Five papers on large scale dynamic discrete choice models of transportation

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Abstract

Travel demand models have long been used as tools by decision makers and researchers to analyse the effects of policies and infrastructure investments. The purpose of this thesis is to develop a travel demand model which is: sensitive to policies affecting timing of trips and time-space constraints; is consistent with microeconomics; and consistently treats the joint choice of the number of trips to perform during day as well as departure time, destination and mode for all trips. This is achieved using a dynamic discrete choice model (DDCM) of travel demand. The model further allows for a joint treatment of within-day travelling and between-day activity scheduling assuming that individuals are influenced by the past and considers the future when deciding what to do on a certain day.

Paper I develops and provides estimation techniques for the daily component of the proposed travel demand model and present simulation results provides within sample validation of the model. Paper II extends the model to allow for correlation in preferences over the course of a day using a mixed-logit specification. Paper III introduces a day-to-day connection by using an infinite horizon DDCM. To allow for estimation of the combined model, Paper III develops conditions under which sequential estimation can be used to estimate very large scale DDCM models in situations where: the discrete state variable is partly latent but transitions are observed; the model repeatedly returns to a small set of states; and between these states there is no discounting, random error terms are i.i.d Gumble and transitions in the discrete state variable is deterministic given a decision.

Paper IV develops a dynamic discrete continuous choice model for a household deciding on the number of cars to own, their fuel type and the yearly mileage for each car. It thus contributes to bridging the gap between discrete continuous choice models and DDCMs of car ownership.

Infinite horizon DDCMs are commonly found in the literature and are used in, e.g., Paper III and IV in this thesis. It has been well established that the discount factor must be strictly less than one for such models to be well defined. Paper V show that it is possible to extend the framework to discount factors greater than one, allowing DDCM's to describe agents that: maximize the average utility per stage (when there is no discounting); value the future greater than the present and thus prefers improving sequences of outcomes implying that they take high costs early and reach a potential terminal state sooner than optimal.

Sammanfattning

Modeller för reseefterfrågan har länge använts av besultsfattare såväl som forskare för att analysera effekterna av transportpolitiska åtgärder. Avhandlingens huvudsakliga syfte har varit att bidra till utvecklandet av modeller för reseefterfrågan som är: känsliga för åtgärder som påverkar tidsval för resor eller tids-rums begränsningar; och konsistent behandlar valet av antalet resor, avresetid, destination och färdmedel för en individ. Detta uppnås genom användandet av en dynamisk diskret valmodell (DDCM) för reseefterfrågan. Modellen klarar vidare av att gemensamt modellera både dagligt resande med hänsyn till hur det påverkar behovet av andra resor över en längre tidshorisont, där individer antas ta hänsyn till både när de senaste utfört olika aktiviteter samt framtida effekter av sina besult.

Papper I utvecklar den dagliga komponenten i den föreslagna modellen för reseefterfrågan, presenterar en estimeringsteknik samt resultat från simuleringar med valideringsresultat. Papper II förbättrar modellen genom att inkludera korrelation i preferenser under dagen med hjälp av en mixed-logit specifikation. Paper III introducerar en koppling mellan dagar genom en DDCM med oändlig tidshorisont. För att den kombinerade modellen skulle vara möjlig att estimera härleddes vilkor under vilka sekvensiell estimering var möjlig. Dessa vilkor möjligör därmed estimering av en specific typ av storskaliga DDCM modeller i situationer när: den diskreta tillståndsvariabeln är delvis latent men där val observeras; där modellen återkommer till ett mindre tillståndrum; och där det mellan återkomsten till detta mindre tillståndrum inte sker någon diskontering, nyttofunktionernas feltermer ges av i.i.d Gumble termer och övergångarna mellan disrekta tillståndsvariabler är deterministisk givet valet.

Papper IV utvecklar en dynamiskt diskret-kontinuerlig valmodell för ett hushålls beslut gällande antalet bilar att äga, deras bränsletyp samt årliga miltal för varje bil. Det därmed till att komibinera dynamiska och diskret-kontinulerliga valmodeller för bilägande.

DDCM med oändliga tidshorisonter är vanligt förekommande och används i bland annat Papper III och IV i den här avhandlingen. Det har varit väl etablerat att diskonteringsfaktorn måste vara strikt mindre än ett för att sådana modeller ska vara väldefinerade. Papper V visar hur det är möjligt tillåta diskonteringsfaktorer större än eller lika med ett, och därmed beskriva agenter som: maximerar den genomsnittliga nyttan per steg (när det inte sker någon diskontering); värderar framtiden högre än nutiden och därmed föredrar förbättrande sekvenser vilket också implicerar att de tar höga kostnader så tidigt som möjligt och når ett potentiellt sluttillstånd tidigare än optimalt.

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List of papers

I Västberg O. B., Karlström A., Sundberg M., Jonsson D. (2017) A dynamic discrete choice activity based travel demand model,

Presented at: Transportation Research Board 93rd Annual Meeting (2014)

II Zimmermann M., Västberg O. B., Frejinger E. and Karlström A., (2017) Capturing correlation with a mixed recursive logit model for activity-travel scheduling,

Presented at: CORS/INFORMS 2015 Joint International Meeting in Montreal (2015)

Resubmitted to: Transportation Research Part C

III Västberg O. B., Karlström A., (2017) A joint between-day and within-day activity based travel demand with forward looking individuals,

Presented at: ITEA, Annual Conference and School On Transportation Economics (2017)

IV Glerum A., Västberg O. B., Frejinger E., Karlström A., Hugosson M. B., Bierlaire M., (2017) A dynamic discrete-continuous choice model of car ownership, usage and fuel type,

Presented at: 3th Swiss Transport Research Conference (2013), the third International Choice Modelling Conference (2013) and the Second Symposium of the European Association for Research in Transportation (2013)

V Västberg O. B., Karlström A (2017) Discount factors greater than or equal to one in infinite horizon dynamic discrete choice models,

Presented at: International Choice Modelling Conference (2015)
and CORS/INFORMS 2015 Joint International Meeting in Montreal (2015)

Declaration of contribution

The idea of paper I and III was proposed by co-author(s) and the methodology was developed in discussion with co-author(s). Oskar Blom Västberg was responsible for writing, coding and analysis of results.

The idea of paper II was proposed by Oskar Blom Västberg and the methodology was developed in cooperation with co-authors. Coding and results generation was done in cooperation with Maëlle Zimmermann. Maëlle Zimmermann was responsible for writing the paper.

In paper IV Oskar Blom Västberg was involved after the main structure of the model, an initial code, the data set and a draft paper already existed. However, the model had not been estimated and no results had been obtained. He was responsible for estimating the model, improving the performance to enable estimation on a larger data set, specify utility functions and generate results. He was also involved in writing the corresponding additional parts of the paper.

The idea of paper V was proposed by Oskar Blom Västberg. The methodology was developed in discussion with co-author. Oskar Blom Västberg was responsible for writing, coding and analysis of results.

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Part I – Introduction

Part II – Papers

Introduction

1. OVERVIEW AND OBJECTIVES

Planners are faced with the problem of determining how to design policies such that the outcomes for the society are as favourable as possible. However, the effect of these policies are often incredibly hard to forecast, which makes mathematical models of the system of interest valuable. Ideally, they should not only be able to forecast the effect of policies but also enable a comparison of their efficiency and tractability. These are some one of the main purposes of travel demand models which aims at both determining how people react to changes, and how they value these change.

Travel is an unavoidable and important part of daily life. We travel to get to work, to meet friends or to pursue other activities which may be necessary or may simply bring us joy. A well-functioning transportation system is thus important for our quality of life, and is further necessary for a well-functioning economy. However, travelling may also have negative external effects on the society; both locally through congestion, noise and emission of air pollutants; and globally through emission of green house gasses. Travel demand models can help planners in designing a transportation system that optimally weights the benefit of its users against the costs incurred on the society.

It is often inefficient to try to solve the problems discussed above by investments in infrastructure alone (Vickrey, 1969). Rather, they need policies that affect how people make choices within the current transportation system. Congestion is, for many cities, a problem mainly during peak hours. Measures that spread the demand for travelling over a larger time period are then beneficial. This could be achieved through congestion charge on the road network which is currently implemented in, e.g., Stockholm (Eliasson et al., 2009), London and Singapore; or time based cost differentiation of public transport fares (Parry and Small, 2009). Forecasting the effect of such measures and optimizing their levels requires models taking into account how people schedule their days and jointly evaluates, e.g., mode of transport, travel time, cost and departure time.

We are currently at a point in time where expected future technological advancements have the potential to profoundly alter the transportation system (Fagnant and Kockelman, 2015). Automatic and autonomous vehicles vehicles may be a reality in the not too distance future and pilot projects with autonomous buses are already in place in several cities world wide (Bischoff and Maciejewski, 2016). Bike sharing systems are increasingly common and electrical bike sharing systems are being introduces world wide (Fishman, 2016). These technologies will likely change the way in which people combine modes during a single trip or during a day. However, it is also possible that they will create an increased demand for road traffic or that empty vehicles will take up road space leading to severe congestion. Whether or how such services should be subsidized and regulated as well as how they should be operated to create the maximum social welfare are open questions that will benefit from advanced travel demand models, capable of dealing with how we chain our travel in a detailed way.

With this background in mind, the main objective of this thesis has been to:

Develop a travel demand model that:

(i) can predict changes in behaviour related to trip-number, -chaining and -timing as well as overall time usage from policies involving, e.g., introduction of time differentiated prices related to transportation services; changing opening hours of facilities; or affecting time space constraints related to working hours, child care facilities etc.

(ii) treats the choice of timing of trips and activity duration consistently and interdependently with the choice of the number of trips to pursue as well as destination, mode and purpose for all trips in a day

(iii) has a microeconomic foundation and can provide measures of user benefits to be used for appraisal and accessibility analysis

As will be highlighted in the literature review in Section 2, there is currently no travel demand model which is both: consistent with microeconomics; treats time at a detailed level interdependently with other choice dimensions in an internally consistent way; and can be used for forecasting in a reasonable time. By contribution towards fulfilling the main objective outlined above, this thesis can therefore hopefully provide methodological and theoretical contributions to the state of the art of travel demand modelling.

This thesis propose a dynamic discrete choice model (DDCM) of travel demand which could potentially obtain the main objective, and further include daily and day-to-day planning of activities in a unified framework. The model builds upon the methodology presented in Rust (1987). Such models has been used extensively to describe, e.g., career decisions (Keane and Wolpin, 1997), migration (Kennan and Walker, 2011) and retirement behaviour (Rust and Phelan, 1997; Karlström et al., 2004). The first conceptualization of a travel demand model based on DDCM was presented in Karlström (2005) and an implementation of such a model was later used to analyse how accessibility changes due to time-space constraints in Jonsson et al. (2014). Before the thesis project started, the largest implementation of a DDCM of travel demand was on a relatively small scale and very time demanding to evaluate ($\sim$ 10 minutes per individual). Partly because of the long computation time, there was a number problems remaining before a DDCM of travel demand could be used in practice, involving: lack of *estimation* due to the long computation time; computationally unsuitable to *simulate* travel patterns for a large number of individual; lack of *correlation* among alternatives; and a lack of treatment for *long term decisions* regarding, e.g., car ownership and work place location. The papers in this thesis in different ways deal with the above problems. The problems will be discussed in greater detail in Section 4, and how the thesis has contributed to the solution of these problems will be discussed in Section 5.

