Pedestrian activity schedule models: review and promises

Zhengchao Wang

Yuki Oyama

Riccardo Scarinci

Michel Bierlaire

Nikolaos Geroliminis

Transport and Mobility Laboratory, EPFL

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Zhengchao Wang, Yuki Oyama,Riccardo Scarinci,Michel Bierlaire
Transport and Mobility Laboratory
EPFL
GC B2 386 (Bâtiment GC), Station 18,
CH-1015 Lausanne
phone: +41-21-693 25 37
fax: +41-21 693 24 08
{zhengchao.wang, yuki,oyama, michel.Bierlaire}@epfl.ch

Nikolaos Geroliminis
Urban Transport Systems Laboratory
EPFL
GC C2 383 (Bâtiment GC), Station 18,
CH-1015 Lausanne
phone: +41-21-693 24 81
fax: +41-21-693 24 79
{nikolas.geroliminis@epfl.ch}

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Abstract

Understanding pedestrian activity schedule, which describes how pedestrians perform and schedule activities in walking space and time, is important for the planning and operations of infrastructure facilities. Currently, while activity schedule models (ASM) have been extensively used for general travel behavior, the focus on pedestrians has been relatively scarce in the literature. In this paper, we review the existing ASMs in the pedestrian context, and investigate the potential use of general models from the literature in this specific context.

Keywords

Activity schedule model, congestion, flexible activity demand, interaction, joint travel, pedestrian

1 Introduction

It is predicted that the world population will be increased from around seven billion to nine billion by 2050. In addition, over 70% of population will live in cities comparing to that of today (50%) (Weidmann, 2012). Even in countries with stagnant population growth, people move to major cities for better economic opportunities and/or other reasons. The increase of urban population results in expanded demand of walking to various infrastructure facilities. This is mainly driven by different types of human activities, for instance, shopping in mall/city center, or catching the scheduled train in a platform. To meet the increasing walking demands of pedestrians, a better management of the existing facilities and/or establishment of new facilities is required, for either of which solutions a better knowledge about how pedestrian behave and interact with the environment is beneficial.

As a pedestrian, there are three different levels of choices to make: the strategic level (departure time choice and activity pattern choice), the tactical level (Activity scheduling), and the operational level (walking behavior) (Hoogendoorn and Bovy, 2004). Specifically, In this paper, we focus on the tactical level choice of pedestrians. So we review the activity schedule models (ASMs) that are already existed in literature, both in pedestrian domain and within general traffic settings, with the objective to investigate the potential application of general ASMs to the study of pedestrian.

1.1 What aspects included in this paper

This paper focus on three critical aspects: *congestion impact*, *flexibility of activity*, and *interaction with other individuals*. These aspects influence significantly the activity schedule decision of pedestrian.

First of all, avoiding congestion is an intrinsic desire of pedestrians that might serve as a primary stimuli of activity scheduling. Therefore, it is interesting to see how congestion is considered in the literature both in pedestrian and in general settings. In addition, empirical studies done by Crawford and Melewar (2003) and Strack *et al.* (2006) show that impulse shopping makes up significant portion of purchase behavior. Therefore, it is also necessary to understand how people would modify their activity schedule (impulse shopping as an example) during the execution of their primary plan. Furthermore, either in a transportation hub or in city center, pedestrians are likely to walk with others. In this case, how pedestrians schedule their activities with their companion(s) (termed as interaction) is an interesting topic to study. To be more precise

- The congestion impact on activity schedule is how congestion would influence the route choice, and the sequence of activities, the timing and duration of activities.
- The flexibility of activity demand refers to the adding/deletion of an activity into /from the activity set. In addition, in this paper, it also refers to the activity swapping or activity duration change.
- The interaction considers the case where at least one activity of a individual will be finished together with another individual. So they need to consider when and where to meet for carrying out the activities together.

In summary, in this paper, the congestion impact, flexibility of activity demand, and interactions of activities and individuals is covered to display a picture of the tactical level activity schedule models and discuss potential application to pedestrians.

1.2 Contribution of this study

- Summarize the scientific literature in pedestrian about activity scheduling.
- Summarize the scientific literature on activity scheduling considering congestion, flexible demand, and interaction in general setting.
- Point out the potential application of ASMs from general setting to pedestrian.
- Illustrate the research gap.

1.3 Structure of this paper

The following of this paper will be organized into 4 sections. Section 2 first discusses the data related to pedestrian activities, and then discusses the existing study in pedestrian activity scheduling. Section 3 summarizes some existing ASMs in the general setting. Section 4 continues to discuss the potential application of general ASMs in pedestrian domain. And finally Section 5 gives a summary and conclusions of what is dicussed above. Note that this paper does not target at providing a comprehensive literature study in activity scheduling, and only works related to the three specific aspects (mentioned above) are presented. Readers who are interested in activity scheduling and searching for more comprehensive review papers can refer to (Garling *et al.*, 1994, Bhat and Koppelman, 1999, Lin *et al.*, 2008b, Timmermans and Zhang, 2009, Rasouli and Timmermans, 2014).

2 State-of-the-Art in pedestrian activity schedule models

In this section, the prerequisite data needed to infer the activity schedule behavior of people will be discussed first, followed by the existing ASMs in pedestrian domain in literature. Since the data acquisition and analysis techniques are not the focus of this paper, only a brief introduction to them will be provided here. Interested readers are kindly referred to Danalet (2015) where a more comprehensive introduction is given.

2.1 Pedestrian activity data

To date, various techniques used to collect pedestrian data have been studied and implemented thanks to the fast development of sensor technologies and the recognition of the importance to understand pedestrian behavior. Moreover, great efforts have been made to improve data processing in transportation using techniques from computer vision, machine learning etc. Following is a quick introduction of the data acquisition and analysis techniques.

2.1.1 Data collection

There are many data collecting technologies that are already applied in practices to count or track the activities episodes of people. These include manual counts and shadowing, mechanical counts, survey data, lasers and infrared sensors, video counting, GPS, RFID tags and readers, smart card, and data from mobile phone (Danalet, 2015).

Different techniques have their own pros and cons, and therefore suit to different purpose. For example, the manual counts and shadowing, mechanical counts, lasers and infrared sensors, RFID tags and readers, etc. are suitable to collect data to understand the strategic (macroscopic) choice (like O-D pairs) of pedestrians. GPS, data from mobile phone, WiFi data can be used to track the tactical (meseascopic) choice (like route choice) of pedestrians in a network with cheaper cost. And video counting or video record can be used to understand the operational (microscopic) choice (walking behaviors) of pedestrians in a walking space. For example, Alahi *et al.* (2014) use networks of cameras to track and analyze pedestrian trajectories. What's more, techniques can be combined together to collect data optimally as claimed by Hogan *et al.* (2015) who implemented a monitor system with the combination of WiFi technology, computer vision tools, and infrared counters. In addition to the actual design of data collecting system, Fetiarison *et al.* (2010) developed a simulation framework which helps the designer to evaluate the collection methods before implementing them.

2.1.2 Data processing

The next step after collecting the data is to extract desired information from these data. Various interesting results are obtained from the data mining. In this section, we will introduce some studies which are critical for building the activity schedule model. They are related to activity sequence detection, O-D demand inference, fundamental diagram statistics, and pedestrian objects recognition.

In activity schedule model, the sequence of activities and route choice are of great importance to the calibration of the models. For this reason, Danalet *et al.* (2014) apply Bayesian approach to detect the sequence of activity episodes visited by pedestrian from WiFi traces data. Bierlaire *et al.* (2013), Chen and Bierlaire (2015) use smart phone data to infer the routes and transportation modes chosen by travelers. Saarloos *et al.* (2010) uses a multidimensional sequence alignment method to identify the types of facilities where pedestrians stopped, and whether or not stops occurred in the main street. Subsequently, five distinctive pedestrian segments are identified by cluster analysis. In the end, meaningful regularities in activity patterns of pedestrian are found despite the complexities of behaviors.

