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School of Transportation Sciences

Master of Transportation Sciences

Master's thesis

Day-Activity Pattern Choice Modelling in Activity-Based Model: Case Study of FEATHERS

Alaa Meshref

Thesis presented in fulfillment of the requirements for the degree of Master of Transportation Sciences, specialization Transport Policy and Planning

SUPERVISOR :
Prof. dr. ir. Tom BELLEMANS

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dr. Muhammad ADNAN

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Preface

Since the current transportation system is facing a significant demand and as we are facing an environmental crisis, the need for a new adaptation is essential to reshape current systems. Since the old approach of building new roads has shown contradictory results, travel forecasting gained popularity since it is a robust approach for predicting the future demand and behavior of people in order to reshape current transportation systems and coming up with policy recommendations to tackle the increasing demand of mobility.

This thesis is an original work by Alaa Meshref of his master's thesis. The "Day-activity Pattern choice modeling in activity-based Model: Case study of FEATHERS" is oriented toward activity forecasting of future travel patterns. This dissertation has been written to fulfill the partial requirements for the master's degree in Transportation Sciences.

I would like to thank my supervisor Prof. dr. Tom BELLEMANS for his help and insights during my thesis. I also would like to thank co-promoter Prof. dr. Muhammad ADNAN for his help, guidance and feedback throughout my thesis. Their encouragement helped me in improving and developing this thesis. I appreciate their help done throughout my thesis period.

I want to thank my friends that even with the distance, their help and support were always there to encourage me. I also want to thank my friends here in Belgium that made this journey easier.

My biggest thanks go to my family for their help, support, encouragement, and patience during my studies. Without them, it would not be possible to be where I am.

Lastly, I want to thank you, the reader for taking the time to go through this paper.

Alaa Meshref

Hasselt, Belgium

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Summary

The rapid change in transportation and the high rate of congestion and emissions are concerning. Thus, traffic forecasting is crucial in order to find out the future behavior of people in terms of their overall activity behaviors. The scope of this thesis is to perform an estimation of activity-based model "ABM" facet, daily activity pattern "DAP" in Rotterdam, the Netherlands, and the Flemish region in Belgium.

While performing travel forecasting is a part of this thesis, however, it is not its main objective. A comparison of the results of these models took place to find out the differences in magnitude between these models. First, the result of the Rotterdammer model was compared with other results from the literature. After that, a comparison between the two results of Rotterdam and the Flemish region was conducted for the same reason

The paper included the accessibility measure in the data to observe the behavior of people while engaging with their day-to-day activities. Accessibility is not a new concept where it has been discussed in various of research. The aim of accessibility measures is to illustrate the returned benefits of a specific location to those who reside close by it. While there are different accessibility measure techniques, activity-based accessibility "ABA" has been used in this thesis.

Data used in this paper is relocation survey in the Netherlands (OViN) which consists of sociodemographic attributes in the area, the process of date collection started in 2010 and stopped in 2017. Multinomial Logit Model "MNL" that follows Random Utility Maximization "RUM" was used in the estimation process for DAP model. The study also compared the result of FEATHERS model with other models in the literature. Similarly, data from the Flemish region were also estimated to illustrate the DAP of the population and a comparison between these two regions are reported.

Overall, the results are logical but further investigation is needed for some of the results. Some household characteristics seem to positively influence the participation of activities such as: the size of a household, possession of public transportation subscriptions, driver's license availability for the most activities, urbanism of a location and accessibility. In contrast, the study showed that number of cars ownership and HH income illustrated a challenge in activity participation. On the other hand, data, data redundancy, and the objective of the study influence the results of the model estimation results.

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1. Introduction

As The globe is experiencing rapid growth in population and urbanization, congestion is increasingly becoming a major problem around the world (Song et al., 2016). A prediction of transport is now considered essential in different applications like transport planning and policy (Næss et al., 2014). Transportation systems are anticipated to endure rapid expansion in the upcoming years due to different socioeconomic factors. This expansion will result in different issues such as congestions, road safety-related problems issues and the generation of greenhouse gas emissions (Bao et al., 2019).

Throughout the years, different techniques were developed to predict travel demand in various forms (Bao et al., 2019). Since the 70s, a shift in the orientation of transportation planning from regional planning linked with investments in long-run strategies improvement in capitals to policy planning took place where the responses of people are the objective (Chu et al., 2012) this also resulted in the shift from the aggregate level to the comprehension of disaggregated level (individual's level) (Pinjari and, Bhat 2011). In 2014, a study by INRIX (an analytical company) and the Centre for Economics and Business Research (Cebr) showed that the combination of the yearly traffic jam cost (like reduction in the productivity and high prices of merchandise) in both Europe and the US will be increased up to $293.1 billion by 2030, almost 50% increase when compared to 2013 (Song et al., 2016). Thus, it is crucial to understand the travel behavior of people as it is changing through time so that the current transportation systems are reshaped to be aligned with the future changes.

The prediction of the future travel behavior of people is a sub-category of transportation planning to have a well-planned transportation system in the future (Siyu, 2015). To reach this goal, transportation planners utilize forecasting models where the combination of mathematical equations, simulation procedures, and realistic behavior are used to present the behavior of people and their decision-making. The core of transportation planning procedures is travel demand, where it is being used to measure the travel demand distribution and the amount of flow in alternative transportation systems (Siyu, 2015). The need for traffic modeling is not only to provide enhancement for proposed projects, but also to provide data for cost optimization, environmental impact, safety-related outputs, and addressing the level of pollution (Næss et al., 2014). Prediction of different dimensions such as mode choice, travel time, and purpose of trips can also be an indicator of the travel behavior of humans which can be also important when understanding to observe whether the behavior is converging or diverging from sustainable mobility. Activity-Based Models

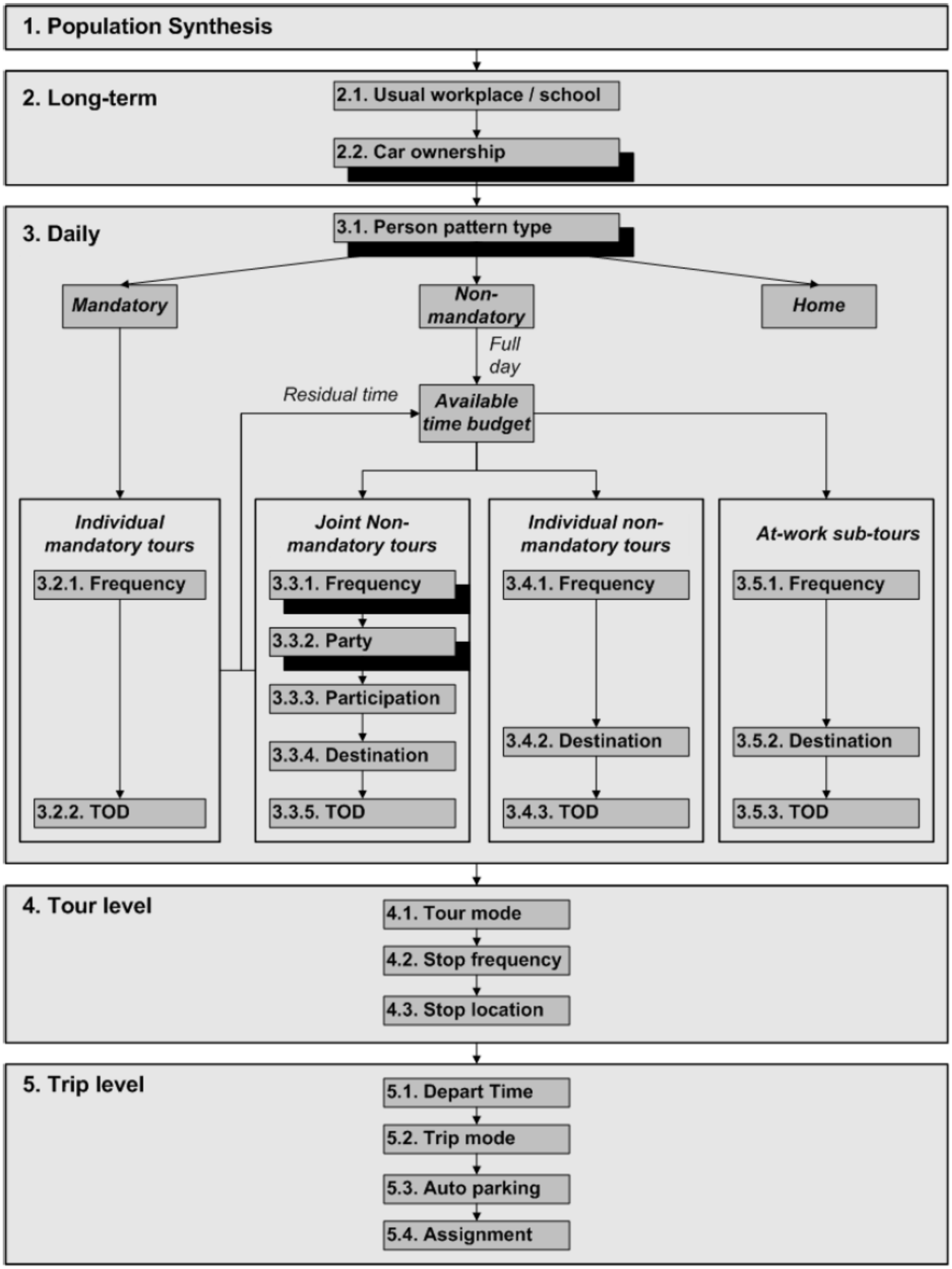


Figure 1. A typical activity-based model with linkages between facets. (Source: Atlanta Regional Commission, 2015).

(ABM) were invented to react to real travel demand models which can help analyze a broad range of policies (Delhoum et al., 2020).

Previously, modeling was done by the approach of Trip Based Travel Model (TBM) which was used in the late 50s of the previous century. This approach used the individual's trips as the analysis unit, and it has four steps: trip generation, trip distribution, mode choice, and assignment. However, this approach has some limitations and the concept of a derived demand of transportation was not reflected in the four steps (Chu et al., 2012) and was reported to always have insufficient evidence in reflecting travel behavior (McNally and Rindt, 2007). More on that, according to McNally et al. (2007), in TBM, the derived demand of transportation was comprehended and accepted yet not reflected. On top of that, these models have complexities such as the changing of trips where it neglects the restraints and chances linked with the scheduling of activities (at-home activities and other tours) (Bowman and Ben-Akiva, 2001).

On the other hand, the authors discussed ABMs where travel is considered as derived demand and according to Ben-Akiva and Lerman, (1985) cited by Bowman and Ben-Akiva (2001), this approach of disaggregated choice modeling (ABM) has been extensively utilized. According to Arentzea et al. (2011), the activity-based approach experienced growth and reached "adulthood" and the current applications of ABMs are replacing the trip-based models (Pendyala et al., 2005).

The early theory was developed by Torsten Hägerstrand (1970). Hägerstrand assumed that activities done by individuals are limited by some constraints both personal and social. Furthermore, Hägerstrand believed that people live in space-time prism, figure (2), and they would only work in different locations at different points. Hence, the theory postulated that going to a certain place (destination) at a specific time of the day by a specific mode of transportation is a result of the demand activity. Since then, activity-based travel caught the attention of researchers and experienced significant progress. Moreover, the representation of the output of this model in terms of choices has been better comprehended as a result of the research of the kind of activity behavior and travel decision making (Bowman and Ben-Akiva, 2001).

According to Hafezi, et al. (2019), the majority of activity-based models contain the following models: activity scheduler and generator, time of day, mode choice of the tour and trip, destination choice of the tour, and trip and network assignment. Figure (1) depicts a detailed typical ABM with linkages with other sub-models. Daily Activity Patterns (DAP) are considered the first output to be estimated as the rest of

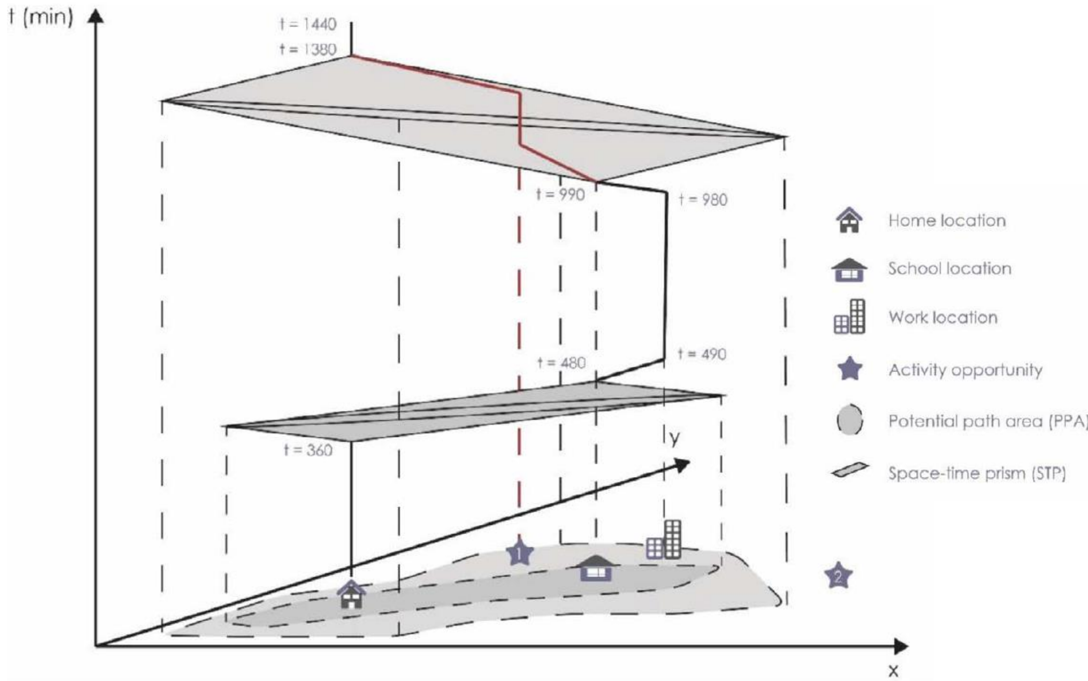


Figure 2. A space-time prism example. (Source: Fransen et al., 2018).

the outputs are conditioned by the activities to be performed and if there is any interaction between household members and any intermediate stop throughout the trip.

For running a ABMs estimation, data is needed to predict the future behaviors of individuals, one of the data needed is time-use survey data which represents the activities that individuals perform during the day (Pinjari and Baht, 2011).