The reminder of the introduction of this thesis starts with an overview of current travel demand models in the literature (Section 2). Following this is a brief review on the literature on day-to-day variability in travel behaviour as well as models trying to explain such behaviour and in some cases use these insights together with daily travel demand models (Section 3).

2. TRAVEL DEMAND MODELLING

Given the usefulness of predicting the consequences of transportation investments and policies, it is not surprising that travel demand models have existed for a long time. The need to compare costs and benefits of alternative projects have further motivated the development of travel demand models with a foundation in microeconomics. Especially Logit based models, for which a closed form formula of the consumer surplus exists (McFadden, 1978), have been used extensively.

A modelling system used to predict travel demand should be able to determine the number of trips per mode for each origin-destination in the region of interest. If one is to analyse congestion, which typically arise during peak traffic, departure time for each trip should further be included. Of course, the decision of destination, mode and departure time for a trip are all interdependent. Likewise, the choice of different trips performed during a day is also interdependent. Therefore, the choice of all trips performed during a day (or longer) could benefit from a joint treatment. However, modelling this interdependence and explaining how households or individuals make choices among the immense number of alternative ways they could plan their days is an inherently difficult task.

The first modelling systems used for travel demand analysis consisted of four independent steps: *trip generation*, determining the number of trips for each origin and/or destination; *distribution*, connecting trips between origins and destinations; *modal split*, determining the share of modes for each origin-destination pair; and finally *assignment*, determining the route used when a specific mode is used between a specific origin-destination pair (see, e.g., Ortuzar and Willumsen, 2002). Of course, as discussed above these choices are all interdependent. The possible routes will determine the relative attractiveness of different modes.

The trip duration with different modes will in turn effect the attractiveness of a specific destination and the accessibility to different destinations will determine the number of trips performed. Further, different trips throughout the day are not independent. People chain their trips, for example by shopping or picking up children on the way home from work.

Adler and Ben-Akiva (1979) presents possibly the first travel demand model considering the joint choice of a full daily travel pattern. A day is said to consist of a number of *tours*, each with multiple *sojourns* (visits to places remote from home). Travelling between sojourns or home is done by *trip links*, and tour is a linkage of such trips, ending and starting at home. A *travel pattern* is finally the set of tours carried out by an individual (or household) during a fixed period of time, typically a day. Adler and Ben-Akiva (1979) assume that households act as if they choose the travel pattern tp which yield the maximum utility U_{tp} among all available travel patterns TP. The problem of finding a daily travel pattern can then be written as a mathematical optimization problem:

$$\begin{aligned} & \underset{tp}{\text{maximize}} && U_{tp} \\ & \text{subject to} && tp \in TP \end{aligned} \tag{1}$$

This is a very general formulation of the problem of choosing a travel pattern and allows an interdependent choice of all aspects of a travel pattern. The utility function could include time spent at all activities, cost and travel time for each trip, components for each intersection in a road network, household specific components for each destination, and thus potentially be extremely comprehensive. However, even if one agrees on the basic assumptions and on the attractiveness of a model based on (1), the development of travel demand modelling does not end after the paper by Adler and Ben-Akiva (1979). This is partly because there are a number of issues when trying to implement a model based on (1):

- Finding the optimal travel pattern is an inherently complex problem as the number of different ways in which one can plan a day is immense. Depending on the spatial and temporal resolution considered, the number of travel patterns available could easily exceed the number of atoms in the universe. The complexity of the problem means that any model has to be based on a number of restrictive assumption. These can involve the choice dimensions to consider. For example, one may choices regarding routes or duration and departure time from the model. Alternatively, the consistency of the model may be compromised, by, e.g., having different choices treated separately or restricting the type of behaviour the model can reproduce.

- The specification of the utility function for a daily travel pattern could be formulated in a infinite number of ways. Certain aspects of a travel pattern, especially time, are continuous and could benefit from being treated continuously. Different travel patterns may share unobserved attributes and correlation should somehow be treated. How these aspects are treated will be a trade-off between realism in different respects and computational tractability.

- A lot of decisions that influence the available daily travel pattern are taken with a different time horizon in mind. These include long-term decisions such as car ownership, work and home locations, work flexibility and children's school location. Certain activities, such as grocery shopping, must be performed with certain frequency. People may not want to perform other activities too frequently, or feel a growing longing if they are performed too seldom. These long-term decisions and day-to-day dynamics in activity participation could also be treated, and ideally consistently with the model of daily travel behaviour.

- Uncertainties in the environment means that rescheduling might be necessary. If individuals take this uncertainty into account, they do not choose a travel pattern on beforehand but rather have a decision rule determining how to act in a specific situation. Models incorporating rescheduling either models such decision rules or allow rescheudling of the remaining day whenever new information becomes available.

- The degree to which households (or individuals) are able to find the optimal travel pattern has been questioned (Gärling et al., 1994; Gärling, 1998; Arentze and Timmermans, 2004a). If they are not, the process in which they search for travel patterns could influence the outcome and a model could therefore benefit from including this process. One stream of research is therefore attempting to mimic peoples actual decision making process, arguing that this can improve the predictive power of their models. Since people are assumed to solve the problem using heuristics that does not involve exploring the entire solution space in search for the optimal travel pattern, it also has the potential to result in simpler and faster computational programs.

A large number of different models of how households or individuals schedule their daily travelling has been proposed and many are still being further developed and improved. They are based on different methodologies and assumption and they all have their strengths and weaknesses. The level of detail in and consistency between each of the choice dimensions varies tremendously among modelling systems. To some extent, more detailed descriptions of a specific choice dimension can be achieved by relaxing constraints on consistency between choice dimensions, and vice versa. For example, returning to Adler and Ben-Akiva (1979): In order to solve the problem in 1979, they introduced a number of restrictions on the utility function to make the model computationally tractable. First, the utility of a travel pattern is assumed to be decomposable as $U_{tp} = V_{tp} + \epsilon_{tp}$ where V_{tp} is observed by both the household and the researcher whereas ϵ_{tp} is unobserved to the researcher but follows a Gumbel distribution and is i.i.d. across alternatives. Further, they did not estimate any parameters related to time choice; and constructed the choice set TP directly from the observations, and used this choice set for both estimation and simulation. Whereas it is possible to use a sampled choice set for estimation in a Multinomial Logit (MNL) model, using it for simulation yields biased results. The probability of a specific travel pattern pt among the set of observed travel patterns TP was given by the MNL model:

$$P(tp|TP) = \frac{e^{V_{tp}}}{\sum_{tp' \in TP} e^{V_{tp'}}}.$$

Travel demand models are usually divided into two groups, dependent on their consistency with neoclassical microeconomic theory. Microeconimcally consistent models assume that individuals are rational[1] and thus act as if they were utility maximizers. The assumption says nothing about how individuals find the alternative with the maximum utility or that they even calculate a utility function in their mind when making their choices. The assumptions is simply that they have a coherent way of ranking different alternatives. The theory says nothing about the process of finding and comparing alternatives, it is instead purely focused on the actually choice made. The benefit of a model with foundations in microeconomic theory is that such models allows calculation of a consumer surplus which can be directly used for cost appraisal. Multivariate Extreme Value (MEV) models of which MNL are a part has been the most common in practice. For MEV models, the log-sum formula ($\log \sum_{tp' \in TP} e^{V_{tp'}}$ in the MNL case) directly gives the expected utility which equals the Marshallian consumer surplus (McFadden, 1978). The fact that there exists a long established theory for how to perform welfare economics with MEV models makes them very tractable from a theoretical and practical perspective.

Random utility based travel demand model has been criticized for the validity of their underlying behavioural assumptions. Plenty of research in behavioural economics and psychology suggests that people rarely act completely rational (Gärling, 1998). The travel scheduling problem is extremely complex as the number of alternative ways one can plan a day is immense. Assuming that individuals wake up every morning and consider all these possible ways to plan a day is thus not realistic. In a review of activity based models at the time, Gärling

[1]Rational meaning that their preferences are complete (all alternatives can be compared) and transitive (if x is preferred to y and y to z then x is preferred to z). See Samuelson (1938a,b).

et al. (1994) emphasized this lack of understanding of how individuals choose a specific alternative from the choice set and argues that Computational-Process Modelling (CPM) could be used for this purpose. If people are making choices of activity patterns based on heuristics that yield satisfactory but suboptimal outcomes, the heuristics will impact the structure of the chosen travel patterns. They therefore argue that models based on these heuristics could yield better predictions. An example of such a model was presented in Gärling et al. (1999) where rescheduling behaviour were assumed to arise from time pressure. Similar ideas has inspired a lot of the model development that will be discussed below.

Next follows a brief review of existing travel demand models, with a focus on activity based models. The purpose of the review is to highlight the trade-off's made during the model development between realism or consistency and computational tractability. For more extensive reviews, see, e.g., Pinjari and Bhat (2011) or Rasouli and Timmermans (2014). This review divides models into Computationally Process/Rule/Heuristic based models, Random utility maximization based models, and finally a third group of models which does naturally fit into either category.

2.1. *Computational process approach to travel demand models*

As discussed above, plenty of research in behavioural economics suggest that people often act irrational and therefore do not act as if they were utility maximizers. Since finding the optimal travel pattern is such a complex task, especially when considering household interaction, a number of models have been developed which departs from microeconomic theory in their assumptions and try to build other models for how households plan their days.

In STARCHILD (Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decisions) households first which gives available activity programs for each household member, including a set of activities which has to be performed during the day. This is done in a model considering attributes and time-space constraints of the household members. The individual then orders these activities into an activity schedule, a set of sequenced planned activities. They are finally assumed to choose the activity schedule which yields the maximum expected utility when realized into an activity pattern, which is an ordered sequence of the activities and trips that are actually carried out (Recker et al., 1986a,b). The expectation is needed as individuals might not now exactly how the day evolves due to, e.g., travel time uncertainties and opportunities to perform unplanned activities might therefore occur. Individuals are assumed to consider the time spent at all activities as well as the travel times required to reach the activity destinations when evaluating an activity pattern. They write that: "by focusing on the individual's entire activity pattern, the theoretical development incorporates the interrelationships among individual activity scheduling decisions" (Recker et al., 1986a, p. 309), and "The basic assumption embodied in the theoretical development of the model is that individuals choose their daily activity schedule in such a way that they maximize their travel and activity utility" (Recker et al., 1986a, p. 315). In practice, a large number of models are used to generate a small set of activity travel patterns. The choice of a pattern from this choice set is then made according to an MNL model, which is simple to estimate. However, the models leading up to this choice set is not calibrated and their effect on the outcome is uncertain.