When activity sequences are not available, O-D pairs are informative to the validation of models. Hänseler *et al.* (2014a, 2015, 2017b) estimate the pedestrian network O-D demands using an assignment mapping model and apply this model to the train station of Lausanne with its collected data. Clifton *et al.* (2016) uses multinomial logit model to estimate pedestrian destination choice which can be integrated into regional travel demand models. Chan *et al.* (2007) use a bi-level programming model to estimate O-D matrix and activity/destination choice model parameters. This is an iterative process composed of upper level of O-D matrix updating and lower level of activity-based user equilibrium assignment model.

Since activity sequences or O-D pairs only provide the location aspect to schedule model, travel time is still missing for the route choice. Fundamental diagram which reveals the travel time with respect to the pedestrian density is of great value to the activity schedule model. In literature, Nikolić *et al.* (2016) estimate from a real scene dataset and a controlled experiment a probabilistic speed-density relationship of pedestrians. Nikolić and Bierlaire (2014, 2017) build a stream-based approach and a data-driven spatio-temporal discretization framework to characterize the flow characteristics of pedestrians from Lausanne train station pedestrian trajectory data.

Besides the above contributions, It is worthy to mention some studies that might play an important role in future. This first one is that Tan *et al.* (2006) validates the utilization of a Stereo panoramic virtual reality (VR)-based system to measure pedestrian activity scheduling behavior by comparing against actual observations of activity-travel sequences of pedestrians. This study benefit us a cheaper and easier way to collect activity scheduling data. However, as the study mention, some differences still exist, which leave the opportunity to improve. Another class of study is the pedestrian detecting and tracking methodologies which convert unreadable video or data into interpretable data. Example can be found in (Nanda and Davis, 2003, Viola *et al.,* 2005, Antonini *et al.,* 2006b, Enzweiler *et al.,* 2008, Dollár *et al.,* 2012, Dehghan *et al.,* 2014, Bhadra *et al.,* 2015, Hasanova, 2017).

In addition to these researches, the collected data can also be used to validate various models that are proposed to explain the walking behavior of pedestrians (Hänseler *et al.,* 2014b, 2017a, Zhang *et al.,* 2008, Yuan *et al.,* 2016, Zhou *et al.,* 2012, Scovanner and Tappen, 2009, Antonini *et al.,* 2006a)

2.2 Pedestrian activity schedule

Pedestrian activity schedule, in general, could contain the activity choice, destination choice, mode choice, route choice, etc. we refer interested readers to Bierlaire and Robin (2009) which contributes to identify the list of choices that pedestrians are facing, summarize how each of them has been addressed in the literature, and discuss how the framework of discrete choice model may be considered in each case.

In this paper, we divide the pedestrian ASMs into two different class: heuristic (rule-based) model and exact utility maximization model. The heuristic models are based on the bounded rationality assumption of people while utility maximization model assumes that people tries to maximize their welfare when carrying out the activities. Both models have their pros and cons with which we discuss in more details.

To understand the activity schedule behaviors, it is beneficial to know the activity travel pattern adopted by people or factors that influence these patterns from the existing data. Some studies have worked on these topics. Liu *et al.* (2014) apply nested logit model to identify travelers' activity patterns by dividing the considered duration into 3 periods: before check-in, before security, and before boarding; and divides the activity into different classes. Kalakou and

Moura (2015) use a multinomial logit model to explain passengers' choices regarding activities (aeronautical and non-aeronautical activity) in the terminal. Ton *et al.* (2015) study based on empirical data the factors that influence the route and activity location choice of passengers in a train station. They find out that travel time, walking distance, train stop location alongside the platform and right side orientation of the vertical infrastructure significantly influence route choice of departing passengers, and that travel time from station entrance to the retail outlet, total distance, the requirement to make a detour for a shop visit, and right side orientation are the most important factors that influence the activity location choice. Equipped with these knowledge, we can begin to study the existing models

2.2.1 Heuristic model

Heuristic models are a class of models that determine the decision of pedestrian based on some pre-specified rules. This class of model is very suitable for multi-agent based simulation because of its easiness to implement. For example,Dijkstra *et al.* (2009, 2011) apply a perceptual field concept to pedestrian agents for modeling impulse and non-impulse store choice processes. Accordingly, they estimate from data the activation level which is a key parameter of perceptual field (Dijkstra *et al.,* 2013). Incorporating the perception field concept for activity schedule, Saarloos *et al.* (2007) build a multi-agent model which focus on the interaction between agents and environment.

There are also other heuristic models that exist in the literature. Usher *et al.* (2010) presents a rule-based, priority-given activity schedule model inside a simulator for inter-modal facilities. Each activity is attributed a priority so that high priority activities will be given a priority when time is tight. In addition, Dijkstra and Jessurun (2013), Dijkstra *et al.* (2014) simulate the planned and unplanned store visit by using Monte Carlo simulation. Moreover, Zhu and Timmermans (2009, 2011) propose and validate the so called Heterogeneous Heuristic Model which can estimate the coexistence of different decision strategies using a single model to simulate the shopping behavior of pedestrians.

From the introduction of the models, we see that different models emphasize on different aspects of pedestrian that the authors want to investigate. This makes the model unsuitable to apply directly to other situation. The perceptual field might be suitable to city center or shopping mall as pedestrians do not have a tight budget or primal target. When apply to transportation hub like train station, this model might fail as pedestrians has a primary object to catch the trainThe pure statistical models like Dijkstra and Jessurun (2013), Dijkstra *et al.* (2014) might have the same problem as same group of pedestrians might behave differently in different environment.

In addition, these models normally depend heavily and extensively on data which itself might be noisy. Therefore, a model which is flexible enough will be of great interest.

2.2.2 Utility maximization model

Based on the concept of utility maximization, Hoogendoorn and Bovy (2004) propose an activity schedule model which considers the randomness of the experienced traffic conditions. A dynamic programming is used to obtain the route choice, activity area choice, and activity scheduling. Later, Hoogendoorn and Bovy (2005) expand their former work by relaxing the discreteness assumption of the routes, which results in a dynamic mixed discrete-continuous choice problem that is analogy with stochastic control theory and dynamic programming in continuous time and space. These models are realistic as they can take the walking behavior of pedestrians and randomness of travel time into consideration.

Another aspect of pedestrian activity schedule is provided by (Zhang, 2009). In this model, activities are regarded as a consumption of goods which cost time and money while a multi-linear time-dependent utility of this consumption is assumed. In addition, the interaction between time and time, expenditure and expenditure, and time and expenditure are considered as well. Finally, a utility maximization protocol is adapted to schedule the activities. Another modeling way is the sequential activity schedule which is adopted by (Danalet *et al.,* 2013). The authors use detected campus activity-episode to build an sequential activity schedule model which determines the next location probability, and activity pattern based on current state. Same as former work, Danalet *et al.* (2016) proposed three models with different dynamic consideration and agent effect to model the activity location choice of pedestrian.

The mathematical rigorousness of utility maximization models is the main advantages of this class of activity schedule models. To obtain the finally schedule model, we need to have the utility of each activity which is normally assumed and estimated from data by now. As a result, the estimated result depends on the input data. In addition, obtaining schedule from these models relays significantly on complex computation which might be impossible for an individual to work out. Moreover, these models might also lose the power to explain pedestrians' behaviors like impulse shopping. Furthermore, individual interaction is not considered in these models. Therefore, Further development of this class of model is needed.

3 General activity schedule models

As we have seen in section 2 that further development of pedestrians ASMs are needed, this section contributes to study the ASMs existing in general setting. Since the prevailing of activity-based demand model (ABM), ASMs, a key component of ABM, are rich in number and content in literature database. Due to the capability of author and other constraints, this paper will only cover ASMs that consider congestion impact, flexible activity demand, and interaction between individuals.

