continuous, some should be expected to have a truncated distribution. Hence, a second valuable line of research would be to compare alternative probability functions on their impact on uncertainty. How to treat categorical data represents another important research topic. Yet other output variables such as value of travel time are a compound of underlying variables. Estimating confidence intervals for these variables represents a challenge in its own right. It should also be noted that most researchers have a priori assumed some form and degree of uncertainty for the input data to explore effects on model outcomes. In real applications, however, the aim of the analysis should be to quantify input uncertainty and predict how it affects final results. It may therefore be helpful to collect data about variability in input data and/or to explore the potential of expert elicitation (i.e. experts making judgments of uncertainty in input data). Such an approach will also likely result in probability distributions other than the commonly assumed multivariate normal distribution. Thus, the exploration and systematic comparison of alternative (non-symmetric) probability distributions, including methods to derive such distributions (e.g. Ng *et al.* 2010) seems another relevant avenue of future research in uncertainty analysis in travel demand forecasting

Figure 1 also captures the idea that projections of complex activity-based models of travel demand at various levels of spatial aggregation (aggregate mobility performance indicators, choice facets, OD matrices and space-time trajectories of activity-travel behavior) are uncertain due to multiple sources of uncertainty: uncertain input, the chosen fraction of the synthetic population, the inherent probabilistic nature of the models involved, uncertain parameters/rules and micro-simulation error. With a few exceptions, most studies have examined only a single source or different sources separately, the impact of the sample fraction of the synthetic population hardly being addressed at all.. Another valuable item on the research agenda is to understand the relative contribution of each of these sources of possible error. This would imply that many runs based on different configurations of input data and parameters, for different fractions of the synthesized population, are required. The

amount of computing time involved is overwhelming. Realizing that a single run of an advanced activity-based model of travel demand may take a night, may be just 2-3 runs per day are possible on a single computer. Because thousands of samples may be required to assess the relative contribution of different sources of error on the uncertainty of model outcomes, especially at high spatial and temporal resolutions, many months of computing will be required, unless parallel computing is an option.

These time demands introduce the issue whether brute force Monte Carlo simulation is the way to go or that most sophisticated sampling schemes should be developed, explored and compared. One possible option is to use (shuffled) Halton draws currently used in mixed logit models, which tend to be more efficient than random Monte Carlo sampling. One step further would be the use of fractional factorial, uniform or sequential experimental designs as employed in stated preference and choice modeling, or replace naïve random sampling methods with more intelligent sampling procedures such as stratified sampling, Latin hypercubes or grid ensemble designs. Another line of research would imply investigating which variables contribute most or most critically to uncertainty and examine their impact in a more detailed manner. Cools *et al.* (2011) analyzed the contribution of the various input variables and complexity of the choice process to the uncertainty in mobility indices. It may even be possible to start at the policy end. If policy-makers could identify the critical thresholds of outcomes which would trigger a shift from one preferred policy option to another, researchers might be able to zoom in on the corresponding parameter subspace and perform a detailed uncertainty analysis in that subspace.

CONCLUDING COMMENTS

This paper has summarized existing work on uncertainty analysis in travel demand forecasting. Based on that, potentially valuable lines of future research have been sketched, with a special focus on advanced activity-based models. It should be realized that uncertainty as discussed in this review paper is strictly tied to the model specification which is assumed to be correct, methodological principles underlying a particular modeling approach and the principles underlying classic statistical inference. The question whether the model is correct will always remain problematic. Activity-based models, based on 1 day forecast, have some limitations that cannot be relaxed with uncertainty analysis. Hence, the need to improve the validity of models of travel demand will remain. Critical mechanisms that are not captured by the model will have a critical effect on model forecasts. Moreover, forecasts of travel demand

are based on the assumption that the relations as reflected in the activity-travel data and picked up by the model will remain stable over time. This assumption may be violated by some models of transport demand, especially those who do not attempt to differentiate between preferences and constraints, and wrongly equate observed behavior with preferences. Preferences are relatively stable, but constraints and market conditions may change more rapidly.

Nevertheless, we hope that this paper will stimulate scholars interested in travel demand forecasting and activity analysis to consider conducting additional research on uncertainty in model forecasts and results of analyses. For analytically oriented scholars, uncertainty analysis will complement their focus on hypothesis testing and make them aware of the accuracy of their results, given sample size and factors affecting uncertainty. For modelers, research on uncertainty analysis will force them to systematically consider the quality and sensitivity of their model outcomes. For professionals, incorporating results of uncertainty analysis allows them to assess and judge the critical implications of inherently uncertain model outcomes against boundaries in policy options. We should not forget however that uncertainty discussed in this article is conditional on the type of model of travel demand forecasting; it does not relate to strengths and weakness of the various modeling approaches per se.