An early example of a model based on some sort of computational process is the Activity-Mobility Simulator (AMOS) (Kitamura et al., 1996). Instead of a model of how a household make the choice of a travel pattern, they assume that households already have derived their baseline travel patterns. They are then assumed to adapt this pattern if a change occur in the transportation system which makes the pattern infeasible. New plans are then created using a "connectionist networks", similar to a neural network, which they argue could be estimated based on observations. They write that "The intent is to simulate the cognitive process in which each individual devises alternate options, prioritizes them and selects possible options" (Kitamura et al., 1996, p. 284). For the evaluation measure used to choose an alternative travel pattern, they further write that "it is critical that the evaluation measure reflect the types of activities pursued, the amounts of time allocated to the respective activities, the timing of the activities, as well as the attributes of the activities and travel" (Kitamura et al., 1996, p. 286). This means that the some sort of utility function considering all aspects of the daily travel pattern should be derived.

Somewhat similar to AMOS, Timmermans et al. (2001) presented a model of activity pattern and duration choice (AURORA), focusing on the rescheduling of travel patterns throughout the day. Individuals are assumed to attempt to maximize the total utility of a daily travel pattern, but are unable to find the true optimum due to bounded rationality and the complexity of the problem. Searching for better ways to plan their days is assumed to be costly. Individuals are therefore assumed to adjust their schedules sequentially, until the increase in utility obtained by further adjustments does not motivate the cost of searching. Choices of destinations and modes as well as estimation was later included (Joh et al., 2003, 2005) but the set of activities to perform must be given exogenously by a different model.

Instead of considering a full daily travel pattern, Kitamura et al. (1998) proposed the Prism-Constrained Activity-Travel Simulator (PCATS) where individuals are making a sequence of choices of purpose, duration, mode and destination of trips while ensuring that time-space constraints are satisfied. Modelling a sequential decision process has the advantage that previous decisions easily can be incorporated into the probability of a choice. However, the expected value of the future is hard to calculate in a consistent way and in PCATS individuals are therefore more or less myopic in that they do not consider the future effects of their actions.

In a Comprehensive Econometric Micro-simulator for Daily Activity-travel Patterns (CEMDAP), a large number of models are combined to construct the daily travel pattern on a household level (Bhat et al., 2004a). The models treating each part of the choice are unusually advanced, having hazard models for activity duration and ordered probit models for the number of tours, but the cost of this is that models treating different aspects of the travel pattern are independent. When making a decision, all previous decisions may influence the utility of an alternative, but just as in PCATS, the future utility considered is not consistent with the models of future choices.

In Albatross the behavioural assumption is that agents develop rules for which action to take in a specific state. Arentze and Timmermans (2004a) develop a decision tree where the probability in each leaf of the tree is given directly by observed choices. When it comes to location choice, the decision tree determine which out of three different rules that is used by the individual to determine the destination, and these rules may be sensitive to level of service attributes such travel times and costs. In each stage of the process, the model evaluates whether any time-space or household/institutional constraints are violated, in which case the decision is dismissed. The decision tree ensures that the probability of a choice is dependent on its history. A problem with the specification presented in Arentze and Timmermans (2004a) is that the probabilities in the decision trees are fixed so that the probabilities influencing the number of tours and trips performed may not be influenced by changes to level of service attributes.

Most of the above modelling frameworks assume that there is a specific order in which activities and trips are planned. ADAPTS avoids such a priori planning orders by allowing different planning orders for different trips (Auld and Mohammadian, 2009). Choices are made at specific discrete events in the simulation and planning of trips might not occur in the order in which they are performed. Previously planed activities are taken into account when a new event occurs. This means that some activities can be planned opportunistically while time space constraints imposed by previous activities are taken into account. They further do not assume a specific order in which other trip characteristics (timing, mode, destination) are planned. Each choice is further conditioned on previous choices but their effect on future choices is, as in Albatross , CEMDAP and PCATS, not considered.

2.2. *Random utility based models*

Most random utility based travel demand models are based on MEV models in one form or the other, like the MNL model in Adler and Ben-Akiva (1979) discussed above. The underlying assumption is that people have transient (can order alternatives consistently) and complete (can rank all alternatives) preferences and thus act as if they were utility maximizers. Just like the model in Adler and Ben-Akiva (1979), individuals are usually assumed to make a joint choice of all trips during a day, but to obtain operational models certain aspects of the choice are typically simplified. Especially the treatment of time is usually very weak, so that just as in some of the rule based models discussed before, the conditional probability and utility of trips can be treated independently from each other. The space dimension is another problem. As trips can be made from each location to each other location, the number of possible tours increases quadratically, cubically or even quartically with the number of alternative locations if two, three of four different destinations are allowed in each tour. To avoid the computational complexity arising from this combinatorial problem it is common to either restrict the type of tours that the model can represent and/or only consider a subset of the locations for each individual.

Building on the same NL framework, Bowman and Ben-Akiva (2001) developed a similar but more detailed system where secondary tours are modelled conditional on a primary tour. They allowed tours with multiple trips, but only a single location and mode was modelled for each tour. Timing of trips was modelled without taking level of service variables into account. Secondary tours are chosen independently of each other restricting the consistency of the model. Especially time choices becomes impossible to include in a consistent matter due to this assumption. In Bowman and Ben-Akiva (2001), they further sample 8 locations out of 786 for estimation. The modelling framework has been continuously developed and in an implementation named SACSIM (Bradley et al., 2010), time-of-day choices are done at 30 minute intervals and tours are allowed to have multiple stops with multiple modes. To allow for this increased complexity, approximations are made throughout the modelling system. Level of service variables may only take four different values depending on time-of-day, allowing log-sums to be reused extensively. They further estimate the model sequentially, reducing computation time at the cost of efficiency. Log-sums that integrate upwards are further obtained using approximations. For example, when considering the destination of a trip, the log-sum for each mode is calculated using a randomly assumed draw. This means that time pressure will have very limited effects on destination choices as well as the number tours and trips performed.

The current travel demand model of Stockholm (Sampers) is based on a Nested-Logit (NL, a special case MEV model) structure consisting of one level determining the number of tours in a day; one level for time of day for each tour; one level determining mode used on each tour; and finally one level determining destination (Beser and Algers, 2002). To become operational, the model only allows one trip per tour and only considers two time periods (peak and off-peak). Since each tour is only have a single destination, they avoid the computational complexity otherwise inherent to the destination choice, but they cannot predict the effects of policies which affect trip-chaining. A slightly more advanced model was presented in Algers et al. (1996), called SAMS. It allowed for household interaction and models tours, but no timing decisions were included. Sampling of locations were used to enable the modelling of tours.

Kitamura (1984) introduced a model for trip chaining with a possibly infinite number of trips, through the concept of a location specific *prospective utility*. The prospective utility is given by an implicit equation system. Individuals are assumed to take into account their possible future trips whenever deciding on a location, and are allowed to value future utilities higher or lower than present. The utility of an alternative contains a random term, but the expectation of this random term is not incorporated in the prospective utility, but otherwise the model would have been a Dynamic Discrete Choice Model (DDCM) within the framework later presented in Rust (1987). They did not include any time dimension, so an infinite number of trips could potentially be made. Building on this framework, Dellaert et al. (1998) introduced a multiple-purpose, multiple-stop model for shopping trips. They calculate the expected future utility correctly (as a log-sum) and include nesting but only allow for a limited number of trips and similarly do not include any time dimension.

2.3. *Emergent and alternative approaches*

In the discrete choice approach in Adler and Ben-Akiva (1979), Bowman and Ben-Akiva (2001) and Algers et al. (1996) the choice set consisting of all alternatives must somehow be specified, and the choice probability of a specific alternative somehow related to the utility of that and all other alternatives in the choice set. A different way to formulate the choice of the optimal travel pattern subject to time space constraints would be to mathematically formulate the set of feasible travel patterns using constraints on, e.g., arrival times in a mixed-integer optimization problem. This is done in the Household Activity Pattern Problem (HAPP) (Recker, 2001; Recker et al., 2008; Kang and Recker, 2013; Yuan, 2014). HAPP currently models the choice of time-of-day, modes and location choices as well as the number of trips and tours for a full day for all members of a household. Although a promising approach, the method is very computationally demanding, currently restricting its usage for large scale simulation. Finding the optimal daily travel pattern for a household is a very time consuming task even for relatively small problems. With 19 location, the computation time was reported to an average of 614 s (Kang and Recker, 2013). It further requires linear-in-attributes utility function, as it relies on efficient linear optimization algorithms to find the optimal pattern for each household (Yuan, 2014).

Yet another approach is proposed in the multistate supernetwork model, initially conceptualized in Arentze and Timmermans (2004b) and recently developed further to include time space constraints (Liao et al., 2013) and durational choices in a dynamic network (Liao, 2016). In their model, individuals make sequential choices of mode, route, location and duration for all trips in a tour or a day consisting of a predefined number of activities. They also allow individuals to park their car. Supernetwork refers to the interconnected networks between different modes, requiring additional links to take changes of modes into account. Multistate refers to the need of multiple states to remember what has been done in the past and what activities that are still left to be performed. This is again a very interesting approach, but it seems as if the computation time would currently be a limiting factor just as in HAPP. In Liao (2016), performing the choice of a daily travel pattern takes 8 s when an individual choose how to 1) drop of children before work and 2) choose one out of 6 shopping locations after work using a private vehicle or public transport. Estimation of the model may also be a remaining issue. They estimate parameters using separate MNL models for different choice dimensions in Liao et al. (2017), but when simulating alternatives in Liao (2016), a shortest path algorithm is usually used. It thus seems as if the estimated model so far would be inconsistent with the models used for simulation.

MATSim is an activity based multi-agent simulation framework. It is has been used to simulate full travel patterns for tens of millions of agents, load their travel plans onto a network and iteratively update the travel patterns until convergence (Horni et al., 2016). Agents considers the joint choice of a full daily travel pattern, conditional on the number activities to be performed during the day. This is modelled separately and independently before simulation starts (Horni et al., 2016). During simulation, agents choose between travel patterns considering route (Lefebvre and Balmer, 2007), mode (Grether et al., 2009), timing (Balmer et al., 2005) and location (Horni et al., 2011) of all trips. However, rather than attempting to find the optimal travel pattern, an algorithm is used to generate, modify and improve alternatives. Based on certain rules, it is added to a choice-set consisting of a few alternatives of travel patterns, and finally an MNL model is used to select an alternative from the obtained choice set. Besides lacking choice of travel patterns, estimation has been a challenge although the a recently developed algorithm in Flötteröd (2017) might eventually solve this problem.

In his thesis, Danalet (2015) presents a model for the choice of activities and their timing in the context of pedestrians in a university campus. Just as in Adler and Ben-Akiva (1979) the choice of a travel pattern is given by an MNL-model. However, to avoid the need to construct a choice-set, which cannot be used for simulation and which might be hard if the number of alternatives is large, Metropolis Hastings (MH) algorithm is used. The MH-algorithm was suggested for simulating paths in a route choice model in Flötteröd and Bierlaire (2013), but could similarly be used to simulate a choice set to use for estimation. The problem discussed in Danalet (2015) is of a very small scale as location and mode choices are excluded and only a few time periods is included. However, the technique is worth highlighting as it could potentially be generalized to more dimensions and as estimation is still a large problem in the models discussed above.