3.1 Activity schedule considering congestion impact

In general, congestion would influence the travelers in two ways: the travel time to destinations, and the waiting time at destinations. Since we stand on the side of transportation, we will focus on the travel time impact of congestion in this review. In literature, there are generally two ways to consider congestion impact. One is to use time-depended link cost, while the other uses traffic assignment to estimate the link flow from which we can deduce the corresponding link travel cost. Because the methodologies adopted to address activity scheduling with congestion impact differ significantly, in this subsection, we divide the collected activity schedule models into three categories, according to the most significant characteristics of the models, in order to make the presentation clear. They are network based models, allocation resembled model, and activity-based model and assignment model integrated models

3.1.1 Models with network representation

Generally, to represent the activity scheduling process, the network should be space-time augmented network. However, exception like the super-network proposed by Liao (2011) exists. In a network, a node is generally denoted as a state while the arcs denote actions that can be taken at the nodes (states). To integrate congestion into network based representation, an easy and intuitive way is to use time-dependent travel cost. The idea is to allow the arcs which represent the same action to have different costs which depend on time dimension of the network. This idea can be verified by simply considering the fact that the travel time on a road during the peak hours is different from that during little utilization. In literature, Liao (2011) incorporate time dependent travel cost into multi-state super-networks to account for the dynamic of traffic network. Liao *et al.* (2013a) develop the super-network further to incorporate space-time constraints and embed time into disutility profiles of activity participation and parking. A year later, Liao *et al.* (2014) integrate stochastic travel time of the arc into multi-state super-network for scheduling the activities.

This super-network concept is very useful to consider various aspects of activity schedule. However, the building of such super-network is very sensitive to the number of activities, potential location choice of each activity, and mobility choices to reach the location. With the increasing of choices, the network will explode.

network representation of activity schedule can be combined with traffic assignment model to consider the congestion impact. Some examples exist. Ramadurai and Ukkusuri (2010) model the activity-travel choices using an activity-travel networks and then formulate into an equivalent variational inequality problem considering the dynamic user equilibrium. Fu and Lam (2014, 2016) integrate the activity-time-space network with the state-augmented multi-model network to explicitly model multi-model trips and individuals' activity schedules. In addition, stochastic utility of activity and congestion effect in the transit vehicles are included in the scheduling of activities. Liu and Zhou (2016) designed a transit network with the consideration of congestion (waiting) on the route.

Comparing with the time-dependent travel cost approach, traffic assignment model could provide an real-time estimation of the traffic state. This might represents a real futures activity scheduling with the assistance of transportation information system so that individuals could obtain real-time information of the traffic states. However, a combination of super-network ASMs and traffic assignment models increase the computational burden as each iteration of scheduling requires a convergence of assignment model.

3.1.2 Integrate household activity pattern problem with congestion effect

Another class of activity schedule model which was proposed by Recker (1995) resembles to a pick up and delivery problem. However, in this model, the travel time of each trip is assumed to be proportional to the distance. Recently, models, belonging to this class and considering the travel time impact of congestion, are published. Chow and Djavadian (2015) expand the HAPP model by integrating the mode choice and travel time inside the representation and mathematical formulation. Liu *et al.* (2017a) integrate the HAPP with a congested transportation networks to study the dynamic household-level equilibrium with household activity interactions.

First of all, this class of model, by its nature, considers both the interaction and congestion impact on activity scheduling. This makes the models closer to the represent real behaviors. Currently, the model requires an activity set in advance which might compromise its capability to model the impulse activities. Therefore, a further extension can be expected.

3.1.3 Models with integration of activity-based model and traffic assignment model

Within the integration of activity-based model and dynamic traffic assignment model, it can be divided into two different sub-categories. One category has a fixed activity set (equilibrium problem), while the other allows the activity set to change or has the activities generated by a simulation model according to the traffic state (fix-point problem).

For the first category, example models can be found in Lam and Huang (2002, 2003), Ramadurai and Ukkusuri (2010), Pendyala *et al.* (2012), Nuzzolo *et al.* (2012), Zockaie *et al.* (2015), Han *et al.* (2015), etc. Lam and Huang (2002) propose a dynamic equilibrium activity/travel choice model (departure time and route choice) during the morning peaks. this model is included in Lam and Huang (2003) which introduces another activity-based time-dependent equilibrium model that could finally reveal an aggregate destination and activity demand. Ramadurai and Ukkusuri (2010) model the activity-travel choices (activity location, time of participation, duration, and route choices) using an activity-travel networks. This model is formulated into an equivalent variational inequality problem considering the dynamic user equilibrium. Nuzzolo *et al.* (2012) present a dynamic assignment model for transit networks which considers the flexibility of passenger departure time, stop and runs choices. Pendyala *et al.* (2012) propose a system which involves a dynamic integration of the activity-travel demand model and the dynamic traffic assignment. Zockaie *et al.* (2015) present a framework which integrates an activity based model and a multi-criteria dynamic traffic assignment model to evaluate various pricing schemes. Han *et al.* (2015) introduces a stochastic user equilibrium model which considers the transit network with capacity constraints.

In a summary, all of these models in nature is a dynamic traffic assignment model. The outcome of these models depends on the freedoms that the authors want to investigate. Normally, they are confined in departure time choice, route choice, location choice, duration choice, etc. The activity sequences can be but seldom considered. This is because the change of the activity sequences will change the network state significantly which is not favorable to convergence of computation. In addition, these models are also incapable to model the impulse activities.

The shortcomings of above equilibrium models could be mitigated by fixed-point models which are the focus of this paragraph. With respect to the fix-point models, examples can be found in (Lin *et al.,* 2008a, Auld *et al.,* 2011, Xu *et al.,* 2017, Halat *et al.,* 2017). Lin *et al.* (2008a) integrate an activity based model (CEMDAP) and a dynamic assignment model (VISTA) to find the fixed point of activity demand and traffic states. After this, Auld *et al.* (2011) integrate a dynamic traffic assignment model into ADAPTS so as to allow the simulation of travel demand considering network condition. Xu *et al.* (2017) introduce a model which allows the integration of activity based model and dynamic traffic assignment. The expected travel time obtained from dynamic traffic assignment is used by the activity-based model to generate the travelers' individual and household activity schedules. Halat *et al.* (2017) integrate dynamic traffic assignment with activity schedule model which allows the cancellation and swapping of activities.

These models are more flexible than the equilibrium models in the sense that they allow activity set modification. This gain comes from the understanding of an additional people's behavior (activity cancellation and reschedule behavior). Good news is that we can use both the equilibrium models and fix-point models to evaluate the performance of network design even though the indexes (Total activity time versus total activity attracted) are different. The choice of the type of model to use depends on our objectives.

3.2 Activity schedule considering flexible activity demand

The models discussed above concentrate on scheduling activities. However, when it comes to execution step, possible randomnesses will make the original schedule unfeasible or not optimal anymore, in which cases rescheduling (deleting or swapping the sequences) might be needed. In addition, individuals might also insert some activities that are not planned. Therefore, it is necessary to understand how people will reschedule their activities. In a word, we consider here the models which include the inserting/deleting/swapping of activities.

3.2.1 Empirical behavior study with respect to flexible activity schedule

Before we review any specific activity reschedule model, we might need to understand firstly how people behave or percept. There are several empirical studies. For instance, Doherty and Miller (2002) focuses on basic process of activity scheduling as it occurs over time, including an examination of how far ahead decisions are made and how they are subsequently modified during their execution. The various modeling structures and decision rules incorporated in the conceptual framework are outlined and discussed. Arentze *et al.* (2004) predicted from stated data that changing route or departure time is the most important way of adapting work trips while changing route and switching to bike are the dominant responses for non-work activities. Ruiz and Timmermans (2008) focus on understanding the modification of the timing of pre-planned activities to accommodate a new activity. The result shows that the characteristics of the activities involved are the most important factors influencing the process of schedule change. Bladel *et al.* (2009) analyses the factors that influence the activity plan and activity rescheduling. The results show that activity and schedule characteristics considerably affect activity planning. The rescheduling model also has several highly significant activity and schedule attributes. Clark and Doherty (2010) tries to understand why and how people reschedule their activities, with an aim to contribute to a more realistic model for the entire schedule process, especially rescheduling and conflict resolution sub-models.

These empirical evidences show us that rescheduling activities depends on the characteristics of individuals as well as the nature of activities, and that the aspects of activities that are chosen to change depends on activity itself. These are valuable information to model activity rescheduling. A rule based reschedule model, for example, should alter the route or departure time first for work trips as suggested by (Arentze *et al.,* 2004).