Acknowledgement

This work has been funded by the European Commission, under the Seventh Framework Program, by Contract no. 248488 within project The Uncertainty Enabled Model Web. The aim of this project is to develop a Web for uncertainty analysis in complex model chains. The views expressed herein are those of the authors and are not necessarily those of the European Commission.

REFERENCES

- Angrainni, R., T.A. Arentze and H.J.P. Timmermans (2009), Continuous choice model of timing and duration of joint activities, *Transportation Research Record*, 2135, 17-24.
- Angrainni, R., T.A. Arentze and H.J.P. Timmermans (2009), Car allocation between household heads in car deficient households: A decision model, *European Journal of Transport and Infrastructure Research*, 8, 301-109.
- Arentze, T.A. and H.J.P. Timmermans (2000), Albatross: A Learning-Based Transportation Oriented Simulation System, EIRASS, Eindhoven University of Technology, Eindhoven, The Netherlands.
- Arentze, T.A. and H.J.P. Timmermans (2004), Re-induction of Albatross' decision rules using pooled activity-travel diary data and an extended set of land use and costs-related condition states, *Transportation Research Record* 1831, 230-239.

- Arentze, T.A. and H.J.P. Timmermans (2004), A learning-based transportation oriented simulation system, *Transportation Research B*, 38, 613-633.
- Arentze, T.A. and H.J.P. Timmermans (2005), Albatross V2: A Learning-Based Transportation Oriented Simulation System, EIRASS, Eindhoven University of Technology, Eindhoven, The Netherlands.
- Arentze, T.A. and H.J.P. Timmermans (2008), Towards longitudinal activity-based models of travel demand, *Proceedings 13th HKSTS Conference*, Hong Kong, China, pp. 439-450.
- Arentze, T.A. and H.J.P. Timmermans (2009), A dynamic model of activity generation: Development and empirical derivation. In: W.H.K. Lam, S.C. Wong, H.K. Lo (eds.), *Companion Volume of the 18th International Symposium on Transportation and Traffic Theory (ISTTT18)*, pp. 311-328.
- Arentze, T.A. and H.J.P. Timmermans (2009), A need-based model of multi-day, multi-person activity generation, *Transportation Research B*, 43, 251-265.
- Arentze, T.A. and H.J.P. Timmermans (2011), A dynamic model of time-budget and activity generation: Development and empirical derivation, *Transportation Research C*, 19, 242-253.
- Armoogum, J. (2003), Measuring the impact of uncertainty in travel demand modelling with a demographic approach, *Paper presented at the European Transport Conference*, Strasbourg, France.
- Ashley, D.J. (1980), Uncertainty in the context of highway appraisal, *Transportation*, 9, 249-267.
- Auld, J. and A.K. Mohammadian (2009), Framework for the development of the agent-based dynamic activity planning and travel scheduling (ADAPTS) model, *Transportation Letters*, 1, 245-255.
- Auld, J., A.K. Mohammadian and S.T. Doherty (2008), Analysis of activity conflict resolution strategies, *Transportation Research Board*, 2054, 10-19.
- Auld, J., A.K. Mohammadian and M.J. Roorda (2009), Implementation of a scheduling conflict resolution model in an activity scheduling system. *Transportation Research Record*, 2135, 96-105.
- Auld, J., T.H Rashidi, M Javanmardi and A.K. Mohammadian (2011), Dynamic activity generation model using competing hazard formulation., *Proceedings 90th Annual Meeting of the Transportation Research Board*, Washington D.C., USA.
- Bang Salling, K. and S. Leleur (2011), Transport appraisal and Monte Carlo simulation by use of the CBA-DK model, *Transport Policy*, 18, 236-245.
- Bellemans, T., D. Janssens, G. Wets, T.A. Arentze and H.J.P. Timmermans (2010), Implementation framework and development trajectory of Feathers activity-based simulation platform, *Proceedings of the 89th TRB Annual Meeting*, Washington, D.C.
- Beser Hugosson, M. (2004), Quantifying uncertainties in the SAMPERS long distance forecasting system, *paper presented at WCTR 2004*, Istanbul.
- Beser Hugosson, M. (2005), Quantifying uncertainties in a national forecasting model, *Transportation Research A*, 39, 531-547.
- Bhat, C.R., J.Y. Guo, S. Srinivasan and A. Sivakumar (2004), A comprehensive econometric microsimulator for daily activity-travel patterns, *Transportation Research Record*, 1894, 57-66.
- Bhat, C. and F. Koppelman (1999), A retrospective and perspective survey of time-use research. *Paper presented at the 78th Meeting of the Transportation Research Board*, Washington DC.
- Bhat C. and F. Koppelman (2000), Activity-based travel demand analysis: history, results and future directions. *Paper presented at the 79th Meeting of the Transportation Research Board*, Washington DC.
- Bhatta, B.P. and O.I Larson (2007), Measurement errors in data used in transportation models and their consequences for parameter estimation, *Paper presented at the 11th WCTR Conference*, Berkeley, USA.
- Bonsall, P.W., A.F. Champerowne, A.C. Mason and A.G. Wilson (1977), Transport modeling: Sensitivity analysis and policy testing, *Progress in Planning*, 7, 153-237.
- Borgonova, E., W. Castaings and S. Tarantola (2011), Model emulator and moment-independent sensitivity analysis: An application to environmental modeling, to appear in *Environmental Modelling and Software*.
- Bowman J. and M.E. Ben-Akiva (1999), The day activity schedule approach to travel demand analysis. *Paper presented at the 78th Meeting of the Transportation Research Board*, Washington DC.