2.4. *Conclusion*

From the above overview of existing travel demand models, some conclusions can be made. In the activity based approach, interdependence between choices are often highlighted and it is often suggested that this could be obtained by considering the full utility of a day including the utility of all travel and activity episodes. Assuming that households (or individuals) consider the joint daily travel pattern in a way that could be formulated by a utility function has been the starting point for many of the models: including the model by Adler and Ben-Akiva (1979); STARCHILD (Recker et al., 1986a,b); AMOS (Kitamura et al., 1996); AURORA (Timmermans et al., 2001); HAPP (Recker, 2001); MATSim (Horni et al., 2016); The multistate supernetwork model (Arentze and Timmermans, 2004b); and the activity-path choice model in Danalet (2015). In trip-chaining over a tour, the same assumption has been made in Kitamura (1984) and Dellaert et al. (1998). In STARCHILD, AMOS and AURORA, the underlying assumption is that households cannot find the optimal travel patterns, and various models attempting to mimic this decision making process is therefore developed.

In MATSim , individuals are not searching for the optimal travel patterns but a process that perturb and change alternatives that may eventually lead to the optimal solution is generated, giving some similarities to the above discussed models but without mimicking any actual decision process. Note that MATSim could be seen as a computational process model, as the once discussed above, if the way in which alternatives are generated to the choice set is considered to represent how people actually find new alternatives. Just as in AURORA, SAMS and STARCHILD, some random process is used to generate alternatives that are evaluated based on the full utility of the travel pattern they represent.

In MEV based models, as in Bowman and Ben-Akiva (2001), the utility of all travelling in a full day is usually considered. The presented NL models could be interpreted as the joint choice of a full travel pattern tp just as the one in (1), but where the random error component in the utility $U(tp)$ of a specific travel pattern tp is correlated over alternatives in the same nest. This random term could be decomposed into one random term for each nest. However, it is still a joint choice of a full daily travel pattern from the universal set of feasible travel patterns TP. Due to restrictions in the dependencies between choices, these models cannot be guaranteed to fulfil any time-space constraints and cannot be interpreted as such a choice. There does not seem to be any model within the logit family which is able to jointly treat all the interdependent aspects of a daily travel pattern.

Although a few models have been proposed and are being developed on the assumption that individuals act as if they maximize the utility of a day, no model in which agents actually try to find the optimal pattern has managed to overcome the computational burden of the problem. If to be used for large scale traffic simulation, the multistate supernetwork and HAPP both needs to overcome significant computational challenges.

To conclude, treating the interdependent choice of a travel pattern has been the goal of many activity based travel demand models up to date. However, models which succeed in this aim are either not consistent with microeconomic theory or are prohibitively time consuming to evaluate. Models within the MEV framework have been very attractive in practice partly because of their microeconomic foundation, but are so far weak in their treatment of time. Especially, before the work on this thesis started, there were no model in the literature combining the benefits of: a MEV model which can be used for appraisal and to produce accessibility measures and; a model which interdependently treats the choice of a full daily travel pattern.

3. DAY-TO-DAY DYNAMICS IN TRAVEL BEHAVIOUR

The models considered in the previous section all focused on the generation of a daily travel pattern. However, the need to perform activities on a specific day may be influenced by the activities performed in the past as well as plans for the future. Individuals might have weekly recurring activities that they wish to perform on a certain day every week. Flexible working schedules might allow them to work more on certain days and less on other, but most people must on average spend a specific amount of time working each day. Certain maintenance activities must also be performed with certain frequency, such a grocery shopping. Social and recreational activities might also be subject to a growing need if they are performed too seldom, or a fatigue if they are performed to frequently. As noted in Kitamura et al. (2006), "a need for grocery shopping does not arise when there is an adequate level of food stock at hand. [...] Likewise, a typical individual would not have the desire to go to the movie theater everyday". Most individuals need to sleep a certain amount of hours each day, but variations in their sleeping patterns is still be possible over the course of a week. There are further strictly monetary restrictions on what and how often activities can be pursued, Individuals may not afford to perform certain activities to frequently even if they desired to do so. All in all, there are many reasons to believe that a considerable amount of day-to-day dynamics in a systematic way affect how households plan their activities on a specific day. To the extent that day-to-day variability in travel behaviour is systematic, accounting for it may improve predictive power of a travel demand model as it explicitly includes factors that otherwise must be treated as unobserved heterogeneity. Treating long term constraints as unobserved heterogeneity might further over-predict households ability to change their behaviour due too changes that affect every day, and under-predict their flexibility with respect to changes that only influence a single day. This dynamics is necessary to account for if the goal is to investigate how a policy that directly only impacts certain days may have a spillover effect on other days. One such question could be how congestion charge on weekdays affect traffic on weekends.

A lot of research has been conducted on the extent with which individuals behaviour varies between days. This of course requires the availability of travel surveys following the same individual for an extended time period. Whereas large cross sectional travel surveys, including tens of thousands of individuals for a single day, are gathered frequently by traffic authorities world wide, relatively few high quality longitudinal data sets following the same individuals for an extended time period has historically existed. One reason for this is the challenge in convincing individuals to put in the time needed to fill in such surveys for every day during, e.g., 6 weeks, making such surveys costly. The research that exist on the subject has therefore historically been based on relatively few surveys. The 1971 Uppsala Household Travel Survey represent one such data set, where 149 individuals from 94 households participated for 5 consecutive weeks (Hanson and Huff, 1982; Huff and Hanson, 1986; Hanson and Huff, 1986, 1988). Another much used data set is Reading Activity Diary Survey from 1973, following individuals for 7 consecutive days, which was used by Pas and Koppelman (1986); Pas (1988, 1987). Mobidrive followed 317 individuals from 139 households over 6 consecutive weeks in 1999 (Axhausen et al., 2002). This data set has given rice to a very large amount of research on day-to-day variability, e.g., Bhat et al. (2004b), Bhat et al. (2005), Cirillo and Axhausen (2010), Cherchi et al. (2017). More recent years has seen a rapid increase in the number of longitudinal data sets, e.g.,: the Toronto Area Panel Survey following 423 individuals from 271 households for two separate weeks and used in, e.g., Buliung et al. (2008); Termida et al. (2016) followed 69 individuals for four times two weeks to investigate their adaptation to a new tram service. With the arrival of smartphone based survey applications, e.g., MEILI (Prelipcean et al., 2017), it is probable that long term data sets will become much easier to gather in the future as they greatly reduces the burden for both respondents and researchers.

The lack of large scale longitudinal travel surveys might be one reason why so few travel demand models to date include day-to-day dynamics. As such data is becoming increasingly more common and will become easier to collect, it is definitely time to include day-to-day planning in travel demand models. The research on day-to-day variability up to date could largely be divided into two parts; the first part focusing on if and how individuals are habitual in their behaviour and in measuring variability in different respects; and one part focusing on building models based on this knowledge.

3.1. *How systematic is variability in travel behaviour?*

Early research into day-to-day variability in travel behaviour argued that the assumption of habitual travel was implicit or explicit in most travel research (Hanson and Huff, 1982). This assumption was considered an argument for the sufficiency of one-day-data. Indeed, if an individual behaves more or less the same each day, the variability which is needed when estimating models will be superior in a data set with many individuals over single days rather than few individuals over many days. Further, variability in individuals travel behaviour is not a problem and the knowledge about it may be of little usefulness in transportation planning if it is purely random. Most models assume that the utility of a day contains a random component, and if the day-to-day variability was purely random it would simply imply that the randomness was unique for an individual and day. However, if there are patterns in the variability that can be explained by non-random factors, these non-random factors can indeed improve travel demand models.

Especially early research focused on methods for assessing the amount of intra-individual variation, on analysing how day-to-day variation was influenced by socio-demographics and to quantify the amount of variability in data due to intra-individual or inter-individual variability. Hanson and Huff (1982) motivates the research into day-to-day variability by asking: "But how much variability exists in a habitual pattern of behavior? What kind of systematic, cyclical, temporal variability in behavior does the one-day window on an individual's travel ignore?" (p. 18). As a first step towards answering this question, Hanson and Huff (1982) divided each trip link into one of several equivalence classes and measured the degree of similarity between two travel patterns by the number of trip links they had in common. In Hanson and Huff (1986), they identified five different travel behaviour groups using principal component analysis and analysed the socio-demographics related to each group. Huff and Hanson (1986) analysed the degree of repetition and variability among full daily travel patterns and find a combining a number of archetypical days could cover most different daily patterns for each individual. Pas and Koppelman (1986) analysed socio-demographic factors effects on day-to-day variability and found that the time-space constraints imposed by work restricted variability, as well as a lack of access to travel resources. Being responsible for household errands naturally increased the variability. By estimating models of the trip-making behaviour of individuals, Pas (1987) found that intra-individual variability accounted for a substantial degree of the total variability in the data set. In a later paper, Pas (1988) combined sets of daily travel patterns into weekly travel patterns and analysed how socio-demographics was related to the choice of such weekly travel patterns. Kitamura et al. (2006) analysed the departure time for work in the morning, and discuss how the impact this has on the possibility to perform future activities through its effect on the time-space prism. Buliung et al. (2008) analysed the variation in choice of locations and find that a great variability exists especially for discretionary activities, although repetitious use of the same locations are also relatively common.

Specifically focusing on the extent to which this variation had a systematic component, Hanson and Huff (1988) analysed if specific behaviour was more likely to occur regularly (with little variation in waiting time between episodes) or clustered (recurring shortly after previous episodes) rather than randomly. They find that both types of non-randomness was visible for all activity types. However, for most individuals it was not possible to neglect the null-hypothesis that the number of days between two occurrences was random. This still indicates that inclusions of a systematic component to account for day-to-day variability could be beneficial, but that randomness may play a bigger role than systematic variation.

The waiting time between trips with a particular purpose could naturally be analysed using hazard models. Kim and Park (1997) used a latent-class model to divide households into regular and erratic shoppers. They find that people with high opportunity costs for grocery shopping, indicated by children and employment status, was more likely to exhibit a regular shopping behaviour. Households with low opportunity costs were more likely to shop erratically or randomly. Similarly, Bhat et al. (2004b) used a latent class model where two classes of non-parameteric hazard functions where estimated. One class represented more erratic and one more regular shoppers, where regular shoppers had a slightly increasing hazard that was at its maximum 7 days after a previous shopping trip. Bhat et al. (2005) developed a joint hazard model for grocery shopping, maintenance shopping, social, recreational and personal shopping trips. They find that the shopping hazard is increasing with time whereas the hazard for other activities are more or less flat although with a rhythmic weekly pattern.

Using Mobidrive data, Cherchi et al. (2017) finds that the individual specific component of cost and time parameters related to mode choices were correlated over day-of-week rather than over days within the same week for a specific individual. Cirillo and Axhausen (2010) uses the same data but analyse the error component with respect to activity choice. They find that for activity choice, the model with error components unique for each day and individual is better than those accounting for panel effects over day-of-week, week or full survey. They further find that the number of days since an activity was last performed has a significant positive impact on the probability that it should be performed again for all activity types analysed, indicating a systematic component in the day-to-day variability.