1.1 Objective of the Study

This paper is focusing on the DAPs estimation of FEATHERS model in two regions, Rotterdam, Netherlands, and the Flemish region, Belgium. After performing the estimation of these two locations, the results of the Rotterdammer model will be compared with different DAP models results from the literature. Similarly, The Flemish model and the Rotterdammer models' results will be compared to find out the differences of the magnitudes of the estimated models and find their effectiveness in relation with ABMs as well as finding the factors that affect the decision making on their patterns.

Ben Akiva et al. (1996) mentioned three types of decision-making of individuals and households. Long-term (years) such as mobility and lifestyle, mid-term (daily basis) activity and scheduling of travel, and short-term (during the day). This thesis will help in understanding the daily pattern of individuals to help the implementation of policy in the demand side of transportation. DAP can be described as the activities that people engage in during a typical day where some of these activities have a priority that limits other facets. The approach that will be used in building the model is Multinomial Logit model (MNL) to develop an estimation of a sub-model for DAP which is considered to be the first sub-model of ABM.

This paper is intended to answer the main question:

- Do different observed travel behavior data sets lead to significant differences in the output of a daily-activity pattern model?
- How can we compare different daily-activity pattern estimation results?

This thesis is organized as following, section (2) will cover the literature review of ABM and DAP, the literature study objective, and their findings. In section (3) the methodology, data used, and background of FEATHERS model and accessibility methodology will be discussed. Section (4) shows the result of the DAP model for Rotterdam data, and the attributes influence individual's comparison between the Rotterdam model and different DAP models results of different papers. Section (5) shows the results of the Flemish model and a comparison between the Flemish model and the Rotterdammer model. Section (6) draws the conclusion and the findings of this thesis with future studies recommendations.

2. Literature Review

ABMs can be grouped into two categories, econometric activity-based models, and rule-based activity where the difference in these two models is the decision-making process. For econometric activity-based models, mathematical functions are used whereas for rule-baes models it is a computational process (Kitamura and Fujii, 1998). The approach of econometric ABM uses the equation of the econometric systems which mainly rely on the utility maximization equations which address the relation between the activity, the characteristics of travel, and estimate the decision result (Pinjari and Bhat, 2011). An advantage of econometric approach is hypothesis testing of alternatives with regard to the connection between activity-travel patterns, land use, and sociodemographic of individuals. However, one disadvantage of this approach is that it does not capture the decision-making process and the mechanism that led to the resulting travel behavior (Yasmin, 2016).

The concept of Random Utility Theory is that the decision-maker chooses the best choice out of available choices. The appearance of discrete choice models sheds light on the Random Utility Maximization "RUM" in the process of decision making in both activities and travel (Ben-Akiva and Lerman, 1985) cited by (Bowman and Ben-Akiva 2001).

Activity patterns are a number of activities and tours (a tour is a journey where the origin and destination is home) performed during the day, figure (3). The activity pattern models define the activity purpose and set one of these activities as a primary activity (Dong et al., 2006).

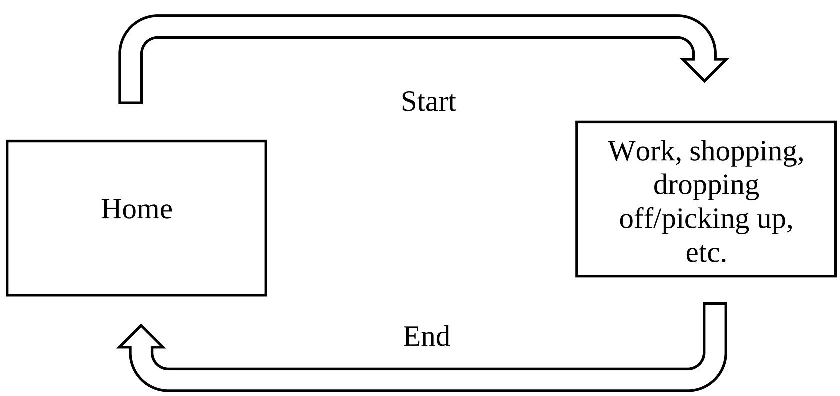


Figure 3. Home-based tour.

DAPs are the sequence of activities and travel that are performed throughout the day. Among all activities performed by individuals, activities such as going to work and school are constrained with spatio-temporal limits when performing various activities (Bowman et al., 2001). However, Pinjari et al., (2006) distinguished activities performed for workers, students, non-workers, and non-students. The authors classified students including adults who are 16 years old or older who go to work or school as well as children who are 15 years old or younger. Conversely, they distinct non-works and non-students for the adults who do not go to work or school and children who do not attend school.

According to Yamamoto and Kitamura (1999), activities are divided into two groups, obligatory (mandatory) activities, and non-obligatory (non-mandatory) activities. These mandatory activities are obliging individuals to engage in these activities in the time range, while on the other hand, non-mandatory activities are activities where individuals are optionally engaging in them.

2.1 Daily Activity Patterns Models

The demand of consumer choices is indicated by the choice that is made from a set of alternatives, furthermore, the understanding of the effects of the movement of people is achieved by grouping the mobility patterns of people. An example of a choice scenario is the type of activity that is made during a day: mandatory or non-mandatory. Some papers are focusing only on the activity sequencing (Bowman et al., 2001), some are focusing on the time spent on activities (activity scheduling) (Arentze and Timmermans, 2004), some papers are focusing on the interaction between household heads and some included all household members, all of these categories are discussed in this section.

A model was performed by Bowman and Ben-Akiva (2001) which considered DAP to consist of a set of tours. The model developed was a disaggregate utility-based estimation of activity-travel patterns for 24 hours that consist of a nested logit model of DAPs (purpose of the activities, priority of activities, and planning of activities of the day). In the study, each tour had two categories: a primary activity and a destination where the primary activity is the reason for making the tour and these tours had two sub-categories, primary tours, and secondary tours. Consequently, daily activity pattern was represented by primary tour, primary activity and the reason and the number of secondary tours.

Throughout the early years when discrete choice modules were established (in the early 1970s), there have been various of studies done to refine the activity-based model theory and to explore new sides influencing activity models. Pas and Koppelman (1987), examined the day-to-day variability in an individual's travel behavior, Pas (1984), cited by Bowman, and Ben-Akiva (2001), found that factors like employment, gender, and children presence influence the choices on activities and the pattern of travel. There have been many papers that developed ABM, such as Vovsha et al. (2002), Miller and Roorda (2003), Bhat et al., (2004), and Delhoum et al. (2020).

2.2 Rule-based Approach Models

An early review of the rule-based approach also known as Computational Process Models (CPM) is Gärling et al. (1994) where the authors argued about the ability of this approach to describe the choices made by individuals in more detail when compared with discrete-choice models without the loss of accuracy. However, Gärling and his colleague illustrated that a typical travel survey is inadequate for such modeling. McNally and Rindt (2008) considered CPM approach to be promising as it has the ability to acknowledge the complication related to holistic design with built-in reductionist components and they considered this approach to be a proving ground to examine the results of policy changes.

Recker et al. (1986) cited by Hafezi et. al. (2019) reported that activities that show similarities are recorded and crucial information (for example, activity start times and durations) are produced by the model. The authors developed a Simulation of Activity Responses to Complex Household Interactive Logistic Decisions (STARCHILD) which consists of three phases. First, all travel activity patterns are generated based on the desire and need of the household (HH) members as well as intra-household interaction which is performed by the algorithm of the model, then, the grouping of the activity pattern takes place to reduce choices sets. Finally, the representation of the pattern for each group category is distinguished by the logit choice model.

SMASH is a model for the scheduling of before-trip activity (Ettema et al., 1996). It estimates daily activity patterns in a sequence of individuals in terms of which type of activity to perform and the sequence of activities in relation to other facets. Different types of activities were presented such as in-home activities, in-home leisure, out-of-home activities, shopping, and out-home personal. The model schedules activities as a process of stepwise decision making meaning it stacks activities in a way that an individual can decide what activities to add from the agenda at any time of the schedule and has the ability to end the schedule by deciding to not add more activities.

Arentze and Timmermans (2004) developed ALBATROSS (A Learning-BAsed Transportation Oriented Simulation System) an activity generation model that sorts activities into two sets, flexible and fixed activities. The input data is a skeleton of data that are fixed scheduled, and the output is a list of mixed fixed and flexible activities. ALBATROS generates activity schedules and orders these activities for each individual being simulated, and when it comes to flexible activities, the model can add more activities to the activity episode. Some of ALBATROS applications were used to assess the emission of vehicles and other related environmental aspects (see Beck et al., 2009). Figure (4) illustrates the scheduling process that the model follows. FEATHERS is an activity-based model that was integrated from ALBATROS (Bellemans et al., 2010), the model has many applications in Flanders, Belgium (the case of Leuven's metro, Bao et al., 2018) and this model is used for this thesis.

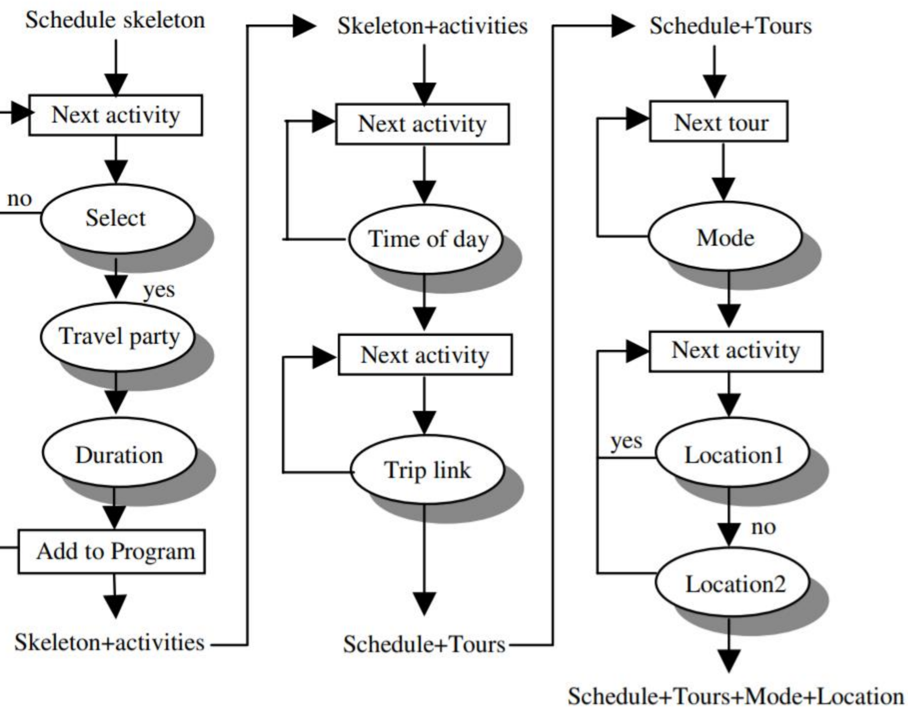


Figure 4. Scheduling process in ALBATROS. (Source: Arentze et al., 2004).

AURORA is an activity-based model and a dynamic model that was developed in Eindhoven, Netherlands (Arentze et al., 2010). The model fixes compulsory activities and sometimes it is empty in the scheduler at the developing the schedule of the day for the remaining activities on a typical day. The schedule is built from scratch at the start of the day and then it starts adding, removing, or shifting the activities, altering locations and altering tip chains choices in a prebuilt order. This is called an iterative process which is after the implementation of each stated change to the schedule will be updated by the utility until there are no more developments in the utility maximization. The simulation process begins at the start of each day. Each individual (agent) decides on its schedule of the day keeping in mind the availability of transport mode and based on that and the agent's comprehension of the land-use and transportation system, the agent evaluates travel, the route taken and time of day of the trip performed. After that, the schedule is placed in spatio-temporal and the execution of the schedule is conducted. The model is capable.

Kitamura et al. (1997) represented an analytical procedure for the generation of artificial DAPs and presented the ability of microsimulation to establish DAPs by using MNL. Authors used characteristics of individuals, characteristics of the household that the individual belongs to, home location, and work location to estimate two types of activity patterns, home-based, and non-home-based. The paper focused on home-based models which is a model associated with trips that start from home or activities that are reachable from home (home-based activity choice), and the identification of the trip purpose was done by identifying the primary out-of-home activity type. Mandatory activates were divided into five groups, work-related (work and school), activity-related with taking a household member, personal business, shopping, and social and recreational.

Meloni et al. (2007) developed a model for time allocation for non-compulsory activities. The model developed follow the form of nested logit which is used to duplicate a chain of coupled choices. The first-choice deals with splitting the non-compulsory time among activities performed in and outside the home. The second choice is below the first choice which recalculates the time between in-home and out-home and activities of trips inside and outside home. As a result, the model provided allows the analysis of the effect of each variable of the trips coming from the activities outside the home.

2.3 Econometric Approach Models

Models which considered to be econometric based are mainly following Random Utility Maximization theory (RUM) which assumes that individuals act rationally when it comes to decision making.

Lekshmi et al. (2016) examined the evolution of ABM in Thiruvananthapuram, India by using a MNL based on Random Utility Maximization (RUM). The study examines 15 analysis zones taking into account the socio-economic and travel pattern factors while data used were divided into two sources, from a survey showing socio-economic and travel characteristics and national data showing population. In the authors' study, data were sorted into groups and activities were divided into four categories, home-work based, home-based education, home-based shopping, and home-based other tours.

The Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns

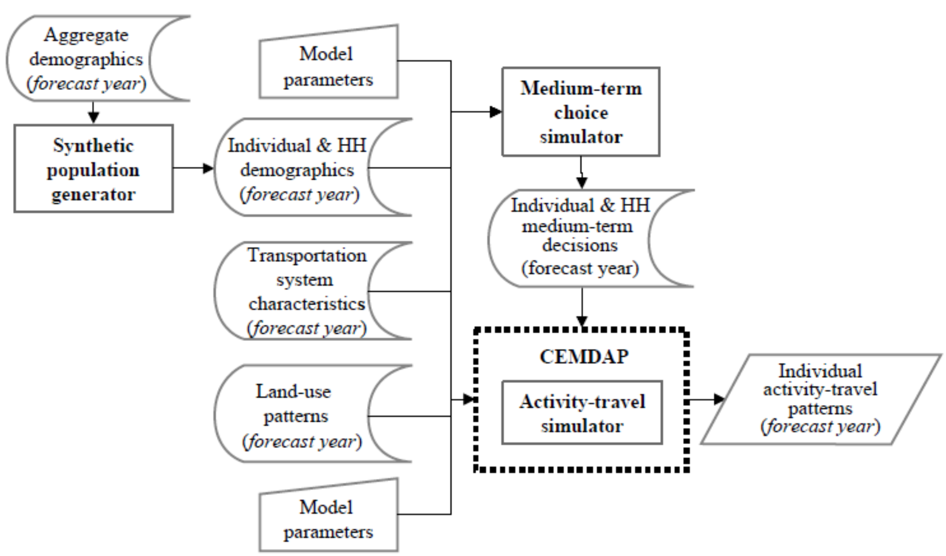


Figure 5. An overview of CEMDAP model. (Source: Bhat et al., 2004).