- Boyce, A.M. (1999), Risk analysis for privately funded transport schemes, *Paper presented at the European Transport Conference*, Cambridge, UK
- Boyce, A.M. and M.J. Bright (2003), Reducing or managing the forecasting risk in privately-financed projects, *Paper presented at the European Transport Conference*, Strasbourg, France.
- Bradley M., M. Outwater, N. Jonnalagadda and E. Ruiter (2001), Estimation of an activity-based microsimulation model for San Francisco, *Paper presented at the 80th Meeting of the Transportation Research Board*, Washington DC.
- Brail, R.K., ed. (2008), *Planning Support Systems for Cities and Regions*, Lincoln Institute, Cambridge, Massachusetts, USA.
- Brundell-Freij, K. (1997), How good is an estimated logit model? Estimation accuracy analysed by Monte Carlo simulations, *Paper presented at the European Transport Conference*, Cambridge, UK.
- Brundell-Freij, K. (2000), Sampling specification and estimation as sources of inaccuracy in complex transport models- Some example analysed by Monte Carlo simulation and bootstrap, *Paper presented at the European Transport Conference*, Cambridge, UK.
- Brunel, J. (2004), Stochastic risk in forecasting vs. policy-oriented uncertainty, *Paper presented at the European Transport Conference*, Strasbourg, France.
- Castiglione, J., J. Freedman, and M. Bradley (2003), Systematic investigation of variability due to random simulation error in an activity-based micro-simulation forecasting model, *Transportation Research Record*, 1831, 76-88.
- Cheung, K. and J. Polak (2009), A Bayesian approach to modelling uncertainty in transport infrastructure project forecasts, *Paper presented at the European Transport Conference*, Noordwijk, The Netherlands.
- Circella, G., M. Dell'Orco and D. Sassanelli (2005), Uncertainty in choice behaviour prediction: a hybrid approach to combine fuzziness and randomness, *Paper presented at the European Transport Conference*, Strasbourg, France.
- Clark, S.D. and D.P. Waitling (2005), Modelling network time reliability under stochastic demand, *Transportation Research B*, 39, 119-140.
- Clay, M.J. and R.J. Johnston (2006), Multivariate uncertainty analysis of an integrated land use and transportation model: MEPLAN, *Transportation Research D*, 11, 191-203.
- Cools, M., B. Kochan, T. Bellemans, D. Janssens and G. Wets (2011), Assessment of the effect of microsimulation error on key travel indices: Evidence from the activity-based model Feathers, *Transportation Research Record* 1558, to appear.
- Duru, O., E. Bulut and S. Yoshida (2010), Modelling and simulation of variability and uncertainty in ship investments: implementation of fuzzy Monte-Carlo method, *Paper presented at the WCTR Conference*, Lisbon, Portugal.
- Geenhuizen, M.S.V., H.J. van Zuylen and P. Nijkamp (1998), Limits to predictability, *Paper presented at the European Transport Conference*, Cambridge, UK.
- Gibb, J. and J.L. Bowman (2007), Convergence of an activity-based travel model system to equilibrium: Experimental design and findings, *Proceedings of the 11th National Transportation Planning and Application Conference of the Transportation Research Board*, Daytona Beach, Florida.
- Habib, K.M.N. and J.A. Carrasco (2011), Investigating the role of social networks in start time and duration of activities: Trivariate simultaneous econometric model. *Proceedings of the 90th Annual Meeting of the Transportation Research Board*, Washington DC, USA.
- Habib, K.M.N. and E.J. Miller (2009), Modeling activity generation: A utility-based model of activity agenda formation, *Transportmetrica*, 5, 3-23.
- Han, Q., T.A. Arentze and H.J.P. Timmermans (2009), Social influence on location choice dynamics, *Proceedings of the 14th HKSTS Conference*, Hong Kong, China, 505-515.
- Han, Q., T.A. Arentze and H.J.P. Timmermans (2010), Habit format and affective responses in location choice dynamics. *Proceedings of the 12th WCTR Conference*, Lisbon, Portugal.
- Han Q., T.A. Arentze and H.J.P. Timmermans (2011), Learning and affective responses in location choice dynamics, *Environment and Planning B*, to appear.
- Han, Q., T.A. Arentze, H.J.P. Timmermans, D. Janssens and G. Wets (2008), Modeling context-sensitive dynamic activity-travel behavior under conditions of uncertainty incorporating