3.2. *Models for day-to-day planning of activities*

From the previous section on travel demand modelling it was clear that considering the utility of a full daily travel pattern was the goal in many models. This is possible and conceptually straight forward as a travel pattern has an obvious start and end after which no more trips are performed. When considering multiple days there does not exist any obvious boundaries on the history and future to consider. The time horizon to be considered must therefore be determined by the researcher. A day-to-day model should firstly treat the history and specifically how the probability to perform an activity on a specific day is dependent on the history. It should secondly treat the future, and how individuals make the trade-off between performing an activity today or in the future. When it comes to the history dependence, many proposed models use the same approach, namely having some sort of state related to the history and having the utility of performing an activity on any given day be dependent on the state. These models thus resembles Markov decision processes in that all the important parts of the history can be captured in a state, and the actions performed influences the state in the next time period.

A problem facing models of day-to-day planning is how to treat the future, or how to define a finite time period of analysis. It has been quite common to assume that individuals consider a week at a time, thus extending the unit of analysis from a day to a week. Individuals are then assumed to act as if they maximized the utility of their actions during that week. One example of this is Hirsh et al. (1986), where individuals are taking previous actions performed during a week as well as the remainder of that week into account when making their decisions. The choice is modelled as a sequence of choices according to a Logit model, where the utility considered during each day is decomposed into two parts: the utility of a decisions on a specific day conditional on the history; and the expected utility of the remaining week conditional on that decision.

In Habib and Miller (2008) individuals are seeking to maximize the utility of their actions over a week. Kuhn-Tucker optimality conditions are used obtain optimal weekly schedules for each individual, where the utility of an activity is conditional on when and whether it has been performed in the past. They accept suboptimal solutions to this problem rather than searching for the global optimums arguing that individuals do not act as if they were global optimizers.

Rather than following a utility maximizing approach, Kuhnimhof and Gringmuth (2009) assumes that individuals has a set of activities, agendas, that they wish to perform during a week. They then schedule each day so that it includes as many as possible of the remaining activities in the agenda. Based on how similar simulated individuals are to observed individuals, they are assigned agendas from the data. Within each day they use a local search algorithm to find sub-optimal schedules that satisfy all time-space constraints.

Two models where individuals only take the history into account but where a detailed treatment of within-day travel are obtained is presented in Cirillo and Axhausen (2010) and Märki et al. (2014) respectively. In Cirillo and Axhausen (2010), a tour-based nested-logit model is used for within-day planning and a combination of mixed-logit and history dependence is used to capture day-to-day dynamics. The utility of performing an activity is then linearly dependent on the number of days since it was last performed, and a significant increase in utility of performing an activity with time is obtained for all activities treated. Instead of a growing need for activities, Märki et al. (2014) assume that individuals have targets related to the frequency with which they wish to perform activities. A deviation from the target frequency causes discomfort, which has effects on the utility off performing the activity on that day.

Arentze and Timmermans (2009) introduced what they called a need-based model for activity scheduling on household level and later show how it can be estimated on single day data (Arentze et al., 2011). This model as presented in Arentze and Timmermans (2009) to some extent moves beyond pure history dependence. The utility of performing an activity is dependent on the need an individual has for that particular activity. The need evolves over time depending on what activities are performed. The effect any activity have on the need for any other activity can be considered given by a transition in the need-state, and the transition is parametrized so that it can be estimated from data. They finally assume that an activity is performed on the first day when the utility of performing that activity is greater than a certain activity and household specific threshold. These threshold values represents an individuals time-use opportunities for any given day, and if set correctly households should act close as if they optimized the long-term utility of their actions. The framework treats the choice of whether or not to perform each activity during a day as independent choices, as the threshold for each activity is treated separately.

3.3. *Conclusion*

A number of remaining issues can be identified in the above models of day-to-day planning. Firstly, with regards to models over a finite time horizon: Although it might be reasonable to assume that households or individuals have a finite time horizon in mind when they plan their activities, it is unlikely that they would not take the following day into account when pursuing activities on the last day of a period, or that activities performed right before the period started would not influence their actions in the beginning of the period. If a finite time horizon such as a week is used, a more feasible alternative would be to assume that they act as if they maximize the utility of an average week, but no model based on such an assumption has been proposed, probably because it is theoretically complicated.

Secondly, although it overcomes the problem with a predefined time horizon, assuming that individuals does not take future days into account when planning their activities is not realistic. Although it is possible that this assumptions allows capturing most of the intra-individual variability generated by day-to-day dynamics, it will likely predict unintuitive behavioural adaptation to policy changes. For example, if an individual needs to work extra hours or for other reasons have a full day on a Wednesday, it is likely that they sometimes perform maintenance activities such as grocery shopping on the preceding Tuesday anticipating their future lack of time. A myopic model, where individuals does not take the future into account, will never predict this behaviour. The same problem might occur when predicting adaptations to a weekday congestion charge. Individuals may adapt their weekend behaviour both because they have postponed certain activities during the preceding week, but also because they know that it will be costly to pursue them during the following week.

The only model that overcomes both these problems related to the time horizon is the need-based model presented in Arentze and Timmermans (2009), but it is uncertain if their threshold values actually allows obtaining an optimal long-term behaviour which they argue should is their goal. It is further not consistent with microeconomics, so it cannot be used for appraisal.

It would arguably be preferable if a within-day model of the choice of a travel pattern and a day-to-day model of activity scheduling were consistent with each other, so that the utility of a day including a specific set of activities as considered in the day-to-day model was related to the (expected) utility obtained from performing a travel pattern with this set of activities from the within-day model. Or similarly, that individuals considers not only the history but also the future consequences of their actions in the within-day model when choosing what activities to perform. Such history dependence in a within-day model is the case in Cirillo and Axhausen (2010) and Märki et al. (2014), but forward looking behaviour is then missing.

To conclude, before the work on this thesis started there were still no model which: treated day-to-day planning without a priori defined time horizons but with forward looking individuals in a micro economically consistent framework; or combined a within-day model with a day-to-day model including forward looking behaviour.

4. DYNAMIC DISCRETE CHOICE, A POSSIBLE WAY FORWARD AND REMAINING ISSUES

As the literature review in Section 2 suggest, an interdependent treatment of the choice of a travel pattern has been one of the main targets of activity based modelling. For this purpose it has been common to have a joint utility function for all the travelling and activity participation of a day. On the other hand, MEV models are attractive for the existence of a well developed welfare theory as well as accessibility measures based on the log-sum. But especially the treatment of time has usually been weak in existing MEV models, making them less suitable for analysis of policies affecting time usage or time-space constraints by changing, e.g., flexibility of working hours, school hours, or travel costs at different times of the day.

Outside the group of MEV models it is still a problem to obtain a micro economically consistent model which treats the joint choice of a full travel pattern. In particular, no such model currently exists which can both: be estimated; interdependently model the choice of the number of trips to perform, their purpose, timing, mode and destination; and be used for large scale travel demand forecasting in a reasonable time.

Furthermore, as highlighted in Section 3, no travel demand model combining within-day and between-day dynamics with individuals considering the future effects of their actions is currently available. Even models only treating day-to-day dynamics typically fall short in their treatment of the future. They often consider a limited time period only (e.g., a week) or assume that individuals are myopic. This is an unrealistic assumption which could lead to biased prediction results. This would especially be a problem when considering how people adapt to changes in the transportation system which only affects certain days of the week or disruptions they know will occur in the future.

This thesis involves developing a dynamic discrete choice model for both within-day and between-day modelling. Dynamic Discrete Choice Models (DDCM) treats choices as sequential in time where individuals are assumed to take the expected future utility of their actions into account when making decisions. The utility they obtain in a specific choice situation is further dependent on their past actions. A MEV-based DDCM takes a computationally tractable form and allows for a consistent treatment of time. As discussed before, this has been hard to obtain within existing MEV based travel demand models. A DDCM based travel demand model would still give an analytical consumer surplus in the form of a log-sum, which is a tractable property unique for MEV models.

In a DDCM model individuals take the history as well as the long-term consequences of their decisions into account. An individual can for instance experience a greater need for shopping as the number of days since the last shopping episode increases. When making decisions during a day, they may take this into account when determining whether or not to pursue a shopping activity, but also take into account the possibility and expected utility of shopping on a later day instead. As an other example, the may consider to work more on a certain day to leave earlier on another day, when they wish to pursue some other activity. The combination of within-day and day-to-day planning with forward looking agents is, as far as we know, unique to the proposed model. As mentioned in the introduction, DDCM models have been used extensively in related fields, for example treating career decisions (Keane and Wolpin, 1997), migration (Kennan and Walker, 2011) and retirement behaviour (Rust and Phelan, 1997; Karlström et al., 2004). The theoretical properties and estimation techniques are therefore well established and very large scale models has been implemented in the past.

A DDCM of travel demand has previously been proposed in Karlström (2005) and preliminary results from an early implementation together with numerical experiment on a very small example problem was given in Jonsson and Karlström (2005). Attempts to speed up the implementation was later done using a Restricted Boltzmann machine, a type of neural network which can be used for reinforcement learning, but they did not succeed in generating an operational model (Karlström et al., 2009). Jonsson et al. (2014) used an non estimated prototype model to obtain time-of-day and location specific log-sum based accessibility measures taking future time-space constraints into account. However, calculating the log-sum for a single individual with 30 possible locations, 60 time steps per day and time-space restrictions in the morning and afternoon, the implementation consumed 20 GB of memory and required 10 minutes of computation time. It is not conceptually difficult to estimate a DDCM, e.g., maximum likelihood could be applied using the Nested Fixed Point (NFXP) algorithm (Rust, 1988). However, given the computation time of previously proposed DDCMs of travel demand, directly applying NFXP would be extremely time consuming.

4.1. *Remaining issues*

As argued above, a DDCM travel demand model could potentially overcome many of the remaining issues with current daily and day-to-day activity based travel demand models. Still, in order to obtain such a model that could be used for policy analysis and travel demand forecasting a number of methodological issues had to be solved. These remaining issues are discussed below, and how the papers presented in this thesis has contributed to the solution of these problems will be discussed in Section 5.

Estimation

Due to the computational complexity of the model, directly applying methods available in the DDCM literature would not be possible. In order to estimate such a model, methodological developments related either to estimation techniques or approximative methods for computing the choice probabilities were needed. An estimation technique is presented in Paper III and I.

Simulation

Even if estimated parameters would have existed, previous implementations of the model were to slow to be used for forecasting purposes. The most complete implementation before the start of this thesis was further restricted to 30 locations, which is only a fraction of the total number of locations available. It was therefore necessary to develop a method that allowed simulation of travel patterns in a reasonable time.

At a first stage it was not necessary to obtain a model which could be used directly for travel demand forecasting. For this it is likely that some sort of sampling or approximative solutions will be needed, which is not dealt with in this thesis. The purpose was to allow evaluation without a priori restrictions on the choice set for a large group of individuals to 1) allow validation against data and 2) have a base model towards which approximate solutions can later be compared.

With the methodological development presented in paper III and I a new implementation of the model could be developed which can simulate an individual taking 1240 locations into account for each trip in 10 s for the single day model.