(CEMDAP) is a microsimulation model that is used for activity-travel modeling (Bhat et al., 2004) an overview of the model can be seen in figure (5). CEMDAP is distinguished by its activity generation assignment and scheduling model. The authors used disaggregate socioeconomic attributes of the individuals, aggregate zonal-level land use and demographic characteristics and level of service of the transportation system by the time of day to study the activities of workers (students and employees). The activity pattern of an adult is attributed to the decision on whether the person will perform a mandatory activity outside home and the activity patterns were structured in three levels: stop, tour and pattern while each level is associated with its attributes (intermediate stops, chain of stops, type of mode). The work start and end times were assumed to act as a temporal constraint, and thus, worker's day was divided into 5 periods before-work, home-work commute, work-based, work-to-home commute the after-work.

Kitamura and Fujii (1998) utilized the Prism Constrained Activity-Travel Simulator (PCATS) which is a detailed econometric model that utilizes time-space to model activity decisions that are conditioned with previous activities. The approach done by the model is dividing the day into two periods, open periods, and block periods. Open periods are the activities that have the choice of traveling which are filled in with flexible activities. Blocked periods have fixed activities such as work, and education-related activities where individuals engage in defined activities at known locations. By utilizing discrete choice models, each activity, type of activity, the destination of activity, mode choice and duration of activity are found. The authors assumed that when activity sequences are generated, the decision by individuals are dependent of past activities but not conditioned by future ones.

SACSIM is a regional travel prediction model which considered to be the first comprehensive of the first parcel based that is used for urban forecasting (Bradley et al., 2010). According to the authors, this was. This model is used in California and referred as the Sacramento Area Council of Governments. DaySim is a built-in SACSIM which is an activity-based disaggregate economic model which is used to replicate each individual's full-day activity and scheduling process. DaySim establishes a single-day activity and scheduling for each individual in the population which consists of a list of the tours and trips within these tours, the model has more than 10 components (DAPs, main mode choice, etc.). DaySim formulates the episodes of DAPs and intermediate stops (0 or 1+) for 7 different activity reasons, which are work, school, escort, personal business, shopping, meal, and social/recreational activities which took a nested logit form. In order to model DAPs, authors used households and individual attributes, land use, accessibility at residence and when needed, location of work. The authors found that the possibility of participation in various activities during the day is influenced by significant factors and the chance of performing these activities is made on another tour or a stop with a compound tour. The factors include student status, employment status, age group, gender, the availability of a vehicle, income status, the existence of children, presence of other household individuals and the status of family/non-family.

Daisy et al. (2018) introduced a cluster approach to model trip chaining, mode choice and the complexity of tours. There were five clusters of non-work-related that were derived from STAR data in Halifax, Canada based on DAPs and time-use. Activities were grouped into nine different groups, in and out of home-related groups. As a result, factors like age, gender, and marital status have a positive effect on tours. Furthermore, the number of cars owned influences the number of tours performed.

Dianat et al. (2020) developed a gab-based activity scheduling to estimate activities out of home for non-work and non-school for a full day. In the model developed, work, school, and sleeping time at night were assumed to be pre-defined and are fixed in the daily schedule which gives "gaps" in the schedule as illustrated in figure (6). This results in a fixed skeleton for the mandatory activities (work/school) and gaps for non-work/non-school activities to be filled in. The developed model considers mandatory activities to be the core of daily schedules around which out-home non-school/work activities are scheduled and took into account both temporal constant and time consumption of individuals as essential keys

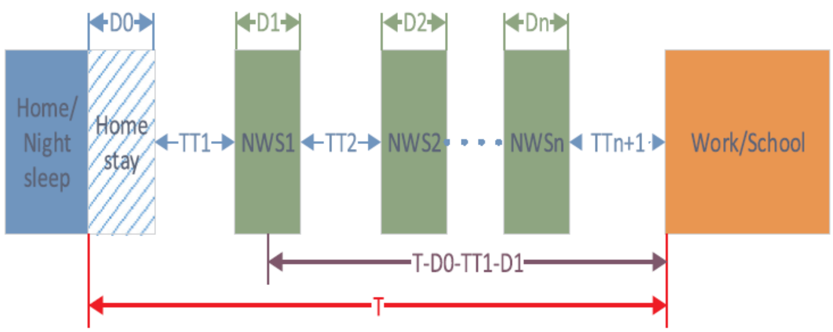


Figure 6. Remaining gaps after performing both mandatory and non-work/school activities. (Source: Dianat et al.,2020).

influencing activity scheduling. The authors argued that these activities illustrate peoples' spatial constraints and that the decision-making regarding the characteristics of mandatory activities is part of the medium- or long-term decision.

Bhat and Signh (2000) illustrated a detailed representation of attributes that distinguish workers' activity patterns on daily basis. The authors took into consideration the socio-demographics of households and persons to be an exogenic stimulus of the activity-travel pattern of the workday. Furthermore, they assumed that the beginning of the day is 3:00 a.m. and all household members are home. The authors considered the sociodemographic (of households and each individual) and the environment of activity-travel (transportation systems and land-use environment) to be an external factor of performing activity-travel patterns for workday activities, where choosing these attributes were justified with the association of performing mid-term decisions (related employment matters, duration of work and location), residence (type and location) and car-ownership.

Rajagopalan et al. (2009) developed a model that is based on the multiple discrete-continuous extreme value (MDCEV) framework for estimating non-work out of home

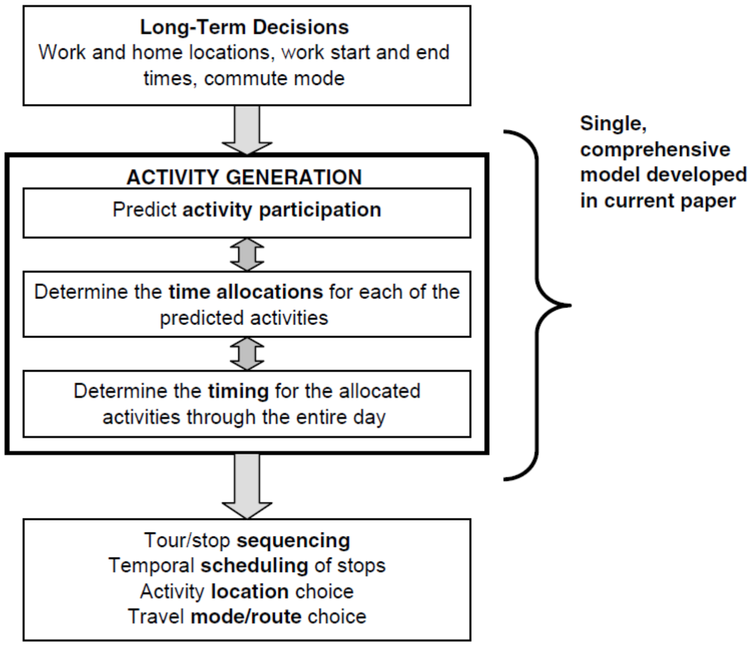


Figure 7. Schematic representation of MDCEV. (Source: Rajagopalan et al. (2009).

activity generation model that utilizes random utility framework which was used to estimate the activities performed by workers, figure (7). Data from 2000 San Francisco, California, Bay Area Travel Survey (BATS) which contains activity episodes, sociodemographic data, and spatial data for travel environment in the region were used for the estimation. Out of home, non-work-related activities were divided into 7 groups, meals, recreation, non-maintenance shopping, maintenance shopping, personal business, socializing and drop off/pick up. A division of worker's day was done similar to the study early mentioned (Bhat and Signh, 2000) which are before home-to-work travel, work-based, work-to-home travel, and after home arrival.

Habib et al. (2017) utilized a Comprehensive Utility Maximizing System of Travel Options Modelling (CUSTOM) approach to examine the activity scheduling and pattern by non-workers for a whole day. In figure (8), illustration of the model framework of activity-travel scheduling. The authors presented important segments of activity type and other facets of activity-based models where activities were serially added to create activity-travel behavior for non-workers. Data from a household travel survey

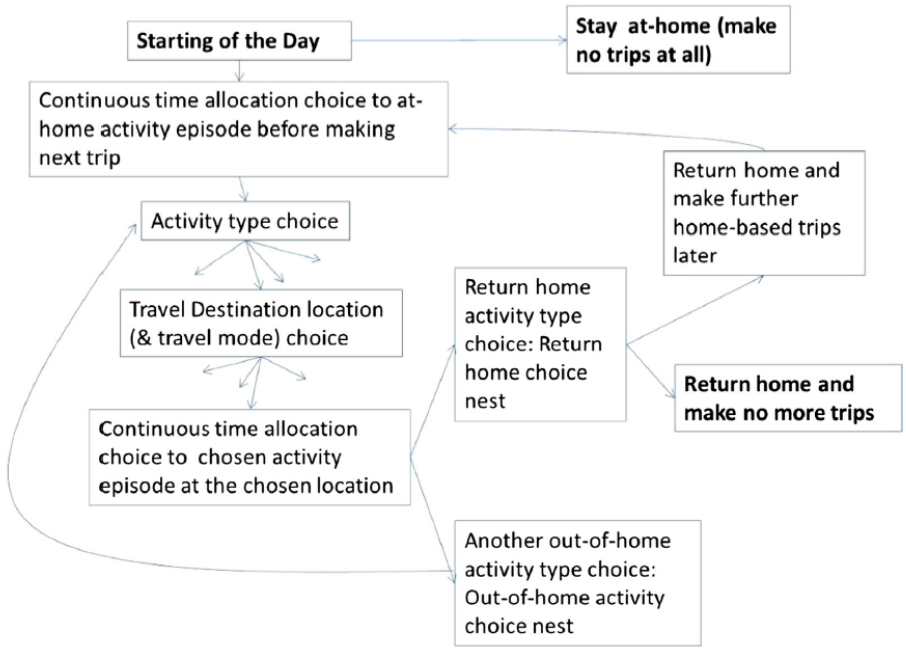


Figure 8. CUSTOM model activity travel choices chain. (Source: Habib et al., 2017).

in the National Capital Region in Canada was used which contains sociodemographic data and travel diaries of a typical day. Modeling of the decision of activity type was made on the basis of non-workers' and household characteristics and maximum utility of location choice. Habib and his colleagues illustrated influencing factors of activity type performed where the existence of a child at home, the status of homemaker, employment status, private car availability, gender and income status were factors that were found to influence on activity type. Also, they found that the more cars available the more activities that a person would perform. The types of activities presented in the study were, work-related activities, education, shopping/household maintenance, restaurants, recreation, social activities, personal, dropping off/ picking up and, other activities.

A study by Ahmed et al. (2020) intended to present a methodology that focuses on non-home activity sequences of individuals based on socio-demographic characteristics. The reason of studying an individual sequence pattern rather than a household pattern is justified by the fact that the methodology used for building the model would give a coherent result at the individual level. The authors studied the sequence of activities regardless of the duration and location of activities and the data used was the German household travel survey for the year 2008 which illustrates travel in the form of person trips made and sociodemographic characteristics were used for the generation of activities. In the study, there were 7 activity types for the sequence generation of activities, home, work, education, shop, leisure, private errands and accompanying. The authors utilized a two-step method for building the model. Initially, the analysis of activity sequence patterns is done and then the relationship among the sequence and the socio-demographic is created. In the second step, based on the relationship found, an estimation of the framework is built to estimate the probabilities of the activity sequence patterns for each individual.

Medina and Sergio (2015) used binary logistic models to extract and model non-mandatory activities to be used for activity sequence generation and to understand how individuals plan their daily activities. Based on the known places and activity scheduling, the approach proposed utilizes socio-demographic variables to link them with behavioral parameters of the decision-maker, so the activity sequencing takes place. The paper focused on the activity sequences and was created by using spatio-temporal network method. Data from Singaporean carried out in 2012 was used which contains sociodemographic characteristics, car availability and household characteristics. eating, shopping, social activities, running errands, recreation) and accessibility for each place.

Xu et al. (2018) used a combination of utility estimation and integer linear programing for modeling activity patterns. The Household Activity Pattern Problem (HAPP) was utilized for optimizing functions and the estimation was done by utilizing path-size logit models. HAPP is based on a mathematical path that is used to analyze the travel underneath the tree of activity-based models. The study focused on three main activities, home-related activities, work-related activities, and travel-related activities. The authors utilized random utility theory to select a specific path from traveler's continuous path. The proposed model consisted of three procedures the generation of choice set (activity-travel patterns are shown as a choice from a choice set), separating choice sets individually, and the estimation of parameters.

2.4 Intra-household Interaction

Intra-household interaction means the interaction among household members in performing activities. This is an essential factor as in some cases activities will be influenced if a household member or members will be preset while performing an activity. Intrahousehold interaction is important as members assign and share tasks and activities and they can engage in activities together or separately (Bhat and Pendayla, 2005). These activities can involve shopping, social-related activities or dropping off/picking up (Bhat et al., 2005; Vovsha et al., 2002).

Some papers discussed the interaction between household head members while performing activities. Borgers et al. (2002) studied the amount of time spent on performing activity alone or together between couples. The authors added factors like the presence of children, ownership of cars, socio-economic and work status as they would influence the time allocation of an activity. Ettema et al. (2006) on the other hand studied the activity scheduling between partners based on the sociodemographic, number of car ownership and location factors. The authors found that car ownership and locations are not significant factors when compared with other factors. However, it is important when it comes to inter or intrapersonal decisions.

Also, Gliebe and Koppelman (2002), and Zhang and Fujiwara (2006) studied the interaction between the head of households.