- reinforcement learning, habit formation, and behavioral and cognitive adaptation strategies, *Proceedings of the 87th Annual Meeting of the Transportation Research Board*, Washington D.C.
- Han, Q., T.A. Arentze, H.J.P. Timmermans, D. Janssens and G. Wets (2009), Developing dynamic models of activity-travel behavior: Principles, mechanisms, challenges in data collection and methodological issues, *Proceedings of the 88th Annual Meeting of the Transportation Research Board*, Washington D.C.
- Han, Q., T.A. Arentze, H.J.P. Timmermans, D. Janssens and G. Wets (2011), The effects of social networks on choice set dynamics: Results of numerical simulations using an agent-based approach, *Transportation Research Part A*, 45, 310 - 322
- Henson, K.M., K. G. Goulias and R.G. Golledge (2009), An assessment of activity-based modeling and simulation for applications in operational studies, disaster preparedness, and homeland security, *Transportation Letters*, 1, 19 – 39.
- Janssens, D., G. Wets. T.A. Arentze and H.J.P. Timmermans (2007), Modelling short-term dynamics in activity-travel patterns: Conceptual framework of the Feathers model, *Proceedings WCTR Conference*, Berkeley, USA.
- Jeon, C.M., Y. Chang and A.A. Amekudzi (2010), Incorporating uncertainty into transportation decision making: A sustainability-oriented approach, *Paper presented at the 89th annual Meeting of the Transportation Research Board*, Washington, D.C., USA.
- Joh, C-H., T.A. Arentze and H.J.P. Timmermans (2004), Activity-travel rescheduling decisions: Empirical estimation of the Aurora model, *Transportation Research Record*, 1898, 10-18.
- Jong, G. de, A. Daly, M. Pieters, S. Miller, R. Plasmeijer and F. Hofman (2005), Uncertainty in traffic forecasts: literature review and new results for The Netherlands, *Proceedings European Transport Conference*, Strasbourg, France..
- Jong, G. de, A. Daly, M. Pieters, S. Miller, R. Plasmeijer and F. Hofman (2007), Uncertainty in traffic forecasts: literature review and new results for The Netherlands, *Transportation*, 34, 375-395.
- Jonnalagadda N, J. Freedman, W Davidson and J. Hunt (2001), Development of a micro-simulation activity-based model for San Francisco destination and mode choice models. *Paper presented at the 80th Meeting of the Transportation Research Board*, Washington DC.
- Krisnamurthi, S. and K.M. Kockelman (2006), Propagation of uncertainty in transportation-land use models: An investigation of DRAM-EMPAL and UTPP predictions in Austin, Texas, *Proceedings of the 81st Annual Meeting of the Transportation Research Board*, Washington, DC
- Kuwano, M., J. Zhang and A. Fujiwara (2011), Dynamic discrete choice model with multidimensional social interactions, *Proceedings of the 90th Annual Meeting of the Transportation Research Board*, Washington DC, USA.
- Leurent, F. (1998), Sensitivity and error analysis of the dual criteria traffic assignment model, *Transportation Research B*, 32, 189-204.
- Margvelashvili, N. and E.P. Campbell (2011), Sequential data assimilation in fine-resolution models using error-subspace emulators: Theory and preliminary evaluation. To appear in *Journal of Marine Systems*.
- Matas, A., J-L. Raymond and A. Ruiz (2010), Traffic forecasts under uncertainty and capacity constraints, *Paper presented at the WCTR Conference*, Lisbon, Portugal.
- McNally, M.G. (2007), The four step model. In: D.A. Hensher and K.J. Button (eds.), *Handbook of Transport Modelling*, Elsevier Science, Oxford, UK.
- Meister, K., M. Balmer, F. Ciari, A. Horni, M. Rieser, R.A. Waraich and K.W. Axhausen (2010), Large-scale agent-based travel demand optimization applied to Switzerland, including mode choice, *Paper presented at the 12th World Conference on Transportation Research*, Lisbon, Portugal.
- Miller, E.J. and M.J. Roorda (2003), Prototype model of household activity/travel scheduling (TASHA), *Transportation Research Record*, 1831, 114-121.
- Mishra, S., S. Khasnabis and S. Swain (2011), An approach to incorporate uncertainty and risk in transportation investment decision making: Detroit river international crossing case study, *Paper presented at the 90th annual Meeting of the Transportation research Board*, Washington, D.C., USA.
- Mitra, R., R.N. Buliung and M.J. Roorda (2010), Built environment influences on school travel mode choice in Toronto, Canada. *Transportation Research Record*, 2156, 150-159.