Correlation and scale of errors

In previous work on a DDCM travel demand model, all error terms were assumed to be i.i.d. over alternatives and time. Error terms are interpreted to model unobserved attributes to a choice or decision maker which influences the utility of alternative. If certain dimensions or attributes of a choice are not treated correctly, the size of this error will obviously be effected. Since a DDCM travel demand model consistently include the value of future time in the utility function, it is possible that a part of what would be treated as unobserved heterogeneity and captured by the error term in previous MEV models would explicitly be modelled by the expected value of future time. Even with this in mind, the assumption of i.i.d. error term is restrictive.

That the error term is independent implies that all unobserved attributes related to a specific alternative, such as mode, activity, arrival time to work, is unique in each state. If the same choice is simply perturbed in time, the random terms are thus assumed to be independent from the ones at a the previous point in time. Secondly, that they are identically distributed means that the variance of these unobserved attributes are assumed to be equally large with respect to all aspects of a choice.

Paper II and III are both discussing methods to overcome these restrictions..

Discounting between days

In previous work on DDCM travel demand models it was assumed that individuals discount the utility of future days. This was a restriction arising from the usage of an infinite horizon DDCM model, for which discounting has been needed in order for the model to be defined. A possibly more plausible assumption which would be more in line with previous work on day-to-day modelling would be that individuals act as if they maximize the utility on an average day or over an average week. In order to model such behaviour with a DDCM, an extension of the existing theory was needed which is presented in Paper V.

Lack of long-term decisions

Many constraints on an individuals daily travel behaviour are caused by long-term decisions. In a model described how people travel subject to such constraints, a number of attributes are assumed fixed, involving: car ownership; work location; home location; existence and location of school/childcare; and work hours and flexibility. The motivation for not treating these decisions is that they do not generally change on a daily basis, and they are especially not influenced by decisions on how to travel on a specific day. However, they have a profound impact on the way in which individuals plan their days and models for long-term decisions are therefore needed in conjunction with model for daily travel demand in order to correctly predict the effects of policies.

A car ownership model has been developed in Paper IV which could be seen as a first step in this direction.

5. CONTRIBUTIONS

This section will address how this thesis has contributed methodologically to the development of a DDCM of travel demand and thus contributing towards the main objective stated in Section 1. The developed model have the following properties which together, to the best of our knowledge, makes it unique in the literature:

Daily travel demand model

- The model treats an interdependent and joint choice of a full daily travel pattern including the number of trips to perform, their purpose, timing, mode and destination
- Time is treated consistently and time-space constraints are easily incorporated, so that individuals, e.g., considers how their morning departure time or mode choice in the morning influence their anticipated departure time in the afternoon, any associated costs, and any potential afternoon obligations.

Day-to-day model

- The utility of performing an activity on a specific day is dependent on the history and can, e.g., be dependent on the number of days since it was last performed.

- Individuals are assumed to be forward-looking, and consider the alternative of doing an activity in the future rather than today.

Combination

- The model is based on the MEV framework, so it is consistent with microeconomics and gives log-sum measures of consumer surplus
- Combines within and between-day model in consistent framework
- Produce log-sum measures of accessibility dependent on time-usage and time-space constraints

The theoretical problems that had to be addressed in order to operationalize such a model was outlined in 4 and how this thesis has contributed to the solution of these problems are discussed below.

5.1. *How to estimate a DDCM of travel demand?*

Paper I and III provides methodological contributions allowing estimation a large scale DDCM of travel demand and further provide estimation result for a new implementation of such a model. The proposed DDCM is an infinite horizon model, and a number of estimation techniques for such models exists in the literature. However, the very large number of states and possible actions makes direct usage of existing methods impossible due to computational limitations.

Paper III provides conditions under which the likelihood function of the infinite horizon model can be divided into two parts: one part dependent on daily decisions that influence transitions in day-to-day states; and one part for the choice of a travel pattern conditional on such a transition. Under the provided conditions, the infinite-horizon model can be estimated sequentially to obtain consistent parameters, by first estimating parameters which influence the choice of a daily travel pattern conditional on the day-to-day transition, and secondly estimate the remaining parameters which does not influence that conditional choice. Once parameters and log-sums from the within-day model are obtained, the remaining day-to-day problem is relatively small and standard methods (e.g., the NFXP method) can be applied.

Paper I provides a new specification of a single-day DDCM of travel demand, which is proved to be estimatable using sampling of alternatives. The method relies on the equivalence between an MNL-model of travel patterns and a specific type of DDCM. The DDCM formulation is useful for simulation, but too time consuming for estimation. The equivalence can therefore be used to simulate choice sets using the true model with some set of guessed parameters and estimate the model using the MNL-specification. As the number of alternative travel patterns is so vast, this equivalence could greatly improve the sampling procedure.

5.2. *How to use a DDCM of travel demand for simulation?*

When working on estimating the model, a new implementation with a greater focus on computational performance was developed for Paper I, II and III. In the current state, it takes around 10 s[2] to evaluate the within-day model for a single individual when 1240 locations are considered for the model presented in Paper II. The implementation is still too slow to be used for large scale simulation, as that requires hundreds of thousands of individuals to be simulated multiple times while iterating with a traffic simulation model. However, it enables the simulation of thousands of individuals in a reasonable time without any approximations. Any future approximative solutions can therefore be compared against the result of the full model. One obvious such approximation would be to sample a set of locations. As locations are both states (origins) and actions (destinations), the computation time increases quadratically with the number of locations, so if 100 locations were sampled the computation time could potentially be reduced to less than 0.1 s per individual. This is the direction taken in an ongoing project.

5.3. *How to relax the i.i.d assumption?*

In Paper II, a Mixed Logit specification is used to capture the panel effect over a day with respect to preferences for specific modes. This, as expected, turns out to have a large impact on the model fit. However, augmenting the state space by keeping track of whether or not a bike was brought from home had an even greater effect on the log-likelihood of the model, both in and out of data. In Paper III a Nested Logit model is used that in a similar way models the panel effect over a day with respect to the need to perform grocery shopping during that day. Both of these papers show that it is possible to introduce more complex correlation patterns a DDCM of travel demand.

5.4. *How to model average utility maximizing behaviour in a DDCM infinite horizon framework?*

Paper V develops a new methodology that allows infinite horizon dynamic discrete choice models with discount factors greater than or equal to one to be estimated. When the discount factor is equal to 1, the model describes agents who maximize the average utility per stage. In the context of day-to-day planning, it means that they act as if they maximize the utility of an average day (or average week).

Infinite horizon dynamic discrete choice models are common in the literature and is used in both Paper III and Paper IV in this thesis. If the time horizon is

[2]A single core on a 2.7Ghz Intel(R) Core(TM) i7-6820HQ CPU has been used for computation

infinite and people are assumed to discount the future, what happens in the very distance future will have no effect on their decisions today. The expected future discounted utility in any state given any decision rule is then also finite. This expected future utility is given by Bellman's equation and can be obtained using dynamic programming. This gives a one-stage problem (maximizing during one stage conditional on the expected future utility) and acting optimal according to that problem is equivalent to optimally solving the infinite horizon problem. However, if the discount factor is greater than or equal to one, the expected future utility will in general not be finite. Assuming that people discount the future is often reasonable and there may often be economic arguments that rationalize such behaviour. However, discount factors very close to one are often obtained in empirical work and the likelihood has been reported to increase as the discount factor approaches one (see, e.g., Rust, 1987).

The motivation behind paper V was partly pure curiosity; what happens to the model when the discount factor is actually equal to one, and what does it mean? Can some extension be made so that models can be estimated with discount factors greater than one, and will the optimal discount factor ever be greater than one? What is the behavioural interpretation of a discount factor greater than one in an infinite horizon setting? But the motivation was also practical, motivated by the intuition that to the extent that people actually do plan for the future, for example by planning when to perform grocery shopping, they might not (or at least everyone might not) discount future days. A discount factor equal to one might often be behaviourally reasonable, and it would be nice if statistical tests could be used to check whether the discount factor was actually significantly different from one.

In Paper V, conditions for the existence of a solution to Bellman's equation are given for infinite horizon dynamic discrete choice models. In the optimal stopping problem, it is further found optimal to act according to Bellman's equation when the utility of remaining in the system is negative. In the optimal stopping problem, a discount factor greater than one implies that an individual prefers to finish tasks with the highest costs first and/or reach the terminal state sooner than optimal. If a terminal state does not exist, acting according to a normalized version of Bellman's equation yields the maximum average utility per stage when the discount factor is one. When the discount factor is greater than one, no behavioural explanation is currently available.

5.5. *How to model long-term decisions?*

In Paper IV, a DDCCM of car ownership and usage is developed and estimated. The model can be used to forecast changes in car ownership on household level due to policies or changes in household demographics. It could thus potentially be used to generate a synthetic population or how households a will react to increases in fuel price or changes to income. It should however ideally use some sort of log-sum accessibility measure derived from the travel demand model to increase the model consistencies, but as it is estimated using register data rather than travel surveys this may pose a challenge.

5.5.1. *How to jointly model car ownership and mileage in a dynamic framework?*

Paper IV presents a DDCCM for a household's choice of car ownership, usage and fuel type. The model thus combines the continuous choice of mileage through an indirect utility function with the discrete choice of whether or not to purchase or scrap a car during a specific year. The model accounts for forward looking behaviour, so that households takes into account that they can sell a car at a later time when they purchase the car, as well as how much it decrease in value each year. Trade-off's in how to use cars with different fuel types is treated using a constant elasticity of substitution (CES) utility function for mileage. Discrete-continuous models as well as DDCM models have both been common in the car ownership literature, but the combination has seen much less treatment. This is likely because of the methodological challenges related to including a continuous choice in a dynamic model. This paper is therefore considered to provide a significant contribution in bridging the gap between discrete-continuous and DDCM models in general and for car ownership modelling in particular. In short, the model has the following properties which together is considered to makes it a contribution to the literature on car ownership modelling:

- Households make a joint decision of the number of cars to own, their fuel type and the mileage to drive with respectively car
- Forward-looking households, can sell/buy this year or in the future
- Combines discrete choice (number and type of cars) with continuous (mileage) in a dynamic model

6. FUTURE WORK

This section contains a number of directions for further research related to the DDCM of travel demand developed in this thesis.

Household interaction

Many decisions that an individual make are influenced by other members of the household and modelling household. This can be due to coordination of joint activities, usage of shared cars or division of household duties such as grocery shopping or escorting children. Treating this interactions could therefore improve travel demand models and is often considered an important part of the activity based approach (see, e.g., Recker et al., 1986a; Recker, 2001; Kitamura et al., 1996; Arentze and Timmermans, 2004a; Bhat et al., 2004c)

In the proposed DDCM of travel demand, household decisions regarding how to use shared resources (such as cars) or perform household duties (escorting children or doing grocery shopping) could be included before the day starts similarly to how grocery shopping is included in Paper III. Including decisions regarding joint dinners or joint activities at a specific time of the day may be possible by imposing time space constraints on both individuals. However, if decisions regarding joint activities should be taken within the day in a consistent manner it would require all household members to know the state of all other households members at all times. Such interaction may therefore be very hard to include in the proposed framework with reasonable computational performance. This is easier to include in models such as Albatross where individuals only considers previous decisions when determining what to do next.