Vovsha et al. (2002) represented a joint modeling of DAP for the interaction among all household members. The authors divided the activity into three categories, compulsory, non-compulsory and staying at home. The authors studied factors like income, gender, household size car ownership, accessibility to destination and other factors and found that the interaction between women and children was higher than males. This interaction was justified but the environment of urban travel.

In 2005, Bhat et al. discussed the implementation of interaction among households in daily activity patterns. According to the authors, the standard travel demand models focused only on the individual trips without distinguishing to which member is performing the trip. The authors mentioned that recent studies in ABMs were associated with the generation of tours on the single level without acknowledging the presence of other members on the tour as they can have a joint activity, or they can take specific activities to perform alone.

Srinivasan and Bhat (2008) used the American Time Use Survey which consists of a comprehensive single level time of day usage information to study the joint activities among both households member and none-household members in multiple contexts, the generation of activity, location of activity and scheduling of joint activities (daily activity by type of the person in the joint activity, activity and travel episode, duration of activity with the type of joint person, location of activity with the type of joint person, time of day in non-work activity with the type of joint person and the sequence of activity). The study made a detailed comparison when a person performs the activity alone or with a joint person.

Wen and Koppelman (1999) represent a structure of DAPs and the interaction between the household members in Nested Logit Model. The study was divided into two parts, where the first part discussed the decision of the generation of stops and stop/auto-assignment. The second part discussed the formulation of tour model including the number of tours and stops of each person. This work is considered to be the first theoretical work based on a discrete choice Model in terms of intra-household interaction in an activity-based model.

Srinivasan and Baht (2005) studied household interaction throughout weekdays for in and out-of-home activities. In the authors' paper, a seemingly unrelated regression modeling system was used to Model the generation of in-home maintenance activity by exploring the duration spent by both males and females (the head of household). On the other hand, the out-home maintenance activities were done by using a joint mixed-logit hazard duration model with the regard to the decision-making of the household performing an activity, activity assigned to the person and the duration spent. The study done was for both types of households, with children (with a maximum age of 15) and without children. For households who have children the authors assumed the following, compulsory activities (work/school/ pick or drop children from school) are significant and are done in a strict time-space constraint, ambiances activities (household-related activities) are done for the household upkeeping and lastly, non-compulsory activities such as recreation, social visits and similar activities are performed either alone or in a joint trip, where the priority of activities go for the compulsory activities. The study found that in-home activity generation is influenced by household characteristics and the compulsory activities performed during the day. Furthermore, a direct relationship between the participation of non-compulsory activity participation for the household head without no children and time spent performing a compulsory activity during the day. Similar findings were recorded for household heads with children.

Kato and Atsumoto (2007) presented a paper on intra-household interaction by using the time allocation model which maximizes the household utility function under the restriction of time allocation and budget. The study considered only non-compulsory activities as they have fewer constraints as the authors assumed that compulsory activities are fixed and have their fixed times. The study focused on the household composition of three members (wife, husband and one child) and compared activities participation for both weekdays and weekends. The model developed was a short-term model and the classification of non-compulsory activities were single participation and joint participation with the assumption that a household member would perform a joint activity with a member which he/she wants to participate with.

2.5 Further Application in Daily Activity Patterns and Clustering Methods

Hafezi et al. (2019) developed an evolutionary model of recognizing the patterns similar to Daisy et al. (2018), by using activity data to form up a homogeneous clustering of DAPs to be used in ABM. The study used Halifax STAR, a large household travel diary survey. By using fuzzy c-means there were 12 distinguishable clusters for DAPs. The pattern recognizer consisted of four models. Initially, the authors used a reduction clustering algorithm for starting the amount of clustering and the core of the cluster. After that, similar patterns of persons were distinguished and sorted by utilizing a clustering algorithm of fuzzy c-means. The shown patterns were sorted with the aid of the multiple sequence alignment method. Finally, the clustering algorithm was used to examine the linkages among the characteristics in each cluster and sort these clusters with associated socio-demographic characteristics.

The San Francisco County Chained Activity Modeling Process (SF-CHAMP) was developed for the San Francisco County Transportation Authority to provide a comprehensive prediction of the travel demand for different planning applications (Outwater and Charlton, 2006). The aim of the authors' study was to precisely illustrate the complexation of the destination, spatial and model options to represent detailed information on the discrete choices done by travelers. The paper used the Metro Poland which in this paper the DAP was developed to have more primary tours and secondary tours which results in advanced choices.

Daisy et al. (2017) examined the association of tour complexity and escort activities for both maintenance and non-compulsory out-of-home tours by applying the poison regression model. The authors analyzed this complication by performing a clustering to the travelers based on their socio-demographic attributes and personal characteristics, examples of these characteristics (age, gender, education level, etc.). The authors used 2010 General Social Surveys time use data of Canada and they used weekday personal related activities to group the travel pattern of activities performed by non-workers. There were 6 types of tours: home-work-home, home-school-home, home-shopping-home, home-hobbies-home, home-entertainment-home, and home-sports-home and the activity purpose performed by non-workers were distinguished based on the duration of activity.

A new methodology was proposed by Li and Lee (2015) in modeling and learning ABMs where they utilized probabilistic context-free grammars. The authors defined daily activity patterns by embracing activity sequence, and they utilized activity sequences, sociodemographic attributes, trip making and activity participation from Household Interview and Travel Survey that was conducted in Singapore in 2008. The approach used is capable of replicating non-homogeneous daily activity patterns of people by learning the probability non-context language developed, where initially, activity sequences were treated as a context-free language. The characteristics of the surveyed people had three activity patterns which are simple work tour, staying at home and education tour. The authors studied the resemblance among the pattern of activities and languages (artificial strings) and then they drew up activity patterns and the languages with symbols. These symbols correspond letters that represent the pattern of activities (for example h for home activity). When identifying a daily pattern, a corresponding string will be formulated according to the creation of that activity. Finally, these languages and the activity patterns are then characterized by a subtle allocation. Different patterns were introduced in the study, home activity, work activity, education activity, shopping activity, recreation activity, personal errands, meal activity, escort activity, and other activities. These patterns were formulated as activity sequences for each full-time employed, part-time employed, full-time students, retired observer, homemaker observer and unemployment observer. The authors mentioned a promising variable in their study where person type which illustrates the economic activities and social role.

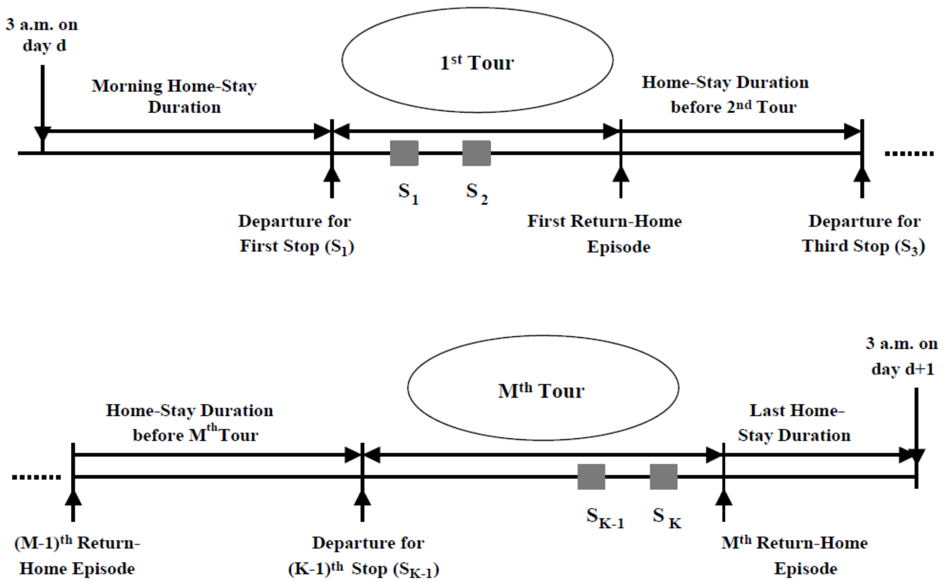
Jiang et al. (2012) analyzed an activity-based survey to understand the daily activity pattern structure of people in Chicago, differences in activities performed and to come up with a clustering method for daily activity patterns. comprehensive travel and activity survey for Northeastern Illinois Data was used which illustrates activity sequence and sociodemographic characteristics, household attributes, trip details and locations to examine both workday (8 clusters) and weekend (7 clusters). The classification of the households were workers, students, and non-workers. The study utilized the principal component analysis and the K-means clustering algorithm (which is a well-known repeated clustering method). clustering weekdays were grouped into eight categories, students, workers, early workers, afternoon workers, staying home all day, morning recreation, afternoon recreation, and overnight recreation. On the other hand, for the weekend activities, they were grouped into seven categories including the weekend workers, the afternoon stay-at-home, staying home all day, the afternoon recreation, the evening recreation, the overnight recreation (specified activities) and the overnight recreation (not specified activities).

Joh et al. (2002) Developed a methodology "multidimensional sequence alignment" which permits the inclusion of both sequential and nominal information to be compared in activity patterns that are derived from the degree of resemblance in the pattern composition such as activity type. The method is used to measure the similarities of classifications of activity patterns and to measure the fitting in other ABMs studies. The authors took into account nominal, interval, series (sequential), and dependent information. The method developed was based on comparing two multidimensional activity patterns, source, and target patterns in terms of qualitative characteristics. These characteristics can be activity type or any other facets and each activity type is associated with attribute sequences. The study used the Dutch activity diary and studied the type of activity and the location of the activity, and they assumed that the day starts at 3:00 am. The patterns of activities were divided to 25 out of home activities and 24 out of the home.

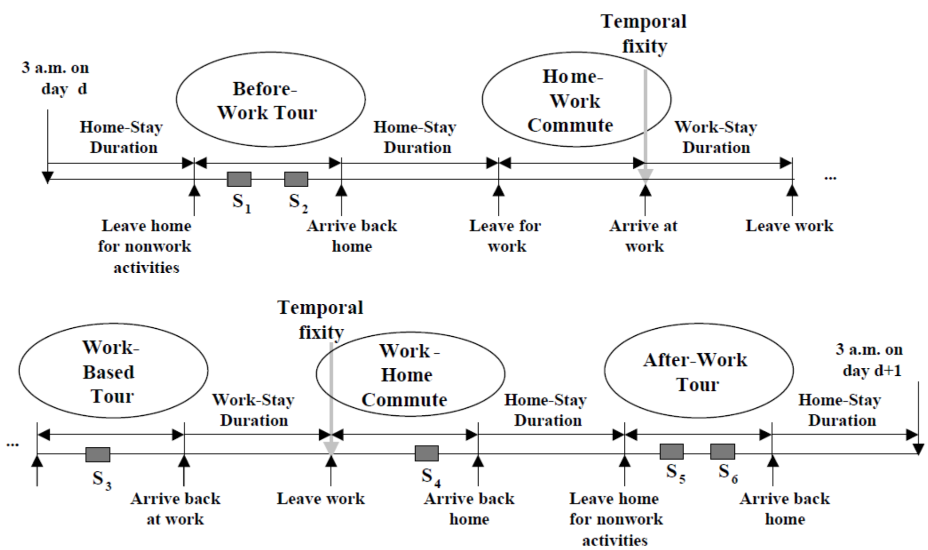
Chen and Kwan (2012) developed four models to recognize various flexible activities of choice sets between two fixed locations with spatiotemporal constraints. The precise set-theoretic formulations were utilized in the models developed which are implemented on a choice set of multiple flexible activities where the focus was on the members of household individual activities. These activities were influenced by the unique characteristic of members and the constraints that hinder the location of activity choices.

2.6 Summary of Literature Review

Initially, TBMs were used for travel forecasting, however, due to their limitations, ABMs have been utilized for this purpose. There have been various of ABMs that have emerged in order to illustrate the principle of activity participation from a different point of view. While building a model, there have been different methodologies used. When comparing the rule-based approach and econometric approach, human behavior modeling differs and fixated assumptions (Siyu, 2015). ABMs have different sub-models (facets) and DAP is the first face in the model. DAPs have seen a significant development throughout the years. Initially, only classification of activities was studied and after that research focused on household heads only without



(1)



(2)

Figure 9. DAP of workers (1) and non-workers (2). Source (Bhat et al. 2004).

considering the presences of children where further studies actually found a significant influence in activity scheduling and activity engagements when children were presented in the modeling process. Different approaches were developed where some used map data, and some used other data, however, mainly time-use survey data has been used to perform modeling of DAPs as well as sociodemographic attributes. Depending on the scope of the paper, activities were divided according to the purpose (work, school, recreation, etc.), or were clustered as mandatory and non-mandatory activities, or were divided to the individual (worker or non-workers) as illustrated in figure (9). Various attributes were reported to influence the activity participation such as income, presence of a child, HH size and other attributes, however data is a challenge to collect and process data as it is both time and resources consuming.

3. Methodology

3.1 FEATHERS Module

FEATHERS (the Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS) is a model that was developed by the Research

Figure 10. FEATHERS model structure. (Source: Research Institute of Hasselt University).

```
FEATHERS' AB model kernel
while get person from synthetic population do
  1.1 Daily Activity Pattern (0 or 1+ tours for 6 primary activity types)
  1.2 Number of Tours per Primary Activity (For prim. act. types with 1+ tours: 1-4 tours)
  if 0 < NrOfTours then
    for TourIndex = 1 to NrOfTours do
      2.1 Primary Activity Location (1 of 7786 zones)
      2.2 Primary Activity Transport Mode (1 of 7 transport modes)
      2.3 Primary Activity Start time (The time period arriving at the prim. loc.)
      2.4 Primary Activity Duration (The duration of the activity at the prim. loc.)
      for 1st-half tour do
        3.1.1 Secondary Activity Pattern (Number and act. type of sec. stops on the half tour)
        for ActivityIndex = NrOfSecondaryActivities to 1 (= in reverse temporal order) do
          4.1.1 Secondary Activity Location (1 of 7786 zones)
          4.2.1 Secondary Activity Transport Mode (1 of 7 transport modes)
          4.3.1 Secondary Activity Duration (The duration of the activity at the sec. loc.)
        end for
      end for
      for 2nd-half tour do
        3.1.2 Secondary Activity Pattern (Number and act. type of sec. stops on the half tour)
        for ActivityIndex = 1 to NrOfSecondaryActivities do
          4.1.2 Secondary Activity Location (1 of 7786 zones)
          4.2.2 Secondary Activity Transport Mode (1 of 7 transport modes)
          4.3.2 Secondary Activity Duration (The duration of the activity at the sec. loc.)
        end for
      end for
    end for
  end if
end while
```

Institute of Hasselt University assesses policy changes for Flanders, Belgium (Linh et al., 2019). The model is an activity-based micro-simulation model that is applied in the Flemish region of Belgium (Bellemans et al., 2010) which was integrated from the module ALBATROSS model (A Learning Based Transportation Oriented Simulation System). FEATHERS is capable of implementation of large-scale activity-based simulations and methodologies for the analysis of the outputs from various modules within the model (Bao et al., 2018). This model comprises of three levels: daily patterns, tour, and intermediate stops similar to ALBATROS. Bao et al. (2018) mentioned that the decision-making of DAPs and discrete choice models is made by merging the heuristic rules utilized in ALBATROSS, however, FEATHERS has seen a paradigm change. FEATHERS has been completely transformed and now is following an econometric approach. The sub-models follow RUM principle where choice facets are modeled using discrete choice modeling methodology, mostly MNL model (Knapen et al., 2021). Figure (10) illustrates FEATHERS model structure for Rotterdam, the Netherlands.