- Mohammadian, A. and S.T. Doherty (2005), Mixed logit model of activity-scheduling time horizon, incorporating spatial-temporal flexibility variables, *Transportation Research Record*, 1926, 33-40.
- Mohammadian, A. and S.T. Doherty (2006), Modeling activity scheduling time horizon: Duration of time between planning and execution of pre-planned activities, *Transportation Research A*, 40, 475-490.
- Moons, E.A.L.M.G., G.P.M. Wets, M. Aerts, T.A. Arentze and H.J.P. Timmermans (2005), The impact of irrelevant attributes on the performance of classifier systems in generating activity schedules, *Proceedings of the 81st Annual Meeting of the Transportation Research Board*, Washington, DC
- Moons, E.A.L.M.G., G.P.M. Wets, M. Aerts, T.A. Arentze and H.J.P. Timmermans (2005), The impact of simplification in a sequential rule-based model of activity-scheduling behavior, *Environment and Planning A*, 37, 551-568
- Mosa, A.I. (2011), Mixed multinomial logit model of household interactions in daily in-home and out-of-home maintenance activity participation and social behavior, *Proceedings of the 90th Annual Meeting of the Transportation Research Board*, Washington DC, USA.
- Nagel, K. (2004), Routing in iteration transportation simulations. In M. Schreckenberg and R. Selten (eds.) *Proceedings of the Workshop on Human Behaviour and Traffic Networks*, 305-318. Springer, Berlin, Germany.
- Ng, M., K.M. Kockelman and S.T. Waller (2010), Relaxing the multivariate normality assumption in the simulation of transportation system dependencies: An old technique in a new domain, *Transportation Letters*, 2, 63 - 74.
- Lam, W.H.K., H. Shao and A. Smalee (2008), Modelling impact of adverse weather conditions on a road network with uncertainties in demand and supply, *Transportation Research B*, 42, 890-910.
- Lawe, S., J. Lobb, A.W. Sadek and S. Huang (2009), TRANSIMS Implementation in Chittenden County, Vermont: Development, calibration and preliminary sensitivity analysis, *Transportation Research Record* 2132, 113-121.
- Oppeheim, N. (1995), *Urban Travel Modeling*, John Wiley & Sons, Inc., New York.
- Paez, A. and S. Farber (2011), Recreation and leisure by persons with disabilities: analysis of transportation factors based on Canada's participation activity limitation survey, *Proceedings of the 90th Annual Meeting of the Transportation Research Board*, Washington DC, USA.
- Pas, E.I. and S. Sundar (1995), Intrapersonal variability in daily urban travel behaviour: Some additional evidence, *Transportation*, 22, 135-150.
- Pendyala, R.M., R. Kitamura, A. Kikuchi, T. Yamamoto and S. Fujji (2005), FAMOS: Florida activity nobility simulator. *Proceedings of the 84th Annual Meeting of the Transportation Research Board*, Washington D.C.
- Pontius Jr., R.G. and J. Spencer (2005), Uncertainty in extrapolations of predictive land-change models, *Environment and Planning B: Planning and Design* 32 (2), 211-230.
- Pradhan, A., and K.M. Kockelman (2002), Uncertainty propagation in an integrated land-use-transportation modeling framework: Output variation via UrbanSim, *Transportation Research Record*, 1805, 128-135.
- Robbins J. (1978), Mathematical modelling: The error of our ways, *Traffic Engineering and Control*, 32-35.
- Rodier, C.J. and R.A. Johnston (2002), Uncertain socioeconomic projections used in travel demand and emissions models: could plausible errors result in air quality nonconformity?, *Transportation Research A*, 36, 613-631.
- Roorda, M.J., E.J. Miller and K. Habib (2008), Validation of TASHA: A 24-Hour Activity Scheduling Microsimulation Model. *Transportation Research A*, 42, 360-375.
- Roorda, M.J., E.J. Miller and N. Kruchten (2006), Incorporating within-household interactions into a mode choice model using a genetic algorithm for parameter estimation. *Transportation Research Record*, 1985, 171-179.
- Roorda, M.J. and T. Ruiz (2008), Long and short-term dynamics in Activity Scheduling: A structural equations approach, *Transportation Research A*, 42, 545-562.
- Ruiz, T. and M.J. Roorda (2008), Analysis of planning decisions during the activity scheduling process. *Transportation Research Record*, 2054, 46-55.