3.2.2 Activity schedule models with flexible activity demand

With respect to the activity reschedule models, the main stream is based on bounded rationality assumption of individuals. This assumption differs from utility maximization assumption, which assumes that individual adopts an optimal activity schedule for the whole period considered, in that people would make a activity schedule heuristically.

Based on this concept, Timmermans *et al.* (2001) first illustrates a conceptualization and specification of the process of how individuals adjust their activity programs as a function of anticipated time pressure during the execution of the program. The adjustment is assumed to be a utility maximization process but with a bounded rationality. This paper ignite the following work of a model named Aurora. Joh *et al.* (2001) present an activity scheduling and rescheduling behavior where the decision is not make optimally but heuristically. Following, Joh *et al.* (2003) estimate the non-linear utility function of time use in the activity schedule adaptation model Aurora. After this work, Joh (2004), Joh *et al.* (2004) present how to measure activity reschedule behavior and propose a model of activity reschedule with the estimation of this model using activity-diary data. Arentze *et al.* (2005) implement a dynamic version of Aurora which allows the learning from before.

In addition to the Aurora model, other rule-based activity schedule & reschedule models are proposed in literature and implemented. Auld *et al.* (2009b,a) estimate a rule-based conflict resolution rules using decision trees, and compare its performance with the scheduling rules in TASHA. Auld and Mohammadian (2012) describe a dynamic ASM which is used in the framework of agent-based dynamic activity planning and travel scheduling (ADAPTS) model Auld and Mohammadian (2009).

These two multi-agent simulation models differ from each other in the representation of the travel time and agent interaction. In Aurora, the historical travel times are stored in the memory so that agents could take for reference when schedule of reschedule their activities. However, ADAPTS adopts a traffic assignment model to get the real-time travel time for each timestep. With respect to agent interaction, Aurora assume the activity set of each agent is independent while ADAPTS also has a household agent which could generate activity demand as well, and individual agents could have their own activity demands but are coupled with household agents. In addition, the activity generation of a individual and household are dynamic based on their recent achieved activities and needs. In Aurora, the household activity sets are given.

Besides these scheduling and rescheduling models, models based on different mechanism are also proposed. For instance, Sun *et al.* (2005) present an Bayesian-type of activity schedule framework which allows the reschedule of activities based on the updating of information (link travel time distribution, and deviation from schedules). Gan and Recker (2008) formulate the household activity rescheduling problem in a MILP format. The backbone of the reschedule model is the assumption that reschedule decisions are made to satisfy the newly emerging circumstances while trying to keep the existing preplanned schedule as much as possible intact. Arentze *et al.* (2010) Use a heuristic (iterative searching) to implement the activity reschedule, which allows the inserting or deleting of activity, re-positioning, change location or route of an activity, of an agent inside an agent based simulation network. Habib (2011) apply random utility maximization to the sequential schedule of activity choice, time and location. It is assumed at a given time step, an individual will choose an activity which gives the largest utility to perform. Halat *et al.* (2017) integrate the activity schedule with a dynamic traffic assignment model to allow the activity cancellation and swapping based on the traffic network state.

The mechanism of these models might be different, but most of the models collected focus on understanding how people would behave if there is a discrepancy between the scheduled activities and the truth. The models are important in transportation as they might allow us to predict the traffic impact of potential management measures with a careful integration with assignment models.

3.3 Activity schedule with individual interaction

Among the various interaction between individuals' activity schedule, household is the most often situation where interaction could happen. For example, there are activity distribution among household members, vehicle availability constraints, joint travel etc. Evidence from data also support this claim. He (2013) found that long working hours reduce the likelihood to escort children to school while flexible working hour offset this reduction effect. In addition, if the mother's workplace is to closer to the school, it is more likely that child will be escorted by the parents. Ta *et al.* (2016) found out that household structure make significant influence on men's and women's space-time constraints and reduces the related gender differences in daily activity participation. Social interaction between individuals can also influence the activity schedule of individuals. For example, several friends plan to have dinner and watch a move together after work might change the activity schedule significantly. This necessitate the need of an activity schedule model consider interaction.

There are generally two aspects that interaction can impact activity schedule. One is physical constraints while the other one is the desire to finish activity together. Inevitably, there are studies look at the same problem from different perspectives. Since interaction will involve at least two parties, activity schedule considering interaction will be used interchangeable with joint activity schedule.

3.3.1 Joint activity schedule – physical constraints

In reality, some joint activity schedule are originated from physical constraints (resource, time). For example, the father might drive his children to school and wife to work if there is only one car in the household. This type of scheduling problem can be regarded as a task arrangement problem since that we can regard an activity as a task that needs to be finished. The interactions between activities and individuals resemble that task can only be finished with some order or resources (people, etc.). A famous example of this class of model is the household activity pattern problem (HAPP) proposed by Recker (1995) and its variants (Kang and Recker, 2013), an integrated destination choice model-HAPP. HAPP is regarded a pickup and delivery problem with time window (PDPTW), and is formulated mathematically under different scenarios.

Following this pioneer study, Wen and Koppelman (2000) use a two-stage structure to model the activity schedule of couple. The first step is to determine the number of stops and allocation of stops and vehicles among the members. The second step is to decide number of tours to take and which tour include which stops. This is similar to a combination of cluster problem and routing problem. Miller and Roorda (2003) presents the Toronto Area Scheduling model for household Agents TASHA. This model uses the concept of 'project' to encapsulate activities with a common goal. A rule-based method is used to organize activities into projects, and then to form schedules for interacting household members. Meister *et al.* (2005) generates activity schedule by first generating the activities demand for individuals and find a schedule among household. Finally, Liu *et al.* (2017a) study the interaction (vehicle selection, mode choice, and ride-sharing options) between household members when schedule the activity pattern with a consideration of traffic. The problem is formulated into integer linear programming. The last two models differ from the other models in the sense that the activity demands are not given at a household level but at an individual level. So it is more an individuals time table coordination problem than a task allocation problem.

The advantage of this type of model is that it can incorporate explicitly the physical constraints (open hour, order of activity) and transfer into problems (task arrangement, routing) that are well studied. The outputs of these models are normally who does what at what time with what transportation, which is easily interpretable.

3.3.2 Joint activity schedule – desire propelling

From this perspective, joint activity participation is derived from the desire that individuals want to do some activity together (social activities). A couple want to see a move together after working, friends want to have a union in an evening, etc. Comparing to other independent activities, these joint activities might allow participators an additional sanctification (utility) than doing along. The general way to model this aspect is to add additional utility to joint activities. We can estimate this additional utility from data or we can specify this parameter to simulate its impact on travel schedule outcome.

Examples of this class of model are discussed below. Gliebe and Koppelman (2002) model the activity choice among household by separating the activities into independent activities and joint activity which derive positive utility. In addition, equal joint activity time among all the participants is ensured. Zhang *et al.* (2005) model the time allocation of each household members to different types of activity using a household utility maximization model with a multi-linear group utility function. The interaction is modeled through an interaction parameters. Meister *et al.* (2005) schedules the activities of a household by utility maximization with an increasing factor for joint activity. Bradley and Vovsha (2005) considers the intra-household interactions in modeling activity and travel-related decisions by takes into account added group-wise utilities of joint participation in the same activity. Ronald *et al.* (2012) proposed a social interaction model based on social networks fields and utility-based protocol to schedule the common activity. Kim and Parent (2016) develop a spatial multivariate tobit specification that allows for each individual facing a set of potential destinations to take into account the willingness to travel of other household members Fu and Lam (2016) models the time-dependent two-individual joint activity-travel patterns by a joint-activity-time-space super-network. The motivation to joint travel is modeled by an added utility factors.

A significant difference between these models is the way that they add the interaction factors. Zhang *et al.* (2005), Fu and Lam (2016) use a factor times the multiplication of individual activity utility if the activity is done jointly. Meister *et al.* (2005), Ronald *et al.* (2012) model the utility as a function of time with an augment factor 1+joint parameter which is fixed or depends on the various characteristics of activity, individual, etc. Bradley and Vovsha (2005) add a value to the joint activity rather than multiplication factor. Kim and Parent (2016) minus the social distance between oneself and the other in the utility function to enforce the interaction. Therefore, accounting for the joint activity desire by a reward can be flexible in the sense to choose the reward function.