3.2 Model Building

3.2.1 Multinomial Logit Model

RUM is considered to be the base of discrete choice modules which assumes that individuals pick what they mostly prefer and when this is not applicable and it happens due to a random reason (Domencich and McFadden, 1975). McFadden (1974) cited by (Castro et al., 2012) considered Multinomial Logit as one of the most used modules underneath the tree of RUM approach. Wen and Koppelman, (1999) reported that MNL is advantageous due to its ease of estimation and the simple mathematical functions, however, MNL is limited when an improvement is introduced to any alternative which will have the same impact on all alternatives. This limitation is called the property of independence of irrelevant alternative (IIA). MNL approach supposes that ε_{ni}, the random component, as shown in equation (1) below is following an identical and independent Gumbel distribution which privileges an approximation to the probability of the choice (Castro et al., 2012). In discrete choice models, each choice has a degree of being chosen by each person, and the choice with the high level of utility will be picked.

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{1}$$

Where	U_{ni}	is the utility of the alternative i that is chosen by the individual n
	V_{ni}	is the deterministic portion of the utility
	ε_{ni}	is the random error portion of the utility

The utility function above has two components, the deterministic portion which is the observed part and the error portion (that follows Gumbel distribution), which illustrates the limitation by the analyst to cover all the attributes of the individual's behavior and the uncertainties associated with the limited capability of the analyst (Zargari and Safari 2020). According to (Koppelman and Bhat, 2006), the deterministic portion of the utility function can be divided into three components, exclusively associated to the alternative's attributes, exclusively associated with the decision-maker (individual) attributes and the interaction between the first two types. Hence, the deterministic portion can be illustrated by:

$$V_{ni} = V(S_n) + V(X_i) + V(S_n, X_i) \tag{2}$$

Where
V_{ni} is the deterministic portion of the utility function
$V(S_n)$ is the exclusively portion which is associated with the individual's attributes
$V(X_i)$ is the exclusively portion which is associated to the alternative's attributes
$V(S_n, X_i)$ is the portion of the interaction between individual's attributes and the alternative's attributes

The portion of the utility that is associated with the alternatives contains variables that illustrate the attributes of the alternatives. These attributes affect the utility equation for each individual that is being studied. Some of the attributes can HH composition, income, age, the availability of public transport subscriptions, and other attributes. The same applies to the portion related to the decision-maker.

$$\beta_0 + \beta_{i1} \times S_{i1} + \gamma_{i1} \times X_{i1} + \cdots + \beta_{im} \times S_{iM} + \gamma_{ik} \times X_{ik} \tag{3}$$

Where
β_0 is the alternative specific constant
β_{im} is the value that shows the magnitude of the characteristic of the decision maker
S_{iM} is the value of the characteristics of the individual i
γ_{ik} is the value that illustrates the importance of the effect of attribute k
X_{ik} is the value of the attribute of the individual i
Acc_{ij} is the accessibility measure for individual i to location j

Since the highest utility will be chosen, the probability of chosen such alternative "i" is:

$$\Pr_i = \frac{exp^{(v_i)}}{\sum_{j=1}^{J} exp^{(v_j)}} \tag{4}$$

3.3 Accessibility Measures

There are different definitions of accessibility in the literature, and hence it has a different meaning. One of the definitions is the possible interaction with events or opportunities (Hansen, 1959), the smoothness of reaching a land use from a location by utilizing a specific system of transportation (Dalvi and Martin, 1976), the privilege of a person on participating decision on different opportunities (Burns, 1981), the added value gained from transportation/land-use system (Ben-Akiva and Lerman, 1979), the belonging of geographical area, transportation system, a business or a person (Dong, 2000). One essential element of accessibility is the ability to assess the interconnection among land-use patterns and transportation systems nature (Dong, 2000; Dong et. al, 2006).

According to Geurs and Wee (2004), attributes of accessibility can be divided into four components:

1- Land-use component which is a return of the land use system consisting of the quality and the distribution of events, the demand to these events and opportunities and the encounter between the supply and demand which may result in challenging each other.
2- Transportation components which is a return from the transportation systems consisting of travel time, cost of travel, and effort made.
3- Temporal component reflecting spatial constraints for example the availability of events and time of the day.
4- Individual component reflecting the desires of people.

3.3.1 Accessibility Measures Methods

The concept of accessibility is argued to be an important role in assessing the relationship between land use characteristics and the transportation system which its results (accessibility) are used in transportation modeling and forecasting, examining transportation planning effectiveness and problem-solving (Dong et al., 2006; Cascetta et al., 2013).

From some papers that discussed accessibility measures (Hansen, 1959; Pirie, 1979; Cascetta et al., 2013) it can be grasped that measuring the accessibility is based on two factors, the destination and the appealing of choices and, the constrain of traveling. Therefore, the accessible areas are the ones that have low constrain and destinations that are appealing (Nassir et al., 2016).

There are various methods to measure accessibility in the literature and in this section, a brief discussion of some of these measures will be conducted. According to Handy and Niemeier (1997), accessibility measures can be sorted into three different groups: isochrone, gravity-based and utility-based. The first method is *isochrone measure* or known as "*cumulative opportunity*" euqation (5) is considered to be the simplest method of assessing transferability where it measures the number of opportunities that can be reached in a given travel time or distance. An example of this measure is the number of employments within half an hour from transit (Dong, 2000). However, it has a weakness which its sensitivity to a large size of the range (for example, for a range of more than 30 minutes). Some of the early examples of this method are Wachs and Kumagai (1973), Vickerman (1974) and Black and Corey (1977).

$$Acc_i = \sum_j W_j a_j \tag{5}$$

Where Acc_i is the accessibility measure

W_j is = 1 if $c_{ij} \leq c^*_{ij}$ other wise 0 where c_{ij} is the measure of impedance and c^*_{ij} is a known range which activity to an opportunity can occur

a_j is the opportunities of the location (detitanation) zone j

The second method is the *gravity model* which was initially derived by Hanson (1959). Based on the literature, this method is considered to be more complex than the isochrone measure and it is called the gravity model as it is derived from the denominator in the gravity model in trip distribution. Some of the early examples of this method are Hansen (1959), Huff (1963) and Ingram (1971). The equation of gravity model is illustrated below.

$$Acc_i = \sum_j a_j f(C_{ij}) \tag{6}$$

Where Acc_i is the accessibility measure

a_j is the opportunities of the location (detitanation) zone j

$f(C_{ij})$ is the impedance function

The more proximate to the opportunity is, the more it contributes to the accessibility, and the bigger the opportunity is, the more it contributes to the accessibility (Handy and Niemeier, 1997). However, Dong et al. (2006), mentioned that this method has a limitation which it does not take into account the variation of individuals (for example age variations among individuals).

The third method is *utility-based* accessibility measurement that is based on RUM theory in which the possibility of individuals performing a choice is dependent on the utility of the choice against the utility of all choices. One advantage of this measurement is that it has the ability to illustrate the accessibility in disaggregate point of view (for each individual) according to the preferences of the individual (Pirie, 1979). A detailed discussion regarding this method can be found in Geurs et al. (2004).

However, in this paper, *activity-based accessibility* (ABA) that was initially introduced by Ben-Akiva and Bowman (1998) is applied to the utility function. ABA is obtained from RUM, similar to *utility-based* measurement. The addition provided by this method is that it combines trip sequencing, DAP of the whole day and activity scheduling unlike *utility-based* accessibility measurement which emphasis the purpose of a specific trip without considering the time prism and trip chaining (Dong et al., 2006).

By taking the log of the denominator of MNL, the result is the anticipated utility from a choice and also, it is used to link various choices (Jong, 2007). The log sum can also be utilized to evaluate the consumer surplus in terms of policy changes.

By taking only the denominator of equation (4) and adding the log (ln) we get:

$$Acc = ln\left[\sum_{j=1}^{J} exp^{(v_j)}\right] \tag{7}$$

For each type of location, accessibility measure will be calculated for every primary location for every individual. In this study, four location choices models were used which are, work/business activity, education activity, shopping activity and for all other activities (bring/get and other activities). The accessibility measure for an individual to a location type is the maximum accessibility across all primary locations of an individual. Figure (11) below indicates the relationship between accessibility measures and a DAP model.

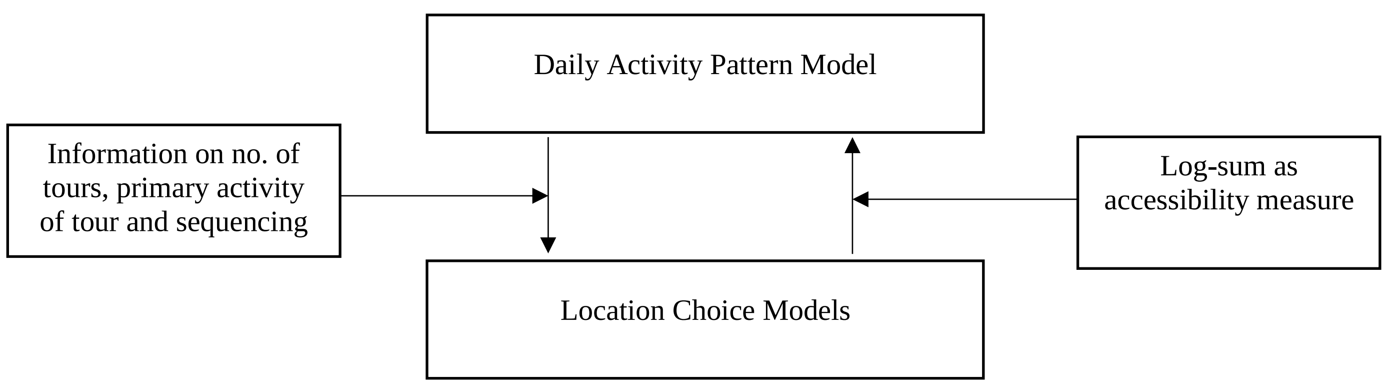


Figure 11. Relationship between accessibility measures and daily activity patterns.

The standard utility function illustrated in equation (3) does not contain the accessibility measures, it is rather an additional attribute that is being added to have either a higher or lower utility of an individual in order to study the accessibility. The final utility function applied in the model is obtained by combining both equation (3) and (7), which results in:

$$\beta_0 + \beta_{i1} \times S_{i1} + \gamma_{i1} \times X_{i1} + \cdots + \beta_{im} \times S_{iM} + \gamma_{ik} \times X_{ik} + Acc_{ij} \tag{8}$$

3.4 Current Study

In this study, the estimation of DAP of individuals will be performed by utilizing MNL model approach that is based on RUM theory. This study is focusing only on activities performed by people without taking into account other facets such as intermediate stops, mode choice, or household interaction. Since this thesis is following MNL approach, ABA measure will be performed to measure the accessibility of locations for each individual in the data set (disaggregate). After performing the estimation, the output of the model will be reported and compared with other DAP models to find the differences between FETHERS model and different models. After that, another estimation result will be reported for Flanders, Belgium which is also a DAP model which ultimately the same comparison will be conducted between Rotterdam, Netherlands, and Flanders, Belgium models results.

3.5 Data and Data Collection

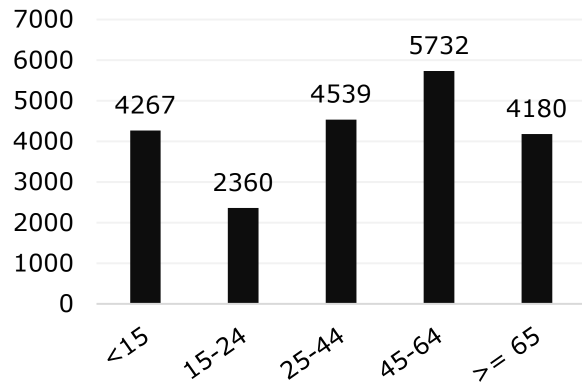
Data used in for Rotterdam model is Relocation survey in the Netherlands (OViN) collection process started in 2010 and stopped in 2017. Table (1) below illustrated the data used for the analysis. Data used to provide information regarding the daily travel and travel behavior of the Dutch population. The methodology for collecting the data was divided into three steps. First individuals were asked to fill in an online questionnaire for their travel behavior. If the individual cannot access to the internet, a phone call was made by the Dutch Statistics and if this was not applicable, then the questionnaire was taken to the individual. Data used consisted of socio-geographic characteristics such as age, gender, household size, origin, urbanity, province, disposable household income, and social group. Furthermore, transport ownership (car ownership, additions for private use of company cars, motorcycle ownership and moped ownership) at personal and household levels. The following table and figures summarize the main characteristics and observed travel behaviors.

Table 1. Sociodemographic attributes in the data set.