- Ruiz, T., and M.J. Roorda (2011), Assessing planning decisions by activity type during the scheduling process, *Transportmetrica*, 7, 417-442.
- Schlich, R. and K.W. Axhausen (2005), Analysing interpersonal variability for homogeneous groups of travellers, *Arbeitsbericht Verkehrs- und Raumplanung* 296, ETH, Zurich, Switzerland.
- Ševčíková, H., A.E. Raftery and P.A. Waddell (2007), Assessing uncertainty in urban simulations using Bayesian melding, *Transportation Research Part B*, 41, 652–669.
- Smith, L, R. Beckman, K. Baggerly, D. Anson and M. Williams (1995), *TRANSIMS: TRansportation ANalysis and SIMulation System: Project Summary and Status*.
- Timmermans, H.J.P. (2009), On the relevance of the principle of parsimony for developing agent-based models in urban planning. In: *Proceedings Complexity Theories of Cities Have Come of Age*, Delft, The Netherlands.
- Timmermans, H.J.P. and J. Zhang (2009), Modelling household activity travel behaviour, *Transportation Research B*, 43, 187-190.
- Veldhuisen, K., H.J.P. Timmermans and L.L. Kapoen (2000), Ramblas: A regional planning model based on the micro-simulation of daily activity travel patterns, *Environment and Planning A*, 32, 427-443.
- Veldhuisen, K.J., H.J.P. Timmermans, and L.L. Kapoen (2000), Microsimulation model of activity-travel patterns and traffic flows: Specification, validation tests and Monte Carlo error, *Transportation Research Record*, 1706, 126-135.
- Vovsha, P., M. Bradley and J.L. Bowman (2004), Activity-based travel forecasting in the United States: Progress since 1995 and prospects for the future. *Proceedings of the Conference on Progress in Activity-Based Models*, Maastricht, 28-32 May (CD Rom).
- Vovsha, P., R. Donnelly and S. Gupta (2008), Network equilibrium with activity-based microsimulation models: The New York experience. *Transportation Research Record*, 2054, 102-109.
- Vovsha, P., E. Peterson and R. Donnelly (2002), Micro-simulation in travel demand modeling: Lessons from the New York “best practice” model, *Proceedings of the 82nd Annual Meeting of the Transportation Research Board*, Washington DC, USA.
- Walker, J.L. (2005), Making household micro-simulation of travel and activities accessible to planners, *Proceedings of the 83rd Annual Meeting of the Transportation Research Board*, Washington DC, USA.
- Walker, J.L., J. Li, S. Srinivasan and D. Bolduc (2010), Travel demand models in the developing world: Correcting for measurement errors, *Transportation Letters*, 2, 231-243.
- Wang, D. and J. Li (2011), A two-level multiple discrete continuous model of time allocation to virtual and physical activities, *Transportmetrica*, 7, 395-416.
- Wilson, I and W. Ralston Jr., (2006), *The Scenario Planning Handbook: Developing Strategies in Uncertain Times*. Thompson Publishing, Washington DC, USA
- Yang, C. and A. Chen. (2011), Uncertainty analysis of a combined travel demand model. In: Sumalee, A., W.H.K. Lam, H.W. Lo and B. Siu (eds.), *Transportation and Urban Sustainability*, HKSTS, Hong Kong, pp. 441-450.
- Yang, C. and A. Chen. (2011), Sensitivity-based uncertainty analysis of a combined travel demand model. *Transportation Research Record*, 1535, to appear.
- Yoon, S-Y. and K.G. Goulias (2010), Impact of time-space prism accessibility on time use and its propagation through intra-household interaction, *Transportation Letters*, 2, 245-260.
- Zhang, T., C. Xie and S.T Waller (2011), An integrated equilibrium travel demand model with nested logit structure: Problem formulation and uncertainty analysis, *Proceedings of the 90th Annual Meeting of the Transportation Research Board*, Washington DC, USA.
- Zhao, Y. and K.M. Kockelman (2001), The propagation of uncertainty through travel demand models: An exploratory analysis, *Annals of Regional Science* 36, 909-921.
- Zheng, F. and H. van Zuylen (2010), Uncertainty and predictability of urban link travel time: A delay distribution based analysis, *Proceedings of the 89th Annual Meeting of the Transportation Research Board*, Washington DC, USA.