Model specification

Many more variables could be included in the utility function. Firstly, there may be a need to include more variables related to socio-demographics. Secondly, the utility of time spent performing an activity is currently linear in time. It is possible that the model would benefit from a different utility function for activity duration, e.g., assuming that the marginal utility is decreasing with time (see, e.g., Horni et al., 2016) or using an S-shaped utility function like in AURORA (Timmermans et al., 2001).

Although research on the correlation structure has been started in Paper II and III, more development in this direction is needed. When it comes to the mixed-parameters, it is necessary to identify the parameters which provides the greatest improvement to the model fit while also improving the policy sensitivity of the model. In Paper II, constants related to mode choice were estimated to mimic a Nested Logit model, but estimation of cost and time parameters as in Cherchi et al. (2017) might be more interesting. It is possible that the best parameters to mix is dependent on the question the model should answer. For example, a policy influencing cost of travelling might benefit from a mixed cost parameter.

When it comes to the Nested Logit structure included in the day-to-day model in Paper III, it could be extended to include nests for other activities as well and some sort of cross-nested logit model could possibly be developed. Mai et al. (2017) recently showed how network based MEV models can be estimated using techniques from dynamic discrete choice theory, and similar ideas can therefore likely be used to estimate DDCM's with correlation patterns given by network based MEV models.

It may also be worthwhile to attempt to include nests within the daily model, making it similar to a Nested Recursive Logit model (Mai et al., 2015). This is not possible with the current estimation technique, but if approximations are made that speed up evaluation for simulation, it is possible that the same approximations could be used for estimation. The resulting estimates could then potentially be validated on the full model.

Long term decisions

There has so far been no work on connecting the proposed DDCM of travel demand with models for work location, working hours, home location, childrens school location and car ownership. Ideally, a joint model for these decisions should be developed by interacting with the log-sums from the travel demand model. At a first stage, it might be necessary to use separate models for different long-term decisions and use a synthetic population generator (e.g., Farooq et al., 2013) to generate a new population. It is common in practice that a feedback from models of short-term decisions back to models of long-term decisions are lacking and that certain choices (such as home location) is fixed (see, e.g., Bradley et al., 2010).

Traffic simulation and assignment

One of the main purposes with the development of the proposed model is of course to predict travel demand. Ideally, it should feed daily travel patterns to a traffic microsimulator such as MATSim (Horni et al., 2016) and reiterate with the obtained level-of-service until convergence.

When simulating a city, it may be necessary to simulate travel patterns for millions of agents multiple times to reach convergence. This is not computationally feasible with the current model specification, where one individual takes 10 s to compute. Methods to speed up the computation is therefore needed. One possible way forward is to sample locations considered by each individual. As mentioned before, the computation time increases quadratically with the number of locations. If 100 locations are sampled for each individual, the computation time per individual would be closer to 0.1 s. This would mean that 100 000 individuals could be simulated on a 12 core computer in less than 15 minutes. As it is possible to evaluate the model with 1240 locations, any sampling procedure can be evaluated with respect to the bias it adds on an aggregated level.

Research has been started in this direction, and preliminary results show that the bias obtained when using importance sampling to obtain 100 locations per individual and simulate travel patterns using these locations are negligible. A connection with MATSim has been implemented where the DDCM of travel demand simulates travel patterns and MATSim simulates route choice and return level-of-service matrices. The combination has further been jointly calibrated, in the sense that a fixed point is found where the level-of-service attributes used to estimate the travel demand model is the same as the level-of-service attributes obtained when MATSim simulates the travel patterns obtained using the estimated parameters.

7. CONCLUSIONS

This thesis presents a number of papers related to the ongoing development of a Dynamic Discrete Choice Model (DDCM) of travel demand. The model allows for a interdependent and consistent choice of an individuals daily travel pattern, including the number of trips and mode, destination, purpose and departure time for all trips conditional on potential time-space constraints. When considering what mode to use for a trip, an agent thus for example takes into account how it will affect the arrival time to that activity as well as the expected future arrival time home, which influence the future utility obtained from being at home. This makes it particularly well suited for analysis of policies affecting timing of trips (e.g., congestion charge) or time-space constraints.

The proposed DDCM of travel demand further allows for a consistent treatment of between-day and within-day planning where individuals take both previous and future days into account when choosing what to do within a specific day. This makes the model suitable for analysis of how people will react to policies only affecting certain days, or how they will react to anticipated disruptions in the transportation system or opening hours of different facilities.

Decisions are modelled sequentially in time and the model therefore allows for rescheduling during the day. It would potentially be possible to model individuals that explicitly consider uncertainty in, e.g., travel time when making their decisions.

As it is based on a MEV framework it can be used for cost benefit analysis as well as provide detailed accessibility measures taking into account time-space constraints. MEV based travel demand models have been commonly used in practice, but no previous implementation has managed to treat the joint choice of a daily travel pattern in a consistent way, and especially the treatment of time has been weak. The log-sum accessbility measures obtained could potentially be used to, e.g., analyse the effect of time-space constraints on expected wage.

This thesis includes an implementation of the proposed DDCM of travel dmenad for the city of Stockholm which was estimated using travel survey data. It further improves the model by relaxing the assumption of i.i.d. error terms, accounting for panel effects using a Mixed Logit specification for mode choice and a Nested Logit model for activity choice.

The thesis also includes a paper presenting a Dynamic Discrete Continuous Choice Model (DDCCM) of car ownership, jointly modelling usage, ownership and fuel type with forward looking agents. Since it treats the combined choice of ownership and mileage, it is usefull for comparing the efficiency of policies affecting running cost or ownership costs against policies affecting transfer costs. It could also potentially be useful for analysis of how households will react due to future increased availability of electrical vehicles with a lower running cost and higher initial price than conventional cars.

Finally, the thesis includes a paper which shows how and when infinite horizon DDCMs can be estimated with discount factors equal to one or above one. It further shows that in the general infinite horizon case, a discount factor of one implies that agents maximize the average utility per stage. In the optimal stopping problem/terminal state problem, the value function has a solution whenever the maximum one stage expected utility obtained in any state outside the terminal state is negative. In such cases, a discount factor greater than implies than an agent maximize the total remaining utility before the terminal state is reached, but such an agent would prefer to take high costs early and/or reach the terminal state as soon as possible. The result is used in the day-to-day model, where individuals thus can be assumed to act as if they maximized the utility of an average week, rather than as if they calculated the expected future exponentially discounted utility of their action.

REFERENCES

Adler, T. and Ben-Akiva, M. (1979). A theoretical and empirical model of trip chaining behavior. *Transportation Research Part B: Methodological*, 13(3):243 – 257.

Algers, S., Daly, A., Kjellman, P., and Widlert, S. (1996). Stockholm Model System (SIMS): Application. Volume 2: Modelling Transport Systems. In *World Transport Research. Proceedings of the 7th World Conference on Transport Research*.

Arentze, T. A., Ettema, D., and Timmermans, H. J. (2011). Estimating a model of dynamic activity generation based on one-day observations: Method and results. *Transportation Research Part B: Methodological*, 45(2):447 – 460.

Arentze, T. A. and Timmermans, H. J. (2004a). A learning-based transportation oriented simulation system. *Transportation Research Part B: Methodological*, 38(7):613–633.

Arentze, T. A. and Timmermans, H. J. (2004b). Multistate supernetwork approach to modelling multi-activity, multimodal trip chains. *International Journal of Geographical Information Science*, 18(7):631–651.

Arentze, T. A. and Timmermans, H. J. (2009). A need-based model of multi-day, multi-person activity generation. *Transportation Research Part B: Methodological*, 43(2):251–265.

Auld, J. and Mohammadian, A. (2009). Framework for the development of the agent-based dynamic activity planning and travel scheduling (adapts) model. *Transportation Letters*, 1(3):245–255.

Axhausen, K. W., Zimmermann, A., Schönfelder, S., Rindsfüser, G., and Haupt, T. (2002). Observing the rhythms of daily life: A six-week travel diary. *Transportation*, 29(2):95–124.

Balmer, M., Raney, B., and Nagel, K. (2005). Adjustment of activity timing and duration in an agent-based traffic flow simulation. In Timmermans, H., editor, *Progress in Activity-Based Analysis*, chapter 5, pages 91 – 114. Elsevier.

Beser, M. and Algers, S. (2002). Sampers — the new swedish national travel demand forecasting tool. In Lundqvist, L. and Mattsson, L.-G., editors, *National Transport Models: Recent Developments and Prospects*, pages 101–118. Springer Berlin Heidelberg, Berlin, Heidelberg.

Bhat, C., Guo, J., Srinivasan, S., and Sivakumar, A. (2004a). Comprehensive econometric microsimulator for daily activity-travel patterns. *Transportation Research Record: Journal of the Transportation Research Board*, 1894:57–66.

Bhat, C. R., Frusti, T., Zhao, H., Schönfelder, S., and Axhausen, K. W. (2004b). Intershopping duration: an analysis using multiweek data. *Transportation Research Part B: Methodological*, 38(1):39–60.

Bhat, C. R., Guo, J. Y., Srinivasan, S., and Sivakumar, A. (2004c). Comprehensive econometric microsimulator for daily activity-travel patterns. *Transportation Research Record*, 1894(1):57 – 66.

Bhat, C. R., Srinivasan, S., and Axhausen, K. W. (2005). An analysis of multiple interepisode durations using a unifying multivariate hazard model. *Transportation Research Part B: Methodological*, 39(9):797 – 823.

Bischoff, J. and Maciejewski, M. (2016). Simulation of city-wide replacement of private cars with autonomous taxis in berlin. *Procedia Computer Science*, 83(Supplement C):237 – 244. The 7th International Conference on Ambient Systems, Networks and Technologies (ANT 2016) / The 6th International Conference on Sustainable Energy Information Technology (SEIT-2016) / Affiliated Workshops.

Bowman, J. L. and Ben-Akiva, M. E. (2001). Activity-based disaggregate travel demand model system with activity schedules. *Transportation Research Part A: Policy and Practice*, 35(1):1–28.

Bradley, M., Bowman, J. L., and Griesenbeck, B. (2010). SACSIM: An applied activity-based model system with fine-level spatial and temporal resolution. *Journal of Choice Modelling*, 3(1):5–31.

Buliung, R. N., Roorda, M. J., and Remmel, T. K. (2008). Exploring spatial variety in patterns of activity-travel behaviour: initial results from the toronto travel-activity panel survey (ttaps). *Transportation*, 35(6):697.

Cherchi, E., Cirillo, C., and de Dios Ortúzar, J. (2017). Modelling correlation patterns in mode choice models estimated on multiday travel data. *Transportation Research Part A: Policy and Practice*, 96:146 – 153.

Cirillo, C. and Axhausen, K. W. (2010). Dynamic model of activity-type choice and scheduling. *Transportation*, 37(1):15–38.

Danalet, A. (2015). *Activity choice modeling for pedestrian facilities*. PhD thesis, École Polytechnique Federale de Lausanne.