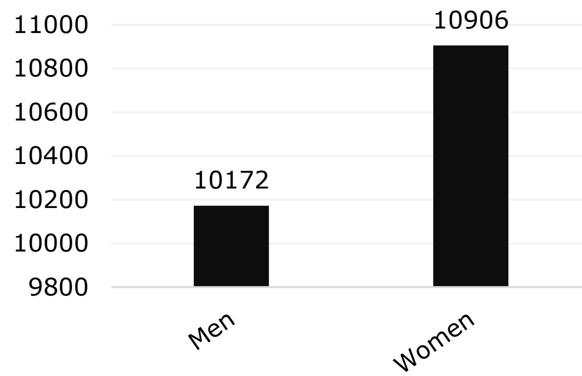
Attribute	Attribute Description	Value	Value Description	Corresponding number of people/category
Inhabitants	Number of inhabitants	0-N	Number of inhabitants	21078
Household	HH composition	1	1 person household	3580
		2	Households without children	5727
		3	Households with children	11771

	HH nr. of cars		0	No cars	3423
			1	One car	10864
			2	Two cars	5911
			3	Three cars	880
	HH Income "based on percentile"		1	Low (<= p40)	4297
			2	Mid-range (> p40 <=p80)	4180
			3	High (>p80)	2429
Individual	Gender	Registered gender of person	1	Men	10172
			2	Women	10906
	Age	Age group of people	1	Age < 15	4267
			2	Age >= 15 & Age < 25	2360
			3	Age >= 25 & Age < 45	4539
			4	Age >= 45 & Age < 65	4732
			5	Age >= 65	4180
	Roots of individuals	Migration background	1	Citizen	15975
			2	Western immigrant	1979
			3	Non-western immigrant	3124
	Driver's license	Driver's license possession	0	No	8142
			1	Yes	12936
	Paid work	Hours of paid work per week	0	No work paid	12198
			1	<12	531
			2	12-30	2179
			3	>30	6170
	Day	Workday indicator	0	Weekend (Sat-Sun)	0
			1	Workdays (Mon-Fri)	21078
	Education	Highest education obtained	1		
			2		
			3		
			4		
			5		
	Student_pt		0	No	20216

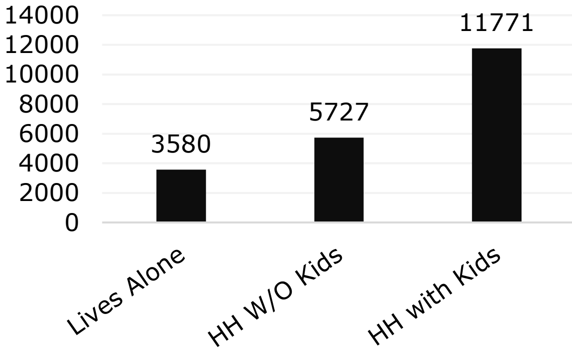
	Possession of a student public transport discount card	1	Student PT card with weekday subscription	802
		2	Student PT card with weekend subscription	60
Urbanized	Urbanization degree, based on address density	1	Very strongly urbanized	9186
		2	Highly urbanized	6346
		3	Moderately urbanized	3225
		4	Low urbanized	1564
		5	Not urbanized	757
Home location	Zone where OPID lives	0-7785	-	0-7785
Vehicle type	Fuel type of owned vehicle	0	Owns no car	12209
		1	Petrol	7384
		2	Diesel	1246
		3	Hybrid (including plug-in hybrid)	71
		4	Lpg	108
		5	E-car	16
		6	Other (cng, hydrogen, alcohol, cryogenic)	44
Bicycle type	Type of bicycle owned	0	Owns no bicycle	4569
		1	Non-electric bicycle	14709
		2	Electric bicycle	1800



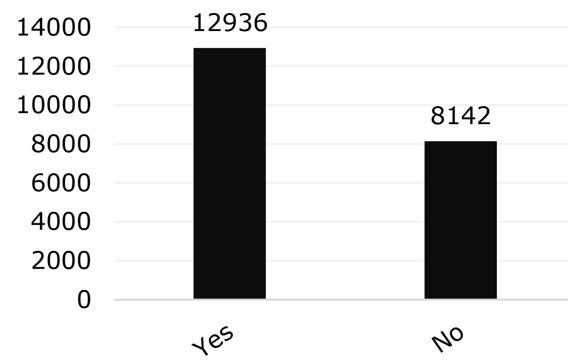
(1) Age distribution of the population.



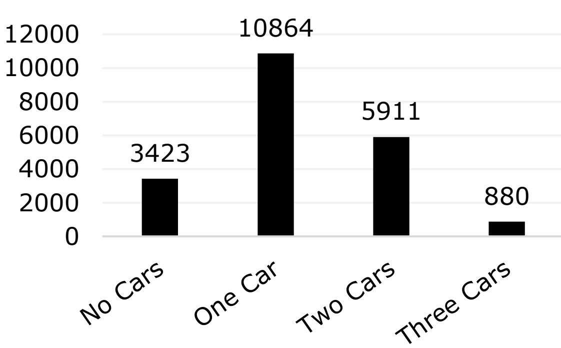
(2) Gender distribution of the population.



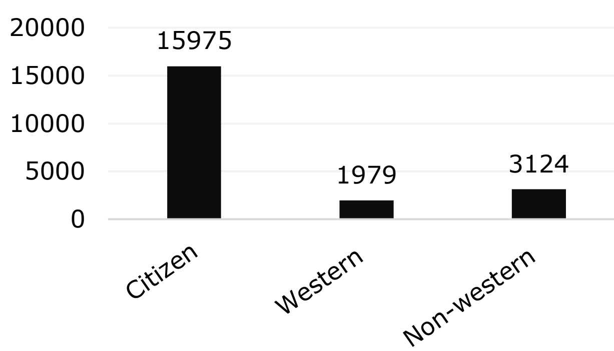
(3) HH composition of the population.



(4) Possession of driver's license.



(5) Number of cars owned.



(6) Roots of the population.

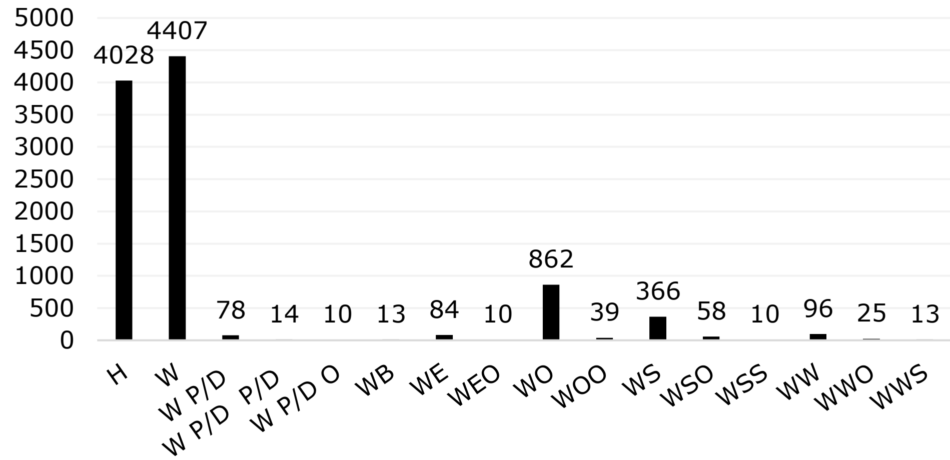
Figure 12. A comparison between the household attributes.

Table 2. Activity patterns observed.

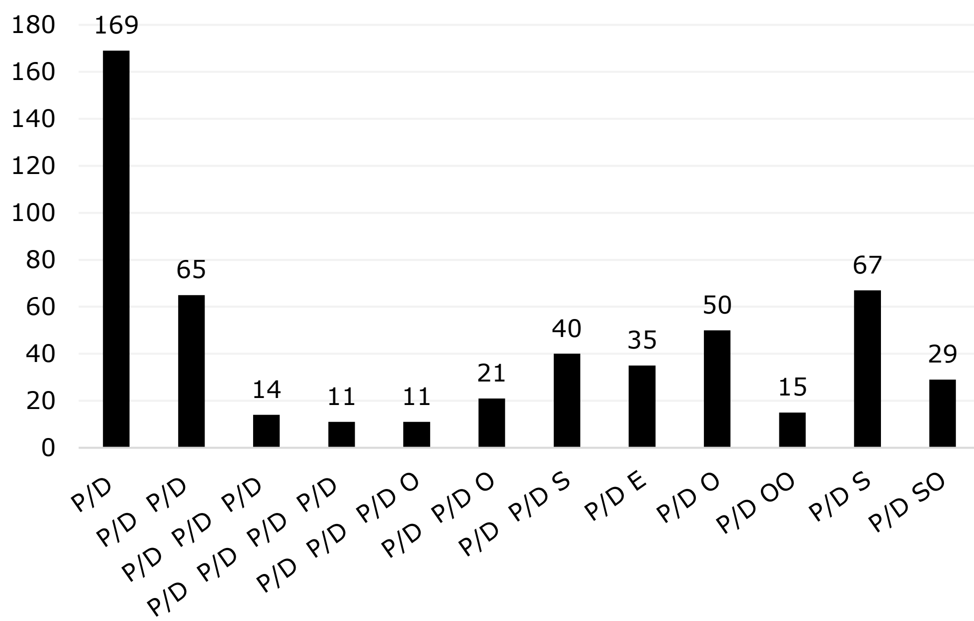
Ranked Activity	Activity type	Frequency	% of total choices
1	W	4407	20,9
2	H	4028	19,1
3	O	2927	13,8
4	E	2349	11,1

5	S	2183	10,3
6	WO	862	4,0
12	P/D	169	0,8
15	B	125	0,6
…..			
50	BS	8	0,04
Total	-	21078	100

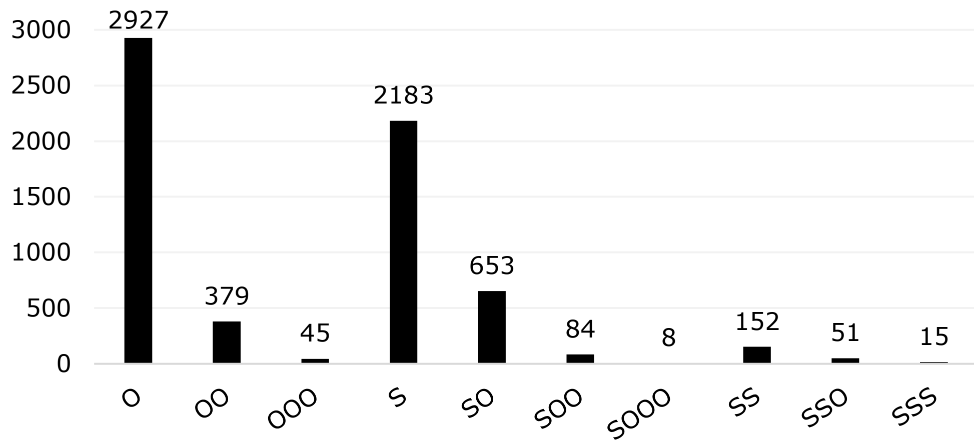
W:Work, H:Home stay, B:Business, P/D: Pick up/drop off, E: Education, S: Shopping, O: Other.



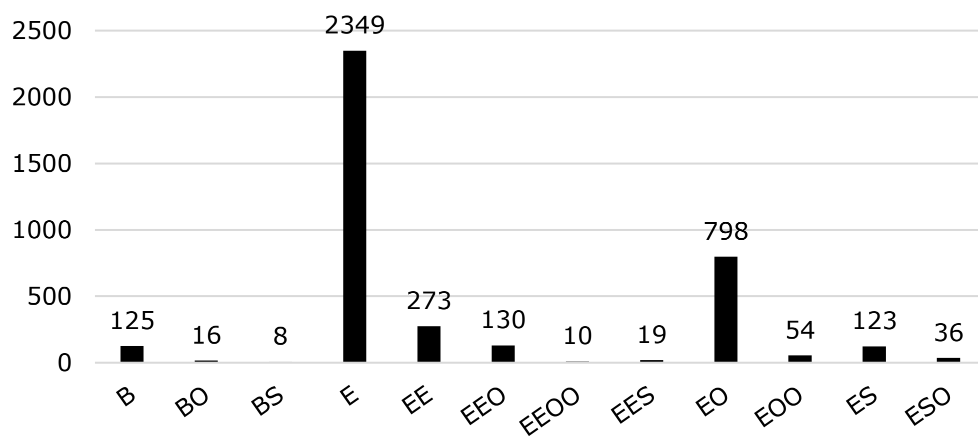
(1) Observed work and home-stay activity chain.



(2) Observed picking-op/drop-off activity chain.



(3) Observed shopping and “other” activity chain.



(4) Observed business and education activity chain.

Figure 13. Share of different observed activity chains.

Figure (12) illustrates some of the HH characteristics in the data used. It can be seen that the majority of the population are between 45-64 followed by 25-44. On another note, females are more than males and HHs who have kids is almost doubling those with no kids and almost quadrupling with those who live alone. The majority of the population holds a Driver’s license and owning a car when compared to the rest of the attributes. Lastly, in the data, citizens are the highest followed by non-westerns and then westerns.

On the other hand, Table (2) and figure (13) illustrate the activity choices observed and their frequencies in the data set. There were 21078 observed choices in the data set ranging from work, education, business, pick up/drop off, shopping and others. It can be observed that most of the population performs a single activity when compared to a sequence of activities per day, especially for work-related and picking-up/dropping/off. Work activity dominates the rest of performed activities with an observed value of 4407 as seen in the figure. On the other hand, home stay was the second-highest activity meaning that people not performing activities for any reason (immobile, home-stay-parent, etc.).

4. Model Estimation: Rotterdam

Activity pattern choices were estimated by utilizing sociodemographic characteristics and, log-sum of accessibility from location choices facets. Table (3) indicates the initial and final log-likelihood of the mode. There was an improvement of 45.7% (rho square of 0.457).

Table 3. Summary of the Rotterdammer model estimation report.

Init log-likelihood	-82457.62
Final log-likelihood	-44785.42
Rho-square for the init. model	0.457
Number of estimated parameters	168

Table (4) on the other hand, depicts the estimation values of the FEATHERS model. Although all related work activities patterns have negative values for the alternative specific constant (ASCs), this can be a result as people have one shift of work rather than two or more. It should be noted that single work activity per day utility was the reference "set to 0".

For gender participating in activities, it seems that men are more likely to engage less in activities regardless of the type of activities, the only exception is business-related activities where men had higher participation.

Table 4. Rotterdam model results (significant values are indicated in bold).