Ziems, S., S. Bhargava, J. Plotz and R.M. Pendyala (2011), Stochastic variability in microsimulation modeling and convergence of corridor-level characteristics. To appear in *Transportation Research Record* 3560

Table 1; Summary overview of uncertainty analysis in travel demand forecasting

Authors	Year	City/ Country	Type of Uncertainty	Sample fraction/ # of runs	Outputs	Measures and findings
Four-step models						
Rodier Johnston	2002	Sacramento	Input uncertainty	Single runs	Trips VMT VHD	<i>Percent change</i> Influence of population and employment projections, not significant for household income and fuel price
Zhao Kockelman	2002	Dallas-Fort Worth	In put uncertainty	100 runs	Link flows Link travel time VMT VHT	<i>CV</i> CV link flows are larger than input uncertainty. And smaller VMT and VHT. average uncertainty is amplified in the first three sub-models of the model chains, but somewhat reduced in the final, route assignment model step, but not below the input uncertainty.
Armoogum	2003	Paris, France	Input uncertainty Model uncertainty	Jackkifing	Trip frequency Daily distance travelled	<i>Percent error and confidence level</i> Errors increased with increasing time horizon Errors higher for frequency than for VMT
Discrete choice models						
Brundell- Freij	1997	Lund & Malmö	Model uncertainty Estimation and specification error	Samples of different size 500 runs	Different model parameters	Various kinds of biases, size of which is increasing with smaller sample sizes.
Castiglione Freedman Bradley	2003	San Francisco	Model (SFCTA model) Stable average	Full population 100 runs	vehicle availability tour generation destination choice mode choice at 3 different levels of spatial resolution	<i>% difference from final mean</i> Less runs required at higher levels of spatial resolution and for models with a lesser number of categories
Beser Hugusson	2004 2005	Sweden	Sampers (nested logit_EMME/2) Sampling uncertainty	999 bootstrap samples	Travel demand OD matrices Link flows VoT	<i>Percent error, standard error</i> Uncertainty in total demand varied between 8.5% (car) and 13.3% (train) Uncertainty in OD-matrices varied between 6.5% and 14%, and was larger for the larger relations Uncertainty at the link level varied between 8.4% and 10.8%, the standard error being larger for the link with the larger flow
Walker		South	4 step discrete	Samples of 500,	VMT	<i>Percent error</i>