3.3.3 Joint activity schedule from other perspectives

Despite the models we mentioned above, other models which are based on the group separation, super-network, and Markov decision process are also existed in the literature. Fang *et al.* (2011) schedule the joint activities of individuals by identifying the candidate space-time opportunities for joint participation using a concept of time-varying network-based prisms and optimal opportunities for joint participation are determined by the non-dominated sorting genetic algorithm-2 Dubernet and Axhausen (2013) present a joint activity schedule model in the microsimulation model MATSim. The joint activity schedule is achieved by a concept of group in which the individuals need to replan their activity together to comply with the constraints or to solve the inconsistency. Liao *et al.* (2013b) use super-network to model the joint-travel of individuals. Fu *et al.* (2016) formulate the series of decisions made by the household as an Markov decision process (MDP). They divide the activities into a non-compulsory activities and compulsory activities which should be completed within the planning horizon. The utility of the joint household is a combination of both individuals and the interaction term.

3.3.4 Summary

In general, models in literature that address the interaction between individuals in activity scheduling process are proposed either from the physical constraints or social desire. Some other models (super-network, MDP, etc) that do not really fit into these two categories are also discussed. By now, most of the models fail to consider the stochasticity of travel time, activity durations, or even activity choices. However, efforts to address this gap is emerging as Fu *et al.* (2016), Liu *et al.* (2017a) are example.

4 Apply general activity schedule models to pedestrian

From the review we have done, we see that the activity schedule model in pedestrian domain is relatively rare compare to the activity schedule in general setting. Therefore, this section contributes to discuss the possibility of applying the models in general setting to pedestrian.

4.1 Models considering congestion impact

Comparing with general setting where a node is generally a set of positions in vicinity, a node in a pedestrian setting generally represent a store. traffic flows in general setting can be replaced by pedestrian flows. In this sense, the activity schedule models in section 3.1 can be applied to pedestrians without significant modification. However, some cares needs to be taken.

- The super-network model proposed by Liao (2011), Liao *et al.* (2013b) can be simplified as pedestrians only involve walking as its mobility.
- When using time-dependent travel time to represent the congestion effect, the time-dependent value needs to correspond to the pedestrians network. For example, the travel time from one activity location to another activity location in a train station various with not only the time in a day but also the timetable of trains. In addition, these dependence relationship needs to be verified through empirical study of data.
- The HAPP models might not be applicable to pedestrians as pedestrians seldom allocate the task but try to walk together.
- For the activity-based and traffic assignment models, we might pay special attention to the traffic assignment models. Compare to traffic, pedestrians are even more complex because of their characteristics and flexibility of walking area than the lanes.

- Probably, an important factor that we need to consider when applying the activity schedule models to pedestrians is the congestion impact on the service level in the store where queue might be formed. This phenomenon might be handled in the location choice model of pedestrian activity scheduling model.

4.2 Models considering flexible activity impact

Pedestrians are more likely to be flexible in their activity rescheduling than vehicle travelers as it might not cost too much to add one additional event. In literature, many studies Bayley and Nancarrow (1998), Crawford and Melewar (2003), Lin and Chen (2013), Gutierrez and Gutierrez (2002), Strack *et al.* (2006) have been undertaken to understand the importance of impulse shopping in airports, supermarkets, etc. It is in a consensus that impulse shoppings (which means inserting activities in our case) is an significant component of shopping behavior. Therefore, taking this impulse activity into consideration is of great importance to pedestrian activity schedule model.

As reviewed in section 3.2, most of the models in literature use heuristic rules to model the activity rescheduling behaviors. For the simulation purpose of pedestrian behavior, this class of model might be favorable, which is consistent to the phenomenon that most of the activity schedule models existing in pedestrian domain are heuristic based Dijkstra *et al.* (2009, 2011), Saarloos *et al.* (2007). The challenge here might be understanding the rules that govern the inserting/deleting/swapping of activity scheduling behavior. Moreover, incorporating a congestion level of stores which reveal the potential waiting time required might make the model more realistic. This is because pedestrian could go to finish another activity in the vicinity of current position and come back again with the potential to gain more utility.

In spite of simulating the activity of each individuals, understanding the fixed point of the activity demands and supply is also critical to the design of facilities. In general setting, Halat *et al.* (2017) proposed a combination of activity reschedule model and dynamic traffic assignment. This framework could suit the pedestrian background as well. The challenges might lie in the fact that pedestrian might change their activity schedule more dramatically than vehicle traveler which might cause convergence problem (slow convergence if converge) to the frameworks. Therefore, further contribution can be made in making such framework convergence better and quickly.

4.3 Models considering joint travel impact

In the context of pedestrian, interaction between individuals also play an very important role. For example, it is normal that family, friends, or colleagues go to airports to travel together. In city center, family and friends might also go shopping or other leisure activities jointly. Thus, understanding the joint activity schedule among pedestrians is crucial. However, the interaction among pedestrians are more probably originated from the desire rather than the allocation of activities or resources. Under this assumption, we will focus on the adaptation of activity schedule models listed in section 3.3.2.

As reviewed, the fundamental idea in this class of modeling is the additional reward of joint activities to each individual. It is necessary to point out that the models in the literature assume that all parties of the individual will perform the same activity. However, in pedestrian setting, this assumption might not hold. For instance, in the context of shopping in city center, one of two friends wants to buy clothes while the other one wants to buy books. It is very likely that these two individuals will visit both cloth stores and book stores together. Both individuals get the utility being together for two activities while each one get utility from finishing their corresponding activity. In this context, we need to adapt the models which allows scheduling the union of activity sets of all individuals together while considering their preference separately.

5 Summary

This paper begins with a review of the activity schedule models in pedestrian domain and general setting with a specific focus on the models which consider the congestion impact, flexible demand, and interaction between individuals. Then, the potential application of the activity schedule models in general settings to pedestrians specifically is investigated. Finally, some interesting research gaps are found.

In general setting, even though the rich of the activity schedule models existed in literature, only a few study from Halat *et al.* (2017), Liu *et al.* (2017b), Fu and Lam (2016) cover congestion effect, flexible demand, and interaction jointly. None of the paper cover all the three aspect together, this is a gap that needs to be filled. In addition, applying and proposing activity schedule models to pedestrian domain is full of opportunity. For example, integrating the congestion and/or interaction concepts in to the pedestrian heuristic models can contribute to a more realistic model. With in mind that pedestrians activities does not show a regular dynamic as general activities, modifying heuristic models from general setting to pedestrians could also be another interesting direction. Especially to us, the models which can incorporate as much aspects as possible together and allow the evaluation of the performance of pedestrian network are of primary needed.

6 References

Alahi, A., M. Bierlaire and P. Vandergheynst (2014) Robust real time pedestrians detection in urban environments with low resolution cameras, *Transportation Research Part C: Emerging Technologies*, **39**, 113–128, ISSN 0968090X.

Antonini, G., M. Bierlaire and M. Weber (2006a) Discrete choice models of pedestrian walking behavior, *Transportation Research Part B: Methodological*, **40** (8) 667–687, ISSN 01912615.

Antonini, G., S. V. Martinez, M. Bierlaire and J. P. Thiran (2006b) Behavioral priors for detection and tracking of pedestrians in video sequences, *International Journal of Computer Vision*, **69** (2) 159–180, ISSN 09205691.

Arentze, T., F. Hofman and H. Timmermans (2004) Predicting multi-faceted activity-travel adjustment strategies in response to possible congestion pricing scenarios using an Internet-based stated adaptation experiment, *Transport Policy*, **11** (1) 31–41, ISSN 0967070X.

Arentze, T., C. Pelizaro and H. Timmermans (2010) An agent-based micro-simulation framework for modelling of dynamic activity-travel rescheduling decisions, *International Journal of Geographical Information Science*, **24** (8) 1149–1170, ISSN 13658816.

Arentze, T., C. Pelizaro and H. J. Timmermans (2005) Implementation of a model of dynamic activity-travel rescheduling decisions: an agent based micro-simulation framework, paper presented at the *Proceedings of the Computers in Urban Planning and Urban Management Conference*, vol. 48, 1–16.