Name	Value	t-test	p-value
Constants			
Home Stay	9.2	24.8	**0.0**
WW	-0.6	-1.5	0.1
WWS	-5.0	-7.4	**0.0**
WWO	-8.4	-9.3	**0.0**
WB	-3.1	-2.9	**0.0**
W P/D	-7.3	-10.6	**0.0**
W P/D P/D	-8.9	-7.8	**0.0**
W P/D O	-14.1	-1.1	0.3
WE	-1.1	-3.3	**0.0**
WEO	-9.5	-12.7	**0.0**
WS	-2.5	-7.0	**0.0**
WSS	-6.1	-5.7	**0.0**
WSO	-10.8	-15.1	**0.0**
WO	-4.8	-8.5	**0.0**
WOO	-7.5	-10.5	**0.0**
B	-1.9	-3.5	**0.0**
BS	-12.6	-1.0	0.3
BO	-14.5	-1.2	0.2
P/D	0.1	0.2	0.8

P/D P/D	-0.7	-1.1	0.3
P/D P/D P/D	-2.1	-2.9	**0.0**
P/D P/D P/D P/D	-2.2	-2.9	**0.0**
P/D P/D P/D O	-2.7	-3.2	**0.0**
P/D P/D S	-4.9	-7.1	**0.0**
P/D P/D O	-2.6	-3.3	**0.0**
P/D E	-2.8	-4.3	**0.0**
P/D S	-4.5	-6.8	**0.0**
P/D SO	-5.0	-7.2	**0.0**
P/D O	-1.3	-2.0	**0.0**
P/D OO	-4.2	-3.6	**0.0**
E	7.4	19.3	**0.0**
EE	5.3	13.5	**0.0**
EES	-0.5	-1.1	0.3
EEO	-1.6	-2.6	**0.0**
EEOO	-5.0	-5.4	**0.0**
ES	1.0	2.4	**0.0**
ESO	-6.6	-9.8	**0.0**
EO	0.1	0.2	0.8
EOO	-2.8	-4.3	**0.0**
S	5.2	13.2	**0.0**
SS	2.2	5.0	**0.0**
SSS	0.4	0.6	0.5
SSO	-6.0	-7.6	**0.0**
SO	-2.2	-3.6	**0.0**
SOO	-4.5	-6.9	**0.0**
SOOO	-12.3	-1.0	0.3
O	2.9	4.9	**0.0**
OO	0.8	1.3	0.2
OOO	-1.8	-2.7	**0.0**
Driver’s license: Home Stay	-0.5	-6.1	**0.0**
Driver’s license: WW	1.4	4.1	**0.0**
Driver’s license: WWS	0.6	0.9	0.4
Driver’s license: WWO	1.7	2.3	**0.0**
Driver’s license: WB	1.7	1.6	0.1
Driver’s license: W P/D	1.8	4.1	**0.0**
Driver’s license: W P/D P/D	1.9	1.8	0.1
Driver’s license: W P/D O	6.6	0.5	0.6
Driver’s license: WE	-1.5	-6.0	**0.0**
Driver’s license: WEO	-0.7	-1.1	0.3
Driver’s license: WS	1.2	7.2	**0.0**
Driver’s license: WSS	1.6	1.5	0.1
Driver’s license: WSO	1.5	3.3	**0.0**
Driver’s license: WO	1.5	11.2	**0.0**
Driver’s license: WOO	1.2	2.4	**0.0**

Driver’s license: B	2.3	5.0	**0.0**
Driver’s license: BS	6.2	0.5	0.6
Driver’s license: BO	7.0	0.6	0.6
Driver’s license: P/D	-0.4	-2.2	**0.0**
Driver’s license: P/D P/D	-0.2	-0.8	0.4
Driver’s license: P/D P/D P/D	-0.4	-0.7	0.5
Driver’s license: P/D P/D P/D P/D	-0.5	-0.7	0.5
Driver’s license: P/D P/D P/D O	0.4	0.5	0.6
Driver’s license: P/D P/D S	0.5	1.4	0.2
Driver’s license: P/D P/D O	0.7	1.3	0.2
Driver’s license: P/D E	-2.8	-5.2	**0.0**
Driver’s license: P/D S	0.5	1.8	0.1
Driver’s license: P/D SO	0.0	0.0	1.0
Driver’s license: P/D O	0.1	0.4	0.7
Driver’s license: P/D OO	1.9	1.8	0.1
Driver’s license: E	-2.9	-31.3	**0.0**
Driver’s license: EE	-3.8	-13.4	**0.0**
Driver’s license: EES	-1.9	-3.4	**0.0**
Driver’s license: EEO	-5.0	-6.9	**0.0**
Driver’s license: EEOO	-8.9	-0.5	0.6
Driver’s license: ES	-2.3	-9.2	**0.0**
Driver’s license: ESO	-1.2	-3.3	**0.0**
Driver’s license: EO	-3.0	-22.1	**0.0**
Driver’s license: EOO	-3.4	-6.4	**0.0**
Driver’s license: S	0.1	0.6	0.5
Driver’s license: SS	0.7	3.2	**0.0**
Driver’s license: SSS	-0.3	-0.6	0.5
Driver’s license: SSO	1.8	3.4	**0.0**
Driver’s license: SO	0.3	2.3	**0.0**
Driver’s license: SOO	0.7	2.5	**0.0**
Driver’s license: SOOO	6.5	0.5	0.6
Driver’s license: O	-0.2	-2.7	**0.0**
Driver’s license: OO	-0.1	-0.5	0.6
Driver’s license: OOO	0.4	1.0	0.3
Gender: Man Home Stay	-0.4	-8.9	**0.0**
Gender: Man WW	-0.4	-2.1	**0.0**
Gender: Man WWS	-1.6	-2.5	**0.0**
Gender: Man WWO	-0.4	-1.0	0.3
Gender: Man WB	0.0	0.0	1.0
Gender: Man W P/D	-0.6	-2.5	**0.0**
Gender: Man W P/D P/D	-1.1	-1.9	0.1
Gender: Man W P/D O	-0.5	-0.8	0.4
Gender: Man WE	-0.2	-0.7	0.5
Gender: Man WEO	-0.7	-1.1	0.3
Gender: Man WS	-0.7	-6.3	**0.0**

Gender: Man WSS	-1.9	-2.4	**0.0**
Gender: Man WSO	-0.5	-2.1	**0.0**
Gender: Man WO	-0.3	-3.8	**0.0**
Gender: Man WOO	-0.4	-1.3	0.2
Gender: Man B	0.6	2.9	**0.0**
Gender: Man BS	1.4	1.3	0.2
Gender: Man BO	0.3	0.5	0.6
Gender: Man P/D	-0.5	-3.2	**0.0**
Gender: Man P/D P/D	-1.1	-4.1	**0.0**
Gender: Man P/D P/D P/D	-1.3	-2.1	**0.0**
Gender: Man P/D P/D P/D P/D	-1.8	-2.3	**0.0**
Gender: Man P/D P/D P/D O	-1.9	-2.4	**0.0**
Gender: Man P/D P/D S	-2.2	-4.8	**0.0**
Gender: Man P/D P/D O	-0.9	-2.0	**0.0**
Gender: Man P/D E	-0.4	-1.2	0.3
Gender: Man P/D S	-1.5	-5.3	**0.0**
Gender: Man P/D SO	-1.3	-3.2	**0.0**
Gender: Man P/D O	-0.8	-2.7	**0.0**
Gender: Man P/D OO	-0.3	-0.7	0.5
Gender: Man E	-0.1	-1.5	0.1
Gender: Man EE	-0.1	-0.4	0.7
Gender: Man EES	-1.5	-2.6	**0.0**
Gender: Man EEO	0.1	0.7	0.5
Gender: Man EEOO	1.3	1.7	0.1
Gender: Man ES	-0.3	-1.8	0.1
Gender: Man ESO	-0.5	-1.3	0.2
Gender: Man EO	0.1	0.8	0.4
Gender: Man EOO	0.4	1.5	0.1
Gender: Man S	-0.8	-14.1	**0.0**
Gender: Man SS	-1.0	-5.9	**0.0**
Gender: Man SSS	-0.5	-0.9	0.4
Gender: Man SSO	-1.0	-3.4	**0.0**
Gender: Man SO	-0.9	-10.6	**0.0**
Gender: Man SOO	-1.1	-4.8	**0.0**
Gender: Man SOOO	-1.6	-2.0	**0.0**
Gender: Man O	-0.6	-11.1	**0.0**
Gender: Man OO	-0.6	-5.5	**0.0**
Gender: Man OOO	-0.4	-1.2	0.2
Age group 2	-4.0	-14.5	**0.0**
Age group 3	-4.8	-17.4	**0.0**
Age group 4	-4.4	-16.0	**0.0**
Age group 5	-1.7	-5.9	**0.0**
HH composition 2	0.1	1.7	0.1
HH composition 3	0.3	4.7	**0.0**
HH income 2	-0.4	-7.4	**0.0**

HH income 3	-0.4	-7.7	**0.0**
No. of cars 1	-0.2	-2.5	**0.0**
No. of cars 2	-0.3	-3.4	**0.0**
No. of cars 3	-0.4	-3.4	**0.0**
Logsum WB	0.4	21.0	**0.0**
Logsum P/D O	0.3	13.3	**0.0**
Logsum ED	0.4	20.9	**0.0**
Logsum S	0.3	22.5	**0.0**
Student PT 1	0.7	5.5	**0.0**
Student PT 2	3.0	2.9	**0.0**
Urbanized 2	0.2	4.4	**0.0**
Urbanized 3	0.3	5.3	**0.0**
Urbanized 4	0.2	2.9	**0.0**
Urbanized 5	0.5	4.5	**0.0**

Values are rounded

Driver's license availability showed high activity participation for work-related activities, business-related activities and some pick-up and drop-off activities. There were some fluctuations in shopping and other activities where some had lower participation depending on the following chain of activities (P/D followed by shopping or other activities had higher participation). Furthermore, driver's license availability shows a positive activity participation for activity chain, besides education, other activities and partial picking-up/dropping-off activities.

Women seem to engage more in education, picking up and dropping off, shopping, more-than-one-work-related activities per day and other activities. Age category seems to be affecting the decision of participating in activity chain. This can be seen from the estimated values for age. However, keeping in mind the reference utility "single work activity", this means that age group in general participated in single work activity.

When it comes to the number of HHs, the higher the number of the family members, the greater the chance of activity participation. However, it seems that income has no influence on activity participation. Unlike HH composition, the higher the income of a HH, the lower the activity participation. On a similar note, the higher the number of cars, the less likely an activity will be performed. Accessibility (Log-sum) reports a positive relationship with activity participation; meaning that the accessible the destination, the more likely it that the individual will participate in an activity.

Students' public transportation subscriptions played an important role in activity participation. Although students commute to their educational institutes during the week "student PT 1", students seem to enjoy their weekends by going around using public transportation more "student PT 2". This also can be another indicator for less car usage. Lastly, more environmental and green locations seem to be more attractive to the people in Rotterdam. The less the urbanized areas, the more activities will be made to that location.

4.1 Comparison of Results

The results of FEATHERS for Rotterdam region are somewhat plausible; however, various models have different results depending on how rich the data is, the considered choices, the scope of the study and other considerations. In this section, a comparison of DAP estimation results of different models is made to see the vibration of FEATHERS model compared to other models. This section is intended to answer the second research question of "How can we compare different daily-activity pattern estimation results?" For that, the magnitudes of the estimations will compare as well as the significance values of the models.

In comparison with CUSTOM Habib et al. (2017), like many other papers, the authors reported the estimation using t-statistics. The sociodemographic attributes were similar to this study. For the occupation attribute, work-related activities were less likely to be made with an estimated value of "-5.7" and t-statistics of "-2.56". On the other hand, FEATHERS illustrated per choice estimation, and when work chain-related activities were estimated, there was also a decrease in activity participation, keeping in mind that the majority are working in one shift rather than multiple, single work activity was not estimated since it was set as the reference activity. In CUSTOM model, picking up and dropping off were two different variables where they had beta values of "-5.0" and "-3.7" respectively and t-statistics of "-2.89" for picking up and "-2.04" for dropping off. On the other hand, FEATHERS model reported positive

Table 5. Summary of the compared attributes of FEATHERS and CUSTOM model.

Activity Type	FEATHERS		CUSTOM	
	Value	t-Statistics	Value	t-Statistics
Work-related activities	Reference Activity	Reference Activity	- 5.7	-2.65
Education/School	7.4	19.3	-11.0	-16.8
Shopping	5.2	13.2	-0.3	-0.1
Picking up/ Dropping off	0.1	0.2	-5.0/-3.7	-2.89/-2.04
Other	2.9	4.9	3.4	8.4

Participation for single P/D with an estimated value of "0.1" and t-statistics of "0.2".

For going to school, a constant estimation of "-11.0" with t-statistics of "-16.8" was reported for CUSTOM while this study showed positive participation with an estimated value of "7.4" and t-statistics of "19.3" for single education activity.

Shopping activities also had low participation with a value of "-0.3" and t-statistics of "-0.1" which is a result that the study was on the first activity of the day. However, this study had overall positive shopping participation, unless it was linked with other activities with a value of “5.2” and t-statistics of “13.2”.

Other purposes activities had a positive engagement with a value of “3.4” and t-statistics of “8.42” while this study showed high participation with an estimated value of “2.9” and t-statistics of “4.9”. On opposing to FEATHERS, in CUSTOM, high activity participation was linked to HH income, while the FEAHTERS, an immobile HH with high income was reported. Table (5) summarizes both of the model's results.

Daisy et al. (2018) made a study on the effect of time use on short-term DAP choices. In comparing with cluster number 5 (workers from 9 to 5), unlike FEATHER’s result, shopping activity participation had a negative relation with tour engagement with an estimated value of “- 0.06” and it was indicated as a non-significant. Conversely, there was a positive magnitude of activity participation in terms of shopping in this study with a value of “5.2” with significance. Furthermore, daisy and her colleagues found out that men were engaging with activities more than women with an estimated value of “0.2” with significance while this study illustrated that women engage with activities more, this can be seen as women were the reference for gender category. Driver’s license showed negative activity participation with an estimated value of “- 0.1” with significance, while in this paper, there was an increase in activity participation with all purposes unless it is related to education or other activities. Similar to the findings of FEATHERS, the number of cars in a HH resulted in lower activity participation with an estimated value of “-0.07” with non-significance, and in this study, the more the cars, the less activity participation. Table (6) summarizes both of the model's results.

Table 6. Summary of the compared attributes of FEATHERS and Daisy et al. (2018) model (significance is indicated in bold).