	2005	Nevada	choice model Model uncertainty	5000, 50000 and 500000 of the synthetic population 10 runs	Number of transit trips	Errors decrease with increasing sample size
De Jong et al	2005	Netherlands	National model system Input and model uncertainty (parameters)	100 runs	number of tours VMT Traffic flows Vehicle miles lost Travel times	<i>Standard deviations and confidence levels</i> Input uncertainty has higher effects than model uncertainty
Yang Chen	2010 2011	Sioux Falls	Combined travel demand model Input and model uncertainty	Full population Analytical sensitivity-based uncertainty analysis	production from zone number of non-travellers from zone 1, O-D demand (total plus car and transit link flows in car and transit networks total travel time (TTT) total vehicle miles (TVM)	<i>CV and confidence levels</i> Output uncertainty of same order as input uncertainty, except for TTT and TVM (lower) Lower uncertainty at assignment stage
Zhang Cie Waller	2011	Sioux Falls	Combined travel demand model Input and model uncertainty	Full population	O-D demand (trip rates] Link flows Vehicle miles travelled (VMT) total vehicle hours travelled (VHT)	<i>CV</i> Lower uncertainty at assignment stage Higher for VHT than for VMT Uncertainty trip rates directly related to input uncertainty Varies uncertainty link flows
Activity-based models: micro simulation						
Veldhuisen Timmermans Kapoen	2000	Netherlands	Model (Ramblas)	Full population 5 runs	OD-tables Traffic intensities	<i>R-square and Robinson agreement measures</i> very high across runs
Gibbs Bowman	2007	Sacramento	Model (SACSIM) Stable average	Different fractions 10 runs	VHT OD travel times	<i>Error bars and standard deviation</i> Evidence of convergence
Lawe Lobb Sadeke Huang	2009	Chittenden County	Model (Transims) Stable average	5 runs	Traffic volume Speed	<i>CV</i> 0-2,59%
Activity-based models: Computational process model						
Cools et al	2011		Model (Feathers-Flemish version of Albatross)	10% fraction (616,160 persons) 200 runs	average daily number of trips per person; average daily distance traveled	<i>CV</i> 5% threshold was often exceeded for public transport.

					per person by mode, age and gender	Error increases with complexity; age has a monotonically increasing effect, while gender has no significant effect
--	--	--	--	--	--	--

CV= coefficient of variation

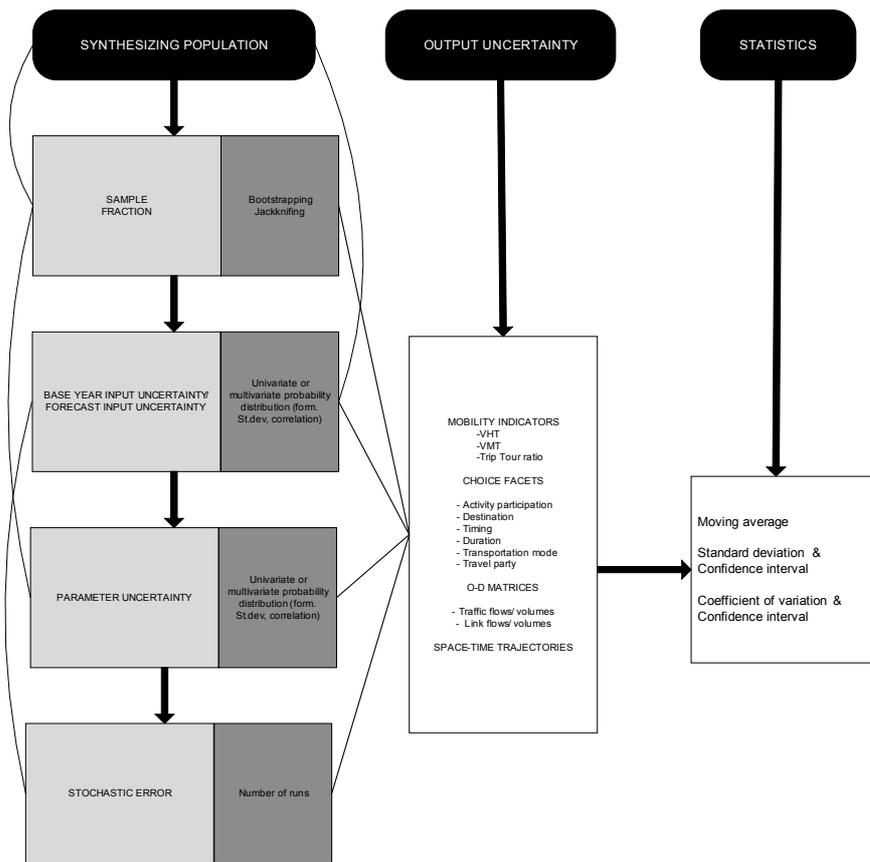


Figure 1: Uncertainty analysis and activity-based model of travel demand.