Auld, J., M. Javanmardi and A. K. Mohammadian (2011) Integration of Activity Scheduling and Traffic Assignment in the ADAPTS Activity-based Model, *Trb*, 1–19.

Auld, J. and A. Mohammadian (2009) Framework for the development of the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model, *Transportation Letters*, **1** (3) 245–255, jul 2009, ISSN 1942-7867.

Auld, J., A. Mohammadian and M. Roorda (2009a) Implementation of Scheduling Conflict

Resolution Model in Activity-Scheduling System, *Transportation Research Record: Journal of the Transportation Research Board*, **2135**, 96–105, ISSN 0361-1981.

Auld, J. and A. K. Mohammadian (2012) Activity planning processes in the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model, *Transportation Research Part A: Policy and Practice*, **46** (8) 1386–1403, ISSN 09658564.

Auld, J., A. K. Mohammadian and S. T. Doherty (2009b) Modeling activity conflict resolution strategies using scheduling process data, *Transportation Research Part A: Policy and Practice*, **43** (4) 386–400, ISSN 09658564.

Bayley, G. and C. Nancarrow (1998) Impulse purchasing: a qualitative exploration of the phenomenon, *Qualitative Market Research: An International Journal*, **1** (2) 99–114, ISSN 1352-2752.

Bhadra, T., J. Sonar, A. Sarmah and C. J. Kumar (2015) Pedestrian Detection: A Survey of Methodologies, Techniques and Current Advancements, *International journal of Scientific research Engineering & technology*, **4** (1) 31–36.

Bhat, C. R. and F. S. Koppelman (1999) Activity-Based Modeling of Travel Demand, 35–61, ISBN 978-1-4020-7246-8.

Bierlaire, M., J. Chen and J. Newman (2013) A probabilistic map matching method for smartphone GPS data, *Transportation Research Part C: Emerging Technologies*, **26**, 78–98, ISSN 0968090X.

Bierlaire, M. and T. Robin (2009) Pedestrians Choices, in *Pedestrian Behavior: Models data collection and applications*, 1–26, ISBN 978-1-84855-750-5.

Bladel, K. V., T. Bellemans and D. Janssens (2009) Activity-Travel Planning and Rescheduling Behavior : an Empirical Analysis of Influencing Factors, 1–22.

Bradley, M. and P. Vovsha (2005) A model for joint choice of daily activity pattern types of household members, *Transportation*, **32** (5) 545–571, ISSN 00494488.

Chan, K. S., W. H. K. Lam, L. Q. Ouyang and S. C. Wong (2007) Simultaneous Estimation of the Pedestrian Origin-Destination Matrix and Parameter of the Activity/Destination Choice Model, *Journal of the Eastern Asia Society for Transportation Studies*, **7**, 1760–1773.

Chen, J. and M. Bierlaire (2015) Probabilistic multimodal map matching with rich smartphone data, *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, **19** (2) 134–148, ISSN 15472442.

Chow, J. Y. J. and S. Djavadian (2015) Activity-based Market Equilibrium for Capacitated Multimodal Transport Systems, *Transportation Research Procedia*, **7**, 2–23, ISSN 23521465.

Clark, A. F. and S. T. Doherty (2010) A multi-instrumented approach to observing the activity rescheduling decision process, *Transportation*, **37** (1) 165–181, ISSN 00494488.

Clifton, K. J., P. A. Singleton, C. D. Muhs and R. J. Schneider (2016) Development of destination choice models for pedestrian travel, *Transportation Research Part A: Policy and Practice*, **94**, 255–265, ISSN 09658564.

Crawford, G. and T. C. Melewar (2003) The importance of impulse purchasing behaviour in the international airport environment, *Journal of Consumer Behaviour*, **3** (1) 85–98, ISSN 1472-0817.

Danalet, A. (2015) Activity choice modeling for pedestrian facilities, Ph.D. Thesis, ENAC, Lausanne.

Danalet, A., B. Farooq and M. Bierlaire (2013) Towards an activity based model for pedestrian facilities, *13th Swiss Transport Research Conference (STRC)*, (April) 1–33.

Danalet, A., B. Farooq and M. Bierlaire (2014) A Bayesian approach to detect pedestrian destination-sequences from WiFi signatures, *Transportation Research Part C: Emerging Technologies*, **44** (Supplement C) 146–170, ISSN 0968-090X.

Danalet, A., L. Tinguely, M. D. Lapparent and M. Bierlaire (2016) Location choice with longitudinal WiFi data, *Journal of Choice Modelling*, **18**, 1–17, ISSN 17555345.

Dehghan, A., H. Idrees, A. R. Zamir and M. Shah (2014) Automatic Detection and Tracking of Pedestrians in Videos with Various Crowd Densities, in *Pedestrian and Evacuation Dynamics 2012*, 3–19, Springer International Publishing, Cham, ISBN 978-3-319-02446-2.

Dijkstra, J. and J. Jessurun (2013) Modeling Planned and Unplanned Store Stops for the Scenario Based Simulation of Pedestrian Activity in City Centers, (November 2014) 107–112.

Dijkstra, J., J. Jessurun, H. Timmermans and B. De Vries (2011) A framework for processing agent based pedestrian activity simulations in shopping environments, *Cybernetics and Systems*, **42** (7) 526–545, ISSN 01969722.

Dijkstra, J., H. Timmermans and B. de Vries (2009) Modeling Impulse and Non-Impulse Store Choice Processes in a Multi Agent Simulation of Pedestrian Activity in Shopping Environments, in *Pedestrian Behavior*, vol. 74, 63–85, Emerald Group Publishing Limited, nov 2009, ISBN 978-1-848-55750-5.

Dijkstra, J., H. Timmermans and J. Jessurun (2014) Modeling planned and unplanned store visits within a framework for pedestrian movement simulation, *Transportation Research Procedia*, **2**, 559–566, ISSN 23521465.

Dijkstra, J., H. J. Timmermans and B. de Vries (2013) Activation of Shopping Pedestrian Agents-Empirical Estimation Results, *Applied Spatial Analysis and Policy*, **6** (4) 255–266, ISSN 1874463X.

Doherty, S. and E. Miller (2002) a Conceptual Model on the Weekly Household Activity-Travel Scheduling Process, *Travel behaviour: spatial . . .* , (January) 1–30.

Dollár, P., C. Wojek, B. Schiele and P. Perona (2012) Pedestrian Detection: An Evaluation of the State of the Art., *IEEE Trans. on Pattern Analysis and Machine Intelligence*, **34** (4) 743 – 761, ISSN 1939-3539.

Dubernet, T. and K. W. Axhausen (2013) Including joint decision mechanisms in a multiagent transport simulation, *Transportation Letters*, **5** (4) 175–183, ISSN 1942-7867.

Enzweiler, M., M. Enzweiler, D. M. Gavrila, D. M. Gavrila, P. A. Group, P. A. Group, C. Science, C. Science, E. Perception, E. Perception, G. Research, G. Research, D. Ag, D. Ag, W. R. St, W. R. St, S. J. Amsterdam and S. J. Amsterdam (2008) Monocular Pedestrian Detection: Survey and Experiments, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 1–35.

Fang, Z., W. Tu, Q. Li and Q. Li (2011) A multi-objective approach to scheduling joint participation with variable space and time preferences and opportunities, *Journal of Transport Geography*, **19** (4) 623–634, ISSN 09666923.

Fetiarison, M., G. Flötteröd and M. Bierlaire (2010) Evaluation of pedestrian data collection methods within a simulation framework, *Swiss Transport Research Conference*, (September) 20.

Fu, X., W. H. Lam and Y. Xiong (2016) Modelling intra-household interactions in household's activity-travel scheduling behaviour, *Transportmetrica A: Transport Science*, **12** (7) 612–628, ISSN 23249943.

Fu, X. and W. H. K. Lam (2014) A network equilibrium approach for modelling activity-travel pattern scheduling problems in multi-modal transit networks with uncertainty, *Transportation*, **41** (1) 37–55, jan 2014, ISSN 0049-4488.

Fu, X. and W. H. K. Lam (2016) Modelling joint activity-travel pattern scheduling problem in multi-modal transit networks.