Dellaert, B. G. C., Arentze, T. A., Bierlaire, M., Borgers, A. W. J., and Timmermans, H. J. P. (1998). Investigating consumers' tendency to combine multiple shopping purposes and destinations. *Journal of Marketing Research*, 35(2):177–188.

Eliasson, J., Hultkrantz, L., Nerhagen, L., and Rosqvist, L. S. (2009). The stockholm congestion–charging trial 2006: Overview of effects. *Transportation Research Part A: Policy and Practice*, 43(3):240–250.

Fagnant, D. J. and Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, 77(Supplement C):167 – 181.

Farooq, B., Bierlaire, M., Hurtubia, R., and Flötteröd, G. (2013). Simulation based population synthesis. *Transportation Research Part B: Methodological*, 58:243–263.

Fishman, E. (2016). Bikeshare: A review of recent literature. *Transport Reviews*, 36(1):92–113.

Flötteröd, G. (2017). A search acceleration method for optimization problems with transport simulation constraints. *Transportation Research Part B: Methodological*, 98:239–260.

Flötteröd, G. and Bierlaire, M. (2013). Metropolis–hastings sampling of paths. *Transportation Research Part B: Methodological*, 48:53–66.

Gärling, T. (1998). Behavioural assumptions overlooked in travel-choice modelling. In Ortuzar, J., Jara-Diaz, S., and Henshe, D., editors, *Travel behaviour research : updating the state of play*, pages 3–18. Elsevier.

Gärling, T., Gillholm, R., and Montgomery, W. (1999). The role of anticipated time pressure in activity scheduling. *Transportation*, 26(2):173–191.

Gärling, T., Kwan, M.-P., and Golledge, R. G. (1994). Computational-process modelling of household activity scheduling. *Transportation Research Part B: Methodological*, 28(5):355 – 364.

Grether, D., Chen, Y., Rieser, M., and Nagel, K. (2009). Effects of a simple mode choice model in a large-scale agent-based transport simulation. In *Complexity and Spatial Networks*, pages 167–186. Springer.

Habib, K. M. and Miller, E. J. (2008). Modelling daily activity program generation considering within-day and day-to-day dynamics in activity-travel behaviour. *Transportation*, 35(4):467.

Hanson, S. and Huff, J. (1986). Classification issues in the analysis of complex travel behavior. *Transportation*, 13(3):271–293.

Hanson, S. and Huff, J. O. (1982). Assessing day-to-day variability in complex travel patterns. *Transportation Research Record*, 891:18–24.

Hanson, S. and Huff, O. J. (1988). Systematic variability in repetitious travel. *Transportation*, 15(1):111–135.

Hirsh, M., Prashkea, J. N., and Ben-Akiva, M. (1986). Dynamic model of weekly activity pattern. *Transportation Science*, 20(1):24–36.

Horni, A., Nagel, K., and Axhausen, K. W. (2011). *High-resolution destination choice in agent-based demand models*. Eidgenössische Technische Hochschule Zürich, IVT, Institut für Verkehrsplanung und Transportsysteme.

Horni, A., Nagel, K., and Axhausen, K. W. (2016). *The multi-agent transport simulation MATSim*. Ubiquity Press London.

Huff, J. O. and Hanson, S. (1986). Repetition and variability in urban travel. *Geographical Analysis*, 18(2):97–114.

Joh, C.-H., Arentze, T. A., and Timmermans, H. J. (2003). Understanding activity scheduling and rescheduling behaviour: theory and numerical illustration. *Modelling Geographical Systems: Statistical and Computational Applications*, 70:73.

Joh, C.-H., Arentze, T. A., and Timmermans, H. J. P. (2005). A utility-based analysis of activity time allocation decisions underlying segmented daily activityâĂŞtravel patterns. *Environment and Planning A*, 37(1):105–125.

Jonsson, D., Karlström, A., Oshyani, M. F., and Olsson, P. (2014). Reconciling user benefit and time-geography-based individual accessibility measures. *Environment and Planning B: Planning and Design*, 41(6):1031–1043.

Jonsson, R. D. and Karlström, A. (2005). Scapes - a dynamic microeconomic model of activity scheduling. In *Proceedings European Transport Conference, 2005*.

Kang, J. E. and Recker, W. (2013). The location selection problem for the household activity pattern problem. *Transportation Research Part B: Methodological*, 55(0):75 – 97.

Karlström, A. (2005). A dynamic programming approach for the activity generation and scheduling problem. In *Progress in Activity-Based Analysis*, pages 25–42. Elsevier.

Karlström, A., Palme, M., and Svensson, I. (2004). A dynamic programming approach to model the retirement behaviour of blue-collar workers in sweden. *Journal of Applied Econometrics*, 19(6):795–807.

Karlström, A., Waddell, P., and Fox, D. (2009). Scaling up the microeconomic dynamic discrete choice model of activity-based scheduling. In *Proceedings European Transport Conference, 2009*.

Keane, M. P. and Wolpin, K. I. (1997). The career decisions of young men. *Journal of Political Economy*, 105(3):473–522.

Kennan, J. and Walker, J. R. (2011). The effect of expected income on individual migration decisions. *Econometrica*, 79(1):211–251.

Kim, B.-D. and Park, K. (1997). Studying patterns of consumer's grocery shopping trip. *Journal of Retailing*, 73(4):501 – 517.

Kitamura, R. (1984). Incorporating trip chaining into analysis of destination choice. *Transportation Research Part B: Methodological*, 18(1):67 – 81.

Kitamura, R., Fujii, S., et al. (1998). Two computational process models of activity-travel behavior. *Theoretical foundations of travel choice modeling*, pages 251–279.

Kitamura, R., Pas, E. I., Lula, C. V., Lawton, T. K., and Benson, P. E. (1996). The sequenced activity mobility simulator (sams): an integrated approach to modeling transportation, land use and air quality. *Transportation*, 23(3):267–291.

Kitamura, R., Yamamoto, T., Susilo, Y. O., and Axhausen, K. W. (2006). How routine is a routine? an analysis of the day-to-day variability in prism vertex location. *Transportation Research Part A: Policy and Practice*, 40(3):259 – 279.

Kuhnimhof, T. and Gringmuth, C. (2009). Multiday multiagent model of travel behavior with activity scheduling. *Transportation Research Record: Journal of the Transportation Research Board*, 2134:178–185.

Lefebvre, N. and Balmer, M. (2007). Fast shortest path computation in time-dependent traffic networks.

Liao, F. (2016). Modeling duration choice in space–time multi-state supernetworks for individual activity-travel scheduling. *Transportation Research Part C: Emerging Technologies*, 69:16–35.

Liao, F., Arentze, T., Molin, E., Bothe, W., and Timmermans, H. (2017). Effects of land-use transport scenarios on travel patterns: a multi-state supernetwork application. *Transportation*, 44(1):1–25.

Liao, F., Arentze, T., and Timmermans, H. (2013). Incorporating space–time constraints and activity-travel time profiles in a multi-state supernetwork approach to individual activity-travel scheduling. *Transportation Research Part B: Methodological*, 55:41–58.

Mai, T., Fosgerau, M., and Frejinger, E. (2015). A nested recursive logit model for route choice analysis. *Transportation Research Part B: Methodological*, 75:100–112.

Mai, T., Frejinger, E., Fosgerau, M., and Bastin, F. (2017). A dynamic programming approach for quickly estimating large network-based mev models. *Transportation Research Part B: Methodological*, 98(Supplement C):179 – 197.

Märki, F., Charypar, D., and Axhausen, K. W. (2014). Agent-based model for continuous activity planning with an open planning horizon. *Transportation*, 41(4):905–922.

McFadden, D. (1978). Modelling the choice of residential location. In *Spatial Interaction Theory and Planning Models*, pages 75–96. A. Karqvist (Ed.), North-Holland, Amsterdam.

Ortuzar, J. d. D. and Willumsen, L. G. (2002). *Modelling transport*, volume 3. Wiley.

Parry, I. W. and Small, K. A. (2009). Should urban transit subsidies be reduced? *The American Economic Review*, 99(3):700–724.

Pas, E. I. (1987). Intrapersonal variability and model goodness-of-fit. *Transportation Research Part A: General*, 21(6):431 – 438.

Pas, E. I. (1988). Weekly travel-activity behavior. *Transportation*, 15(1):89–109.

Pas, E. I. and Koppelman, F. S. (1986). An examination of the determinants of day-to-day variability in individuals' urban travel behavior. *Transportation*, 13(2):183–200.

Pinjari, A. R. and Bhat, C. R. (2011). Activity-based travel demand analysis. In De Palma, A., Lindsey, R., Quinet, E., and Vickerman, R., editors, *A Handbook of Transport Economics*, chapter 10, pages 213 – 248. Edward Elgar Publishing.

Prelipcean, A., Susilo, Y., and GidÃşfalvi, G. (2017). A series of three case studies on the semi-automation of activity travel diary generation using smartphones.

Rasouli, S. and Timmermans, H. (2014). Activity-based models of travel demand: promises, progress and prospects. *International Journal of Urban Sciences*, 18(1):31–60.

Recker, W. W. (2001). A bridge between travel demand modeling and activity-based travel analysis. *Transportation Research Part B: Methodological*, 35(5):481 – 506.

Recker, W. W., Duan, J., and Wang, H. (2008). Development of an estimation procedure for an activity-based travel demand model. *Computer-Aided Civil and Infrastructure Engineering*, 23(7):483 – 501.

Recker, W. W., McNally, M., and Root, G. (1986a). A model of complex travel behavior: Part i-theoretical development. *Transportation Research Part A: General*, 20(4):307 – 318.

Recker, W. W., McNally, M., and Root, G. (1986b). A model of complex travel behavior: Part ii-an operational model. *Transportation Research Part A: General*, 20(4):319 – 330.

Rust, J. (1987). Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica*, 55(5):999 – 1033.

Rust, J. (1988). Maximum likelihood estimation of discrete control processes. *SIAM Journal on Control and Optimization*, 26(5):1006–1024.

Rust, J. and Phelan, C. (1997). How social security and medicare affect retirement behavior in a world of incomplete markets. *Econometrica: Journal of the Econometric Society*, pages 781–831.

Samuelson, P. A. (1938a). A note on the pure theory of consumer's behaviour. *Economica*, 5(17):61–71.

Samuelson, P. A. (1938b). A note on the pure theory of consumer's behaviour: an addendum. *Economica*, 5(19):353–354.

Termida, N. A., Susilo, Y. O., and Franklin, J. P. (2016). Observing dynamic behavioural responses due to the extension of a tram line by using panel survey. *Transportation Research Part A: Policy and Practice*, 86(Supplement C):78 – 95.

Timmermans, H., Arentze, T., and Joh, C.-H. (2001). Modeling effects of anticipated time pressure on execution of activity programs. *Transportation Research Record: Journal of the Transportation Research Board*, 1752:8–15.

Vickrey, W. S. (1969). Congestion theory and transport investment. *The American Economic Review*, 59(2):251–260.

Yuan, D. (2014). *Incorporating Individual Activity Arrival and Duration Preferences within a Time-of-day Travel Disutility Formulation of the Household Activity Pattern Problem (HAPP)*. University of California, Irvine.