Attributes	**FEATHERS**		**Daisy & Colleagues**	
	Value	**P-value**	**Value**	**P-value**
Single Shopping	5.2	**Sig.**	-0.06	Non-sig.
Gender “Male”	Activity Specific	Activity Specific	0.23	**Sig.**
Driver’s License	Activity Specific	Activity Specific	-0.14	**Sig.**
Low Income	Reference Attribute	Reference Attribute	-0.02	Non-sig.
Car Ownership	Between -0.2&-0.4	**Sig.**	-0.07	Non-Sig.

Significance values were not reported in Daisy et al. (2018)

Fransen et al. (2018), studied the relationship between accessibility and activity participation. In the authors' study, age groups fluctuated in terms of activity engaging where low age group “<18” had an estimation of “1.77” with “0.05” significance value, and for the age between “18-34” a significant decrease in activity participation was a report with a value of “-11.53” with “0.87” non-significance value and a value of “1.05” with “0.51” non-significance value for 65 and older. However, age group in FEATHERS were reported to have a decreased activity engaging for all age groups. Age group 2 “-4.0”, group 3 “-4.8”, group 4 “-4.4”, and group 5 “-1.7” with all significant vales “0.0” Opposing to FEATHERS, females were found to engage less in activities with an estimated value of “-0.45” and was also found to be non-

Table 7. Summary of the compared attributes of FEATHERS and Fransen et al. (2018) model (significance is indicated in bold).

Attributes	**FEATHERS**		**Fransen & Colleagues**	
	Value	**P-value**	**Value**	**P-value**
Age	Value Specific/Group	**Sig.**	Value Specific/Group	Non-Sig.
Gender “Male”/ “Female”	Activity Specific	Activity Specific	0.45	Non-Sig.
Driver’s Liscence	Activity Specific	Activity Specific	Reference Attribute	Reference Attribute
Income	Reference Attribute	Reference Attribute	-0.02	Non-Sig.
HH size	Between -0.2&-0.4	**Sig.**	Between -2.0&0.6	Non-Sig.

significant “0.6”. On a similar finding, driver’s license was reported to have a decreased activity participation with an estimated value of not having a driver’s license of “0.54”. While in FEATHERS, most driver’s license ownership repotted to have a decreased activity engaging. HH size had a positive relationship with activity participation and, it was reported to be significant. When one person HH was presented, an estimated value of “-0.4” with p-values of “0.6” was reported, 2 HH members with a value of “-2.0” and p-value of “0.1” and more than 5 people/HH was estimated with “0.6” and p-value of “0.1”. Table (7) summarizes both of the model's results.

5. Model Estimation: The Flemish Region

In this section, the same model, FEATHERS is applied to the Flemish region, Belgium data.

Activity pattern choices were estimated by utilizing sociodemographic characteristics. Table (8) indicates the initial and final log-likelihood of the mode. There was an improvement of 29.9% (rho square of 0.299).

Table 8. Summary of the Flemish model estimation report.

Init log-likelihood	-13825.09
Final log-likelihood	-9684.84
Rho-square for the init. model	0.299
Number of estimated parameters	52

After that, a comparison between the two results is reported. It should be noted that the data used for the Flemish Population is still uncompleted and there are different sociodemographic attributes that are missing as can be seen in the table (9). However, main activity sequencing is reported where the comparison of the available attributes will be reported in the next section.

Table 9. The Flemish model result (significant values are indicated in bold).

Name	Value	p-value
Constants Home Stay	0.2	0.3
WW	-1.9	**0.0**
WWS	-4.7	**0.0**
WWO	-3.6	**0.0**
WB	-3.8	**0.0**
WP/D	-1.2	**0.0**
W P/D P/D	-3.5	**0.0**
W P/D O	-3.1	**0.0**
WE	-3.3	**0.0**
WEO	-10.3	0.4
WS	-1.6	**0.0**
WSS	-4.7	**0.0**
WSO	-3.8	**0.0**
WO	-0.8	**0.0**
WOO	-3.8	**0.0**
B	-1.4	**0.0**
BS	-4.7	**0.0**
BO	-4.7	**0.0**
P/D	0.4	**0.0**
P/D P/D	-1.5	**0.0**
P/D P/D P/D	-3.3	**0.0**

P/D P/D P/D P/D	-4.7	**0.0**
P/D P/D P/D O	-4.7	**0.0**
P/D P/D S	-2.5	**0.0**
P/D P/D O	-2.5	**0.0**
P/D E	-2.9	**0.0**
P/D S	-0.7	**0.0**
P/D SO	-2.0	**0.0**
P/D O	-0.9	**0.0**
P/D OO	-2.9	**0.0**
E	0.4	**0.0**
EE	-3.1	**0.0**
EES	-4.7	**0.0**
EEO	-5.4	**0.0**
EEOO	-10.3	0.4
ES	-3.2	**0.0**
ESO	-4.0	**0.0**
EO	-1.3	**0.0**
EOO	-3.6	**0.0**
S	0.4	**0.0**
SS	-1.8	**0.0**
SSS	-4.3	**0.0**
SSO	-2.5	**0.0**
SO	-0.7	**0.0**
SOO	-2.6	**0.0**
SOOO	-4.7	**0.0**
O	0.8	**0.0**
OO	-1.2	**0.0**
OOO	-3.1	**0.0**
Driver's license	-1.6	**0.0**
Gender: Man	-0.1	0.3

Values are rounded

Overall, it seems that people are engaging more with single activities, however, the magnitude of the estimated values are somewhat low. This can be associated with limited data redundancy. Nonetheless, most of the estimated values are significant, meaning that they explain the choice in this model and that it is affecting the decision.

Coming to the sociodemographic attributes, driver's license reported to have negative activity participation, and men seem to be engaging less activities when compared with women.

5.1 Comparison of Results

Unlike the previous section where the Rotterdam model was compared with other models from the literature, the Flemish model results will be compared with the

Rotterdammer model results. Table (10) illustrates the values of both models and their significance. Similar to the findings of Rotterdam's data, it seems that most of the population work on one shift, where all activity sequencing linked with working had negative activity participation. Similarly, single P/D seems to have a positive engaging table (9), however, the more sequence of this type, the least activity participation. Similar to P/D, single education activity was reported to have a positive activity engaging, however, the more the sequence the least participation. This can be a result as students tend to stay at the university waiting for their lectures or lessons at school. The same results are reported for shopping and other activities where single activities have a positive activity engaging while more activities tend to have less activity participation. Conversely, for both results, business activates had a negative activity engaging, and the more sequences of activities linked with business-related activities, a significant activity engaging can be seen. Overall, for the Flemish model, a negative relationship was reported for both the availability of driver's licenses and men. For the Rotterdammer model, there were specific values

Table 10. Summary of FEATHERS for Flanders and Rotterdam (significant values are indicated in bold).

Name	Flanders's Model		Rotterdam's Model	
	Value	**p-value**	**Value**	**p-value**
Constants Home Stay	0.2	0.3	9.2	**0.0**
WW	-1.9	**0.0**	-0.6	0.1
WWS	-4.7	**0.0**	-5.0	**0.0**
WWO	-3.6	**0.0**	-8.4	**0.0**
WB	-3.8	**0.0**	-3.1	**0.0**
WP/D	-1.2	**0.0**	-7.3	**0.0**
W P/D P/D	-3.5	**0.0**	-8.9	**0.0**
W P/D O	-3.1	**0.0**	-14.1	0.3
WE	-3.3	**0.0**	-1.1	**0.0**
WEO	-10.3	0.4	-9.5	**0.0**
WS	-1.6	**0.0**	-2.5	**0.0**
WSS	-4.7	**0.0**	-6.1	**0.0**
WSO	-3.8	**0.0**	-10.8	**0.0**
WO	-0.8	**0.0**	-4.8	**0.0**
WOO	-3.8	**0.0**	-7.5	**0.0**
B	-1.4	**0.0**	-1.9	**0.0**
BS	-4.7	**0.0**	-12.6	0.3
BO	-4.7	**0.0**	-14.5	0.2
P/D	0.4	**0.0**	0.1	0.8
P/D P/D	-1.5	**0.0**	-0.7	0.3
P/D P/D P/D	-3.3	**0.0**	-2.1	**0.0**
P/D P/D P/D P/D	-4.7	**0.0**	-2.2	**0.0**
P/D P/D P/D O	-4.7	**0.0**	-2.7	**0.0**
P/D P/D S	-2.5	**0.0**	-4.9	**0.0**

P/D P/D O	-2.5	**0.0**	-2.6	**0.0**
P/D E	-2.9	**0.0**	-2.8	**0.0**
P/D S	-0.7	**0.0**	-4.5	**0.0**
P/D SO	-2.0	**0.0**	-5.0	**0.0**
P/D O	-0.9	**0.0**	-1.3	**0.0**
P/D OO	-2.9	**0.0**	-4.2	**0.0**
E	0.4	**0.0**	7.4	**0.0**
EE	-3.1	**0.0**	5.3	**0.0**
EES	-4.7	**0.0**	-0.5	0.3
EEO	-5.4	**0.0**	-1.6	**0.0**
EEOO	-10.3	0.4	-5.0	**0.0**
ES	-3.2	**0.0**	1.0	**0.0**
ESO	-4.0	**0.0**	-6.6	**0.0**
EO	-1.3	**0.0**	0.1	0.8
EOO	-3.6	**0.0**	-2.8	**0.0**
S	0.4	**0.0**	5.2	**0.0**
SS	-1.8	**0.0**	2.2	**0.0**
SSS	-4.3	**0.0**	0.4	0.5
SSO	-2.5	**0.0**	-6.0	**0.0**
SO	-0.7	**0.0**	-2.2	**0.0**
SOO	-2.6	**0.0**	-4.5	**0.0**
SOOO	-4.7	**0.0**	-12.3	0.3
O	0.8	**0.0**	2.9	**0.0**
OO	-1.2	**0.0**	0.8	0.2
OOO	-3.1	**0.0**	-1.8	**0.0**
Driver's license	-1.6	**0.0**	Activity Specific	Activity Specific
Gender: Man	-0.1	0.3	Activity Specific	Activity Specific

Values are rounded

linked to each activity, however, different results can be seen in table (4) for these values. Driver's license had a positive relationship with activity sequencing, meaning that activity chain of two activities and more had a positive engagement besides picking-up/dropping-off activities and educational activities. For both of the models, male had negative activity participation for most of the activities (in the case of Rotterdam) meaning that women engage with activities more than men.

This chapter and the previous chapter were intended to answer the first question of "Do different observed travel behavior data sets lead to significant differences in the output of a daily-activity pattern model?"

To answer this, it is clear that magnitudes differ from one region to another and also from data to another. Data plays a significant role in the estimation and the definition of these attributes in the model also influences the results. For example, in the case of Rotterdam, there were specific values for gender and driver's license, while these provide an in-depth insight into activity participation, it can also make the comparison more difficult as the literature uses a general value for each attribute.

Another reason that can influence the results is the scope of the paper. If the estimated values are for workers or non-workers this can make the results differ from one model to another and can make some of the choices less mobile when compared to another, similarly, activity engaging time. If the activity will be made as the first activity in the day, this will limit various of choices to only a few, mainly, working, education and maintenance.

6. Conclusions and Recommendations for Future Research

Transportation planners showed an increased interest in understanding the link between the human behavior of traveling and sociodemographic attributes. FEATHERS was used to determine the future travel behavior of the residence in Rotterdam, Netherlands in terms of activity sequences that are the first facet of ABM by utilizing MNL approach that follows RUM theory. FEATHERS is a model that was originally developed by the research institute, IMOB of Hasselt University, Belgium. Data from Relocation survey in the Netherlands (OViN) collection process started in 2010 and stopped in 2017 was used for the Rotterdammer model.

The main focus of this thesis was to compare the results of the model with other models from the literature and use FEATHERS to estimate the travel behavior of the people in Flanders, Belgium, and perform a comparison between the two results. The method that was used was comparing the magnitude of the estimated values of activity participation and the significance of the attributes.

Another topic that was incorporated in the thesis is accessibility measures. Accessibility measures aim to illustrate the returned benefits of a specific location to those who reside close by it. For this, location choice models facet results were used to find the accessibility of a location chosen to be linked with activity pattern. There were various accessibility measure methods that were used, however, ABA that was initially introduced by Ben-Akiva and Bowman (1998) was applied for this purpose.

Overall, the results presented are plausible, however, there was a single attribute where there were contrary results that the model showed in comparison with other models. HH income was reported to have a decreased activity participation in FETHEARS model. This was not the case for other models where there was a positive relationship between HH income and activity engaging, the higher the income, the higher activity engaging. Another attribute was car ownership, where it was shown that the more cars owned, the less activities have participated.

The possession of a driver's license had a decreased activity engaging for education activity chain, partial P/D activity chain, and other activities, perhaps this can be a result as the cycling culture is popular in the Netherlands, especially for students where PT subscription had positive activity participation.

On the other hand, FETHAERS for Rotterdam illustrated positive activity participation for accessibility, HH size, ownership of student public transportation subscription and, urbanization (the least the urbanized, the higher the engagement).

For activity participation, overall, single activities are being engaged the most, especially for work-related activities and it seems that women participate in activities more than men.

For the Flemish region, similar results were seen for the population. People mainly participate in a single work-related activity with less participation with activity chain. On the other hand, driver's license possession was linked with a decrease in activity participation. When it came to gender, women were participating in activities more than me.

This thesnis is not without limitations. While data collection is very challenging and resources consume, a more detailed survey on activity participation would provide a deeper insight into the activity performed outside the home. Another limitation is that the data represents the HH size without indicating the age group of these children; this makes it difficult to grasp whether the presences of children do influences on activity participation. A more detailed children's characteristics would help in finding whether age group would limit the activity engagement of HH members.

To this end, the paper concluded that there are various reasons that contribute to different results when it comes to the estimation. Data plays an important role in the estimation since the model actually utilizes it to perform a prediction. Limited data can show little insights for the estimation, an example of that is the Flemish data. Another reason is the scope of the paper and the time for activity participation studied where it would influence some of those activities on another.

For future studies, it would be interesting to examine HH interactions and the presence of children as they play important factors in determining activity participation. Since this thesis compared the results of FEAHTERS and other DAP models, a FEATHERS model can be built for both workers and non-workers and then a comparison between these two models can be made to find out the pattern of these populations. The time of engaging in activities "morning, afternoon and night" can be also incorporated to find out if non-workers also engage in activities during rush hours and what type of activity they engage in. Together with accessibility, an interesting finding can be drawn to understand the behavior of all the population in terms of activity engaging keeping in mind that all of these considerations are data-dependent.

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