Gan, L. P. and W. Recker (2008) A mathematical programming formulation of the household activity rescheduling problem, *Transportation Research Part B: Methodological*, **42** (6) 571–606, ISSN 01912615.

Garling, T., M.-P. Kwan and R. Golledge (1994) Computational-Process Household Activity Modelling, **28** (5) 355–364.

Gliebe, J. P. and F. S. Koppelman (2002) A model of joint activity participation between household members, *Transportation*, **29**, 49–72, ISSN 0049-4488.

Gutierrez, B. E. N. P. B. and B. P. B. Gutierrez (2002) Planned versus impulse buying: implications to retail search strategies, *Strategies*, (0205).

Habib, K. N. (2011) A random utility maximization (RUM) based dynamic activity scheduling model: Application in weekend activity scheduling, *International Abstracts in Operations Research*, **62** (2), apr 2011, ISSN 0020-580X.

Halat, H., H. S. Mahmassani, A. Zockaie and P. Vovsha (2017) Activity Cancellation and Rescheduling by Stressed Households, *Transportation Research Record: Journal of the Transportation Research Board*, **2664**, 100–109.

Han, B., W. Zhou, D. Li and H. Yin (2015) Dynamic Schedule-Based Assignment Model for Urban Rail Transit Network with Capacity Constraints, *The Scientific World Journal*, **2015**, 1–12, ISSN 2356-6140.

Hänseler, F., N. Molyneaux, M. Bierlaire and A. Stathopoulos (2014a) Schedule based estimation of pedestrian demand withing a railway station, *14th Swiss Transport Research Conference (STRC)*, (May).

Hänseler, F. S., M. Bierlaire, B. Farooq and T. Mühlematter (2014b) A macroscopic loading model for time-varying pedestrian flows in public walking areas, *Transportation Research Part B: Methodological*, **69**, 60–80, ISSN 01912615.

Hänseler, F. S., W. H. Lam, M. Bierlaire, G. Lederrey and M. Nikolić (2017a) A dynamic network loading model for anisotropic and congested pedestrian flows, *Transportation Research Part B: Methodological*, **95**, 149–168, ISSN 01912615.

Hänseler, F. S., N. A. Molyneaux and M. Bierlaire (2015) Estimation of pedestrian origin destination demand in railway stations, *TRANSP-OR Report*, (150703), ISSN 0041-1655.

Hänseler, F. S., N. A. Molyneaux and M. Bierlaire (2017b) Estimation of Pedestrian Origin Destination Demand in Train Stations, *Transportation Science*, **51** (3) 981–997, ISSN 0041-1655.

Hasanova, A. (2017) Pedestrian Detection and Tracking in Urban Context Using a Mono-Camera.

He, S. Y. (2013) Will you escort your child to school? The effect of spatial and temporal constraints of parental employment, *Applied Geography*, **42**, 116–123, ISSN 01436228.

Hogan, C., R. Mendelsohn, P. Kurukulasuriya, A. Basist, F. Kogan, C. Williams, D. Puccinelli, M. Haenggi, S. Magazine, D. S. Arjun, A. Bala, V. Dwarakanath, K. S. Sampada, B. B. Prahlada, H. Pasupuleti, A. Baggio, S. M. Saad, L. M. Kamarudin, K. Kamarudin, W. M. Nooriman, A. Zakaria, M. N. Jaafar, G. Bakul, D. Singh and D. Kim (2015) Ubiquitous Monitoring of Pedestrian Dynamics, **11** (2) 1065–1068.

Hoogendoorn, S. P. and P. H. Bovy (2004) Pedestrian route-choice and activity scheduling theory and models, *Transportation Research Part B: Methodological*, **38** (2) 169–190, ISSN 01912615.

Hoogendoorn, S. P. and P. H. L. Bovy (2005) Pedestrian travel behavior modeling, *Networks and Spatial Economics*, **5** (2) 193–216, ISSN 1566113X.

Joh, C.-H. (2004) *Measuring and predicting adaptation in multi-dimensional activity patterns*, ISBN 9068145770.

Joh, C.-h., T. Arentze and H. Timmermans (2003) Estimating non-linear utility functions of time use in the context of an activity schedule adaptation model, *10th International Conference on Travel Behaviour Research*, (August) 10–15.

Joh, C.-H., T. Arentze and H. Timmermans (2004) Activity-Travel Scheduling and Rescheduling Decision Processes: Empirical Estimation of Aurora Model, *Transportation Research Record*, **1898** (1) 10–18, ISSN 0361-1981.

Joh, C. H., T. A. Arentze and H. J. P. Timmermans (2001) Understanding activity scheduling and rescheduling behaviour: Theory and numerical illustration, *GeoJournal*, **53** (4) 359–371, ISSN 03432521.

Kalakou, S. and F. Moura (2015) Modelling passengers' activity choice in airport terminal before the security checkpoint: The case of portela airport in Lisbon, *Transportation Research Procedia*, **10** (July) 881–890, ISSN 23521465.

Kang, J. E. and W. Recker (2013) The location selection problem for the household activity pattern problem, *Transportation Research Part B: Methodological*, **55**, 75–97, ISSN 01912615.

Kim, C. and O. Parent (2016) Modeling individual travel behaviors based on intra-household interactions, *Regional Science and Urban Economics*, **57**, 1–11, ISSN 18792308.

Lam, W. H. K. and H.-j. Huang (2002) A combined activity / travel choice model for congested road, *Transportation*, **29** (Bhat 1997) 5–29, ISSN 00494488.

Lam, W. H. K. and H.-J. Huang (2003) Combined Activity/Travel Choice Models: Time-Dependent and Dynamic Versions, *Networks and Spatial Economics*, **3**, 323–347.

Liao, F. (2011) Incorporating time dependent link costs in multi-state supernetworks, paper presented at the *6th International Conference of Hong Kong Society for Transportation Studies (HKSTS)*.

Liao, F., T. Arentze and H. Timmermans (2013a) Incorporating space-time constraints and activity-travel time profiles in a multi-state supernetwork approach to individual activity-travel scheduling, *Transportation Research Part B: Methodological*, **55**, 41–58, ISSN 01912615.

Liao, F., T. Arentze and H. Timmermans (2013b) Multi-state supernetwork framework for the two-person joint travel problem, *Transportation*, **40** (4) 813–826, ISSN 00494488.

Liao, F., S. Rasouli and H. Timmermans (2014) Incorporating activity-travel time uncertainty and stochastic space-time prisms in multistate supernetworks for activity-travel scheduling, *International Journal of Geographical Information Science*, **28** (5) 928–945, ISSN 13623087.

Lin, D.-Y., N. Eluru, S. Waller and C. Bhat (2008a) Integration of activity-based modeling and dynamic traffic assignment, *Transportation Research Record: Journal of the Transportation Research Board*, (2076) 52–61.

Lin, D.-Y., N. Eluru, S. T. Waller and C. R. Bhat (2008b) Integration of Activity-Based Modeling and Dynamic Traffic Assignment, *Transportation Research Record: Journal of the Transportation Research Board*, **2076**, 52–61, ISSN 0361-1981.

Lin, Y. H. and C. F. Chen (2013) Passengers' shopping motivations and commercial activities at airports The moderating effects of time pressure and impulse buying tendency, *Tourism Management*, **36**, 426–434, ISSN 02615177.

Liu, J., J. E. Kang, X. Zhou and R. Pendyala (2017a) Network-oriented Household Activity Pattern Problem for System Optimization, *Transportation Research Procedia*, **23**, 827–847, ISSN 23521465.

Liu, J. and X. Zhou (2016) Capacitated transit service network design with boundedly rational agents, *Transportation Research Part B: Methodological*, **93**, 225–250, ISSN 01912615.

Liu, X., J. M. Usher and L. Strawderman (2014) An analysis of activity scheduling behavior of airport travelers, *Computers and Industrial Engineering*, **74** (1) 208–218, ISSN 03608352.

Liu, Y., X. Weng, J. Wan, X. Yue, H. Song and A. V. Vasilakos (2017b) Exploring data validity in transportation systems for smart cities, *IEEE Communications Magazine*, **55** (5) 26–33, ISSN 01636804.

Meister, K., M. Frick and K. W. Axhausen (2005) A GA-based household scheduler, *Transportation*, **32** (5) 473–494, ISSN 00494488.

Miller, E. and M. Roorda (2003) Prototype Model of Household Activity-Travel Scheduling, *Transportation Research Record: Journal of the Transportation Research Board*, **1831** (May) 114–121, ISSN 0361-1981.

Nanda, H. and L. Davis (2003) Probabilistic template based pedestrian detection in infrared videos, *IEEE Intelligent Vehicles Symposium, Proceedings*, **1**, 15–20.

Nikolić, M. and M. Bierlaire (2014) Pedestrian oriented flow characterization, *Transportation Research Procedia*, **2** (0) 359–366, ISSN 23521465.

Nikolić, M. and M. Bierlaire (2017) Data driven spatio temporal discretization for pedestrian flow characterization, *Transportation Research Procedia*, **23**, 188–207, ISSN 23521465.

Nikolić, M., M. Bierlaire, B. Farooq and M. de Lapparent (2016) Probabilistic speed density relationship for pedestrian traffic, *Transportation Research Part B: Methodological*, **89**, 58–81, ISSN 01912615.

Nuzzolo, A., U. Crisalli and L. Rosati (2012) A schedule-based assignment model with explicit capacity constraints for congested transit networks, *Transportation Research Part C: Emerging Technologies*, **20** (1) 16–33, feb 2012, ISSN 0968090X.

Pendyala, R., K. Konduri, Y.-C. Chiu, M. Hickman, H. Noh, P. Waddell, L. Wang, D. You and B. Gardner (2012) Integrated Land Use-Transport Model System with Dynamic Time-Dependent Activity-Travel Microsimulation, *Transportation Research Record: Journal of the Transportation Research Board*, **2303**, 19–27, ISSN 0361-1981.

Ramadurai, G. and S. Ukkusuri (2010) Dynamic User Equilibrium Model for Combined Activity-Travel Choices Using Activity-Travel Supernetwork Representation, *Networks and Spatial Economics*, **10** (2) 273–292, jun 2010, ISSN 1566-113X.

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

Recker, W. (1995) The household activity pattern problem: General formulation and solution, *Transportation Research Part B: Methodological*, **29** (1) 61–77, ISSN 01912615.

Ronald, N., T. Arentze and H. Timmermans (2012) Modeling social interactions between individuals for joint activity scheduling, *Transportation Research Part B: Methodological*, **46** (2) 276–290, ISSN 01912615.

Ruiz, T. and H. Timmermans (2008) Changing the duration of activities in resolving scheduling conflicts, *Transportation Research Part A: Policy and Practice*, **42** (2) 347–359, ISSN 09658564.

Saarloos, D., A. Fujiwara and J. Zhang (2007) the Interaction Between Pedestrians and Facilities in Central Business Districts : an Explorative Case Study, *Journal of the Eastern Asia Society for Transportation Studies*, **7**, 1870–1885.

Saarloos, D., C. H. Joh, J. Zhang and A. Fujiwara (2010) A segmentation study of pedestrian weekend activity patterns in a central business district, *Journal of Retailing and Consumer Services*, **17** (2) 119–129, ISSN 09696989.

Scovanner, P. and M. Tappen (2009) Learning pedestrian dynamics from the world, *Proc. International Conference on Computer Vision*, 381–388.

Strack, F., L. Werth' and R. Deutsch (2006) Reflective and Impulsive Determinants of Consumer Behavior, *Journal of Consumer Psychology*, **16** (3) 205–216, jan 2006, ISSN 10577408.

Sun, Z., T. Arentze and H. Timmermans (2005) Modeling the Impact of Travel Information on Activity-Travel Rescheduling Decisions Under Conditions of Travel Time Uncertainty, *Transportation Research Record: Journal of the Transportation Research Board*, **1926** (February) 79–87, ISSN 0361-1981.

Ta, N., M. P. Kwan, Y. Chai and Z. Liu (2016) Gendered Space-Time Constraints, Activity Participation and Household Structure: A Case Study Using A GPS-Based Activity Survey in Suburban Beijing, China, *Tijdschrift voor Economische en Sociale Geografie*, **107** (5) 505–521, ISSN 14679663.

Tan, A. A., B. de Vries and H. J. Timmermans (2006) Using a stereo panoramic interactive navigation system to measure pedestrian activity scheduling behaviour: A test of validity, *Environment and Planning B: Planning and Design*, **33** (4) 541–557, ISSN 02658135.

Timmermans, H., T. Arentze and C.-h. Joh (2001) Modelling the effects of anticipated time pressure on the execution of activity programs, paper presented at the *ANnual meeting of the transportation research board*, no. January, 1–15.

Timmermans, H. J. and J. Zhang (2009) Modeling household activity travel behavior: Examples of state of the art modeling approaches and research agenda, *Transportation Research Part B: Methodological*, **43** (2) 187–190, ISSN 01912615.

Ton, D., W. Daamen, S. Hoogendoorn and A. Central (2015) Route and Activity Location Choice Behaviour of Departing Passengers, (september) 1–21.

Usher, J. M., E. Kolstad and X. Liu (2010) Simulation of Pedestrian Behavior in Intermodal Facilities, *International Journal of Agent Technologies and Systems*, **2** (3) 66–82, ISSN 1943-0744.

Viola, P., O. M. Way, M. J. Jones and D. Snow (2005) Detecting pedestrian using patterns of motion and appearance., *International Journal of Computer Vision.*, **63** (2) 153–161.

Weidmann, U. (2012) *Evacuation*, ISBN 9783319024462.

Wen, C. H. and F. S. Koppelman (2000) A conceptual and methdological framework for the generation of activity-travel patterns, *Transportation*, **27** (1) 5–23, ISSN 0049-4488.

Xu, X. A., A. Zockaie, H. S. Mahmassani, H. Halat, Ö. Verbas, M. Hyland, P. Vovsha and J. Hicks (2017) Schedule Consistency for Daily Activity Chains in Integrated Activity-Based

Dynamic Multimodal Network Assignment, *Transportation Research Record: Journal of the Transportation Research Board*, **2664** (2664) 11–22, ISSN 0361-1981.

Yuan, Y., W. Daamen, D. Duives and S. Hoogendoorn (2016) Comparison of three algorithms for real-Time pedestrian state estimation - Supporting a monitoring dashboard for large-scale events, *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, 2601–2606.

Zhang, J. (2009) A Model of Time Use and Expenditure of Pedestrians in City Centers, in *PEDESTRIAN BEHAVIOR: MODELS, DATA COLLECTION AND APPLICATIONS*, 157–193, ISBN 978-1-84855-750-5.

Zhang, J., H. J. Timmermans and A. Borgers (2005) A model of household task allocation and time use, *Transportation Research Part B: Methodological*, **39** (1) 81–95, ISSN 01912615.

Zhang, Q., B. Han and D. Li (2008) Modeling and simulation of passenger alighting and boarding movement in Beijing metro stations, *Transportation Research Part C: Emerging Technologies*, **16** (5) 635–649, oct 2008, ISSN 0968090X.

Zhou, B., X. Wang and X. Tang (2012) Understanding collective crowd behaviors: Learning a Mixture model of Dynamic pedestrian-Agents, *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2871–2878, ISSN 10636919.

Zhu, W. and H. Timmermans (2009) Modeling and Simulating Pedestrian Shopping Behavior Based on Principles of Bounded Rationality, *Pedestrian Behavior: Models, Data Collection and Applications*, 137–155.

Zhu, W. and H. Timmermans (2011) Modeling pedestrian shopping behavior using principles of bounded rationality: Model comparison and validation, *Journal of Geographical Systems*, **13** (2) 101–126, ISSN 14355930.

Zockaie, A., M. Saberi, H. S. Mahmassani, L. Jiang, A. Frei and T. Hou (2015) Activity-Based Model with Dynamic Traffic Assignment and Consideration of Heterogeneous User Preferences and Reliability Valuation, *Transportation Research Record: Journal of the Transportation Research Board*, **2493**, 78–87, jan 2015, ISSN 0361-1